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DETECTION OF LIKURAI DANCE MOVEMENT TYPES IN MALAKA REGENCY USING YOLOV8 BASED ON VIDEO

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Abstract

Indonesia is rich in traditional dances from every region, including the Likurai Dance, originating from East Nusa Tenggara, specifically in Malaka and Belu districts. This dance carries deep symbolic and historical meaning; however, it is currently threatened by lifestyle changes and globalization. Despite this, accurately and in real-time recognizing Likurai Dance movements remains challenging, particularly in detecting the specific dance movements. This research aims to test the effectiveness of detecting three types of Likurai Dance movements using documented digital video. The detection model is the YOLOv8 algorithm, known for detecting objects quickly and accurately. A YOLOv8-based platform is proposed to detect these dance movements precisely. In the testing, the YOLOv8 model demonstrated outstanding performance, achieving a very high mAP of 99.5% for the Wesei Wehali movement, 99.4% for the Be Tae Be Tae movement, and 99.1% for the Tebe Re movement. These results indicate that the model can detect dance movements with exceptional accuracy, precision, and recall rates above 98%. This research concludes that YOLOv8 has excellent potential in detecting traditional dance movements with high accuracy. These findings are significant for preserving and documenting the Likurai Dance and provide an educational means for younger generations to understand better and appreciate traditional cultural values.

Keywords: *YOLOv8, Movement Detection, Likurai Dance, Digital Video*

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1. INTRODUCTION

The Likurai Dance is a traditional dance rich in symbolism and historical meaning. Its origins can be traced back to the era of kingdoms, where it was performed during significant ceremonies such as the reception of distinguished guests and victory celebrations [1]. The movements in this dance, such as 'wesei wehali,' 'tebe re,' and 'be tae be tae toba lutuhun,' each carry profound symbolic meanings, reflecting local stories and cultural values. However, the passage of time has brought significant changes, with the Likurai Dance now being enjoyed and participated in by a broader audience[2]. This reflects a paradigm shift, where involvement in the Likurai dance is no longer exclusive to the noble classes but has opened up to participation from all societal layers in Belu and Malaka [3].

This means that the Likurai Dance is no longer restricted to the Feto-feto noble class; instead, the general public can partake in performing the dance according to specific contexts and needs. For example, the Likurai Dance is now not only part of the ceremonial reception for prominent figures such as the President, Governor, or Regent but has also become an integral part of events like the procession of a new imam, the reception of a bishop, and is recognized as an artistic expression in various activities related to victories and celebrations [4] [5]. This change characterizes the adaptation and evolution of the Likurai Dance in responding to important events and activities celebrating success and joy in the local community. The dance features graceful and rhythmic movements synchronized with traditional music, and it holds significant cultural and symbolic values for the community [3]. Cultural heritage, as an integral part of cultural arts, involves knowledge, skills, traditions, and objects passed down from one generation to the next [6].

However, with the passage of time and the influence of globalization, many cultural traditions, including the Likurai Dance, have begun to be marginalized. Changes in lifestyle, urbanization, and modernization have reduced participation in this dance, leading to a decreasing interest in preserving it. As a result, the continuity of the dance has become increasingly critical and requires more attention to ensure its preservation[7] [8].

Modern technology, particularly in the fields of artificial intelligence (AI) and machine learning (ML), offers innovative solutions to this problem. One of the highly potential technologies is YOLO (You Only Look Once), an object detection algorithm capable of analyzing movements in video with high accuracy. By using YOLOv8, we can document, analyze, and understand the movement patterns of the Likurai Dance in more depth and accuracy[9] [10].

Research on "Multi-person Dance Tiered Posture Recognition with Cross Progressive Multi-resolution Representation Integration" by Kao [11] developed a new method for recognizing multi-person dance postures. This research employs the YOLOv8 algorithm to detect dancer bounding boxes, followed by HRNet as the backbone network to handle scale variations. The CPMRI method integrates multi-scale features, while the TPR module addresses pose distortions and obstructions. As a result, this approach achieved an mAP of 75.7% on the MSCOCO2017 dataset, demonstrating significant improvements in accuracy and robustness in dance pose recognition compared to other methods. Further research by Pang & Niu [12] on "Dance Video Motion Recognition Based on Computer Vision and Image Processing" developed a motion recognition method using self-organizing mapping (SOM) neural networks. Simulation results showed an accuracy 9.34% higher compared to traditional methods. Additionally, research conducted by Yovi Apridiansyah et al. [13] on image processing based on video processing using the frame difference method for motion detection achieved 16 out of 20 test data correctly detected (True Positive), with 2 test data resulting in False Positive errors and 2 test data resulting in False Negative errors. The accuracy percentage from confusion matrix testing shows precision of 88%, recall of 88%, and overall accuracy of 80%. Further research by Ji & Tian [14] on "IoT-Based Dance Movement Recognition Model Based on Deep Learning Framework" utilized Convolutional Neural Networks (CNN) to extract features from movement data collected by IoT devices, namely three accelerometers recording 3D movements. After feature extraction, Multi-Layer Perceptron (MLP) was used to classify dance movements. The model was tested on a standard dataset including 16 dance steps with three different speeds. The evaluation showed impressive model performance, with an accuracy of 90.74%, precision of 87.12%, recall of 83.78%, and F1-score of 84.39%.

The YOLOv8 method has several advantages over the methods mentioned in these studies. Firstly, YOLOv8 can detect dancer bounding boxes with high accuracy and real-time efficiency, which is crucial for video applications such as dance posture recognition. Its high detection speed makes it superior in processing data quickly and effectively, unlike methods such as Support Vector Machine (SVM) or Random Forest that may not be as fast and efficient in real-time object detection.

Moreover, YOLOv8 excels in detecting multiple objects simultaneously with high accuracy, making it very effective for identifying and analyzing multiple dancers concurrently. Integration with HRNet as the backbone network enhances robustness and accuracy, surpassing simpler video processing methods like frame difference. Consequently, this approach achieved an mAP of 75.7% on the MSCOCO2017 dataset, reflecting significant improvements in accuracy and robustness in pose recognition compared to other methods. This combination of features makes YOLOv8 superior in terms of accuracy, speed, and robustness.

Based on the previous explanation, numerous studies have been conducted on object detection for dance recognition, but the speed and accuracy in capturing movements are still not optimal. Several methods, such as SVM, CNN, and frame difference, face challenges in detection effectiveness. Therefore, this research will focus on recognizing Likurai Dance movements using digital video, through the modification of the YOLOv8 architecture to improve accuracy and speed in object detection.

Implementing this technology not only aids in documenting and preserving dance movements but also provides a deeper understanding of the artistic and cultural values embedded within them. Additionally, this technology can serve as an educational tool for younger generations to learn about and appreciate their cultural heritage.

Thus, this research not only addresses the technical aspects of detecting dance movements but also explores how technology can partner in maintaining the sustainability and relevance of traditional dance arts. Through this research, it is hoped that new perspectives and innovative solutions will emerge to support the preservation of cultural arts in Indonesia, particularly the Likurai Dance in Malaka Regency.

2. RESEARCH METHOD

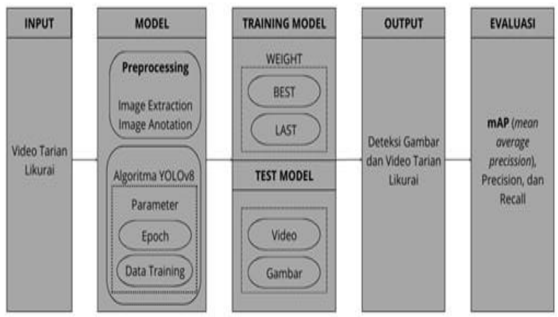

Figure 1. The Model of the Likurai Dance

The detection of Likurai dance types is an effort to document and classify the movements of this traditional dance with the aid of artificial intelligence technology. In this study, researchers used an advanced object detection model to analyze Likurai dance videos and identify its characteristic movements. Figure 1 illustrates the framework or model used in this process, starting from the input of Likurai dance videos to the evaluation of the detection model. Each stage in this framework plays a crucial role in ensuring the accuracy and effectiveness of the detection.

2.1 Input

The first stage begins with the preparation of Likurai dance data in the form of dance videos to be processed in this study. The videos contain live recordings from Malaka Regency, East Nusa Tenggara, at SDK Taelama, East Nusa Tenggara. In this study, the author selected 3 videos featuring 3 different Likurai dance movements, then combined these three videos into a single file, as shown in Figure 2, with a total duration of approximately 3 minutes. This combined video will then be used as the testing data during the model testing process.

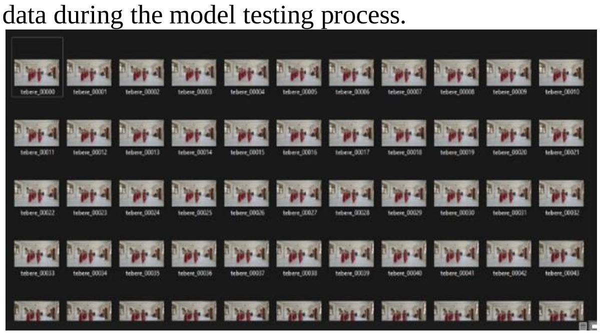

Figure 1. Data of Likurai Dance from NTT

This study aims to develop a YOLOv8-based method capable of estimating the type of Likurai dance from East Nusa Tenggara (NTT) based on the combined video. By utilizing image processing techniques and data analysis, the author hopes to identify patterns and characteristics of the dance associated with the Likurai dance type. The estimation results are expected to provide a better understanding of the variations and characteristics of the dance, as well as support the sustainable preservation and management of the Likurai dance culture.

Figure 3. Image Extraction

2.2 Preprocessing

In this stage, the video is divided into individual frames, with each frame representing a static image of a specific moment in the video, as shown in Figure 3. The video of the "Be Tae Be Tae Toba Lutuhun" movement type was split into 1,369 images, the "Tebe Re" movement type into 1,229 images, and the "Wesei Wehali" movement type into 1,371 images. These three movement types were then combined into a single file for training, resulting in a total of 3,969 images. This process allows the researcher to analyze each moment in the video in greater detail, which would not be possible if only the entire video was used.

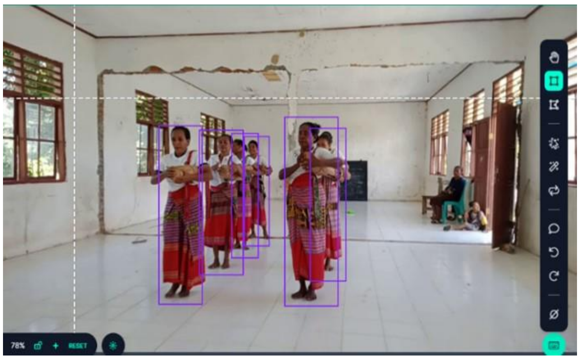

Figure 2. Image Annotation

The extracted frames were then annotated. This process involves labeling key parts within each frame that will be used to train the model. The data labeling process, as seen in Figure 4, is a crucial step in creating a dataset for training the object detection model. During this stage, the researcher marked the objects to be detected in each frame. This annotation was done using bounding boxes and object classes on 3,969 images, resulting in 20,406 annotations with a median image ratio of 1280x720, which were then saved in a format compatible with YOLOv8. This data labeling process requires high precision and accuracy, as errors in labeling can significantly affect the overall performance of the object detection model.

Table 1. Data Training

Split Ratio	Data		
	Training	**Validation**	**Testing**
10%/10%/80%	397	397	397
20%/10%/70%	794	397	2778
30%/10%/60%	1191	397	2381
40%/10%/50%	1588	397	1984
50%/10%/40%	1985	397	1587
60%/10%/30%	2382	397	1190
70%/10%/20%	2779	397	793
80%/10%/10%	3175	397	397

Table 1 displays the dataset divided into 8 sections for training and testing. By separating the data, it helps in evaluating how well the model can generalize to new data. This also prevents overfitting, ensuring that the model performs well not only on the training data but also on unfamiliar data. The split ratio also provides a more comprehensive performance assessment through various evaluation metrics.

2.3 Training Model

After preparing the dataset, the researcher began the model training process by dividing the dataset into eight different ratios as shown in Table 1. The purpose of this division was to find the ratio that provides the best results in terms of precision, recall, and mAP. The training was conducted on Google Colab using 100 epochs, a 640-pixel image size, a batch size of 4, and a learning rate of 1e-4. The time spent on each stage per image was: 0.4 milliseconds for preprocessing, 3.4 milliseconds for inference, 0.1 milliseconds for calculating loss, and 1.5 milliseconds for post-processing, which includes removing duplicate bounding boxes and converting the output format.

2.4 Test Model

After the training process was completed, the researcher then applied the trained model to detect objects in the test video, as shown in Figure 3.6. At this stage, the object detection model was used to automatically identify and label objects within each video frame. This process required 8 rounds of testing to detect the video based on the predetermined split ratio. This step is crucial because it involves applying the trained model in real-world scenarios to assess how well it can detect objects with high accuracy.

2.5 Output

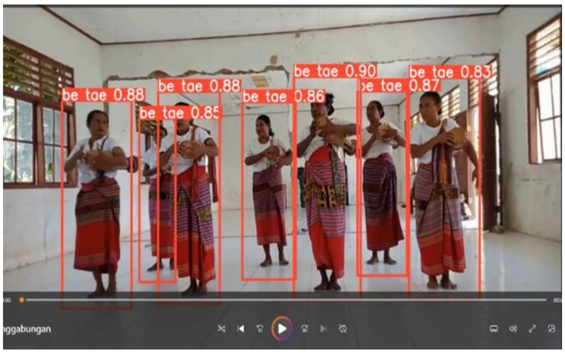

Figure 4. Output video on split ratio

The results from the model in Figure 5 show the detection of images and videos of the Likurai dance, where the dance movements are identified and classified well. However, there are also some prediction errors in certain frames identified as false positives. These errors are likely due to insufficient data representation during the training phase for visual conditions similar to those frames. The colored bounding boxes indicate confidence scores, showing that the model has identified those areas as specific types of movements with its confidence level.

2.6 Evaluasi

In evaluating dance movement detection models, three key metrics are used: precision, recall, and mAP (Mean Average Precision). Precision measures the accuracy of the model's predictions with equation 1, indicating how many of the detected dance movements are correct. A high precision means that most of the movements detected by the model are indeed correct. Recall, on the other hand, assesses the model's ability to identify all relevant dance movements present in the dataset. A high recall indicates that the model is effective in detecting most of the actual dance movements with equation 2. Meanwhile, mAP combines precision and recall to provide an overall picture of the model's performance across various thresholds. A high mAP signifies that the model consistently performs well in detecting different types of dance movements with a balanced accuracy between precision and recall with equation 3. Together, these metrics offer a comprehensive understanding of how well the model recognizes and detects dance movements accurately [15][16].

$$Precision = \frac{TP}{TP+Fp} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$\text{mAP} = \frac{1}{N}\int_{i=1}^{N} APi \quad (3)$$

3. RESULT AND DISCUSSION

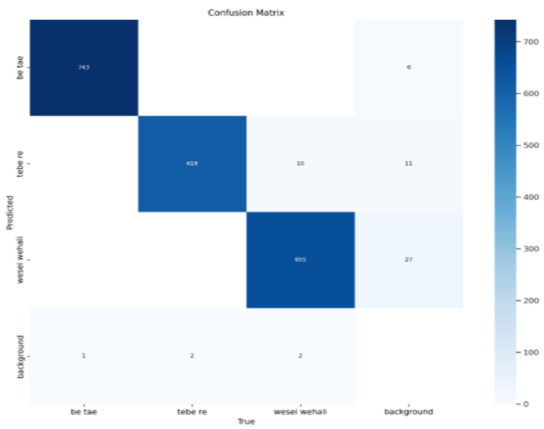

Figure 5 Confusion Matrix

The matrix in Figure 6 includes four classes: be tae, tebe re, wesei wehali, and background. The main diagonal shows the number of instances correctly classified: be tae (743), tebe re (618), wesei wehali (655), and background (2), with darker colors indicating accurate classifications. Misclassifications occur outside the diagonal, such as 1 instance of be tae predicted as background, 2 instances of tebe re as background, and 27 instances of wesei wehali as background, with lighter colors indicating fewer errors. These misclassifications affect the model's overall ability to detect the types of Likurai dance movements, highlighting the need for improvements to reduce errors in the "background" category and enhance the accuracy of detecting the desired dance movements.

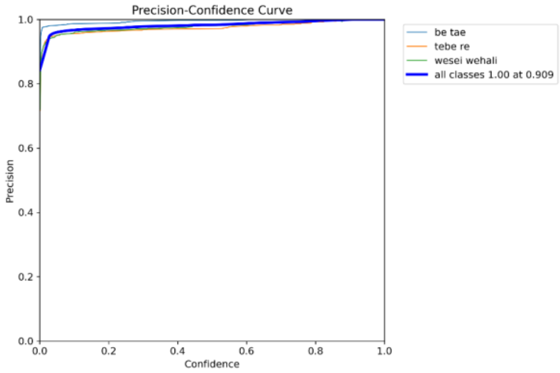

Figure 6 Precision-Confidence Curve

The model in Figure 7 demonstrates excellent precision performance at high confidence levels, with overall precision reaching 1.00 at a confidence level of around 0.909. This means that all positive predictions at this confidence level are true positives, with no false positives. The consistent precision performance across all classes indicates that the model is not biased toward any particular class and maintains balanced accuracy across all classes. The Likurai dance movement detection model shows strong capability in identifying movements with high recall at low to medium confidence levels. This suggests that the model can recognize most movements that should be detected, minimizing the chances of missed movements (false negatives). However, at very high confidence levels, recall decreases, highlighting the importance of selecting an optimal confidence level to ensure reliable detection.

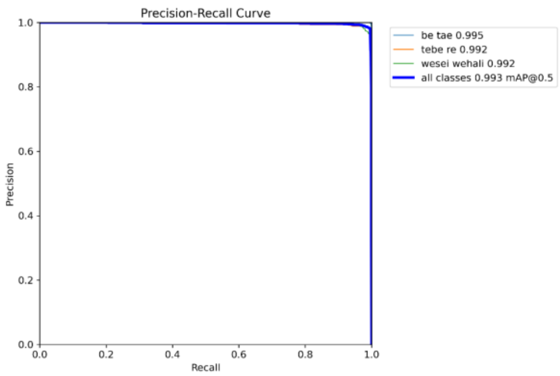

Figure 7 Precission-Recall Curve

The model in Figure 8 demonstrates optimal performance, with both precision and recall nearing 1.0 across the entire recall range. The consistency among classes is evident from the similar curves, indicating that the model performs stably across different classes. An mAP value of 0.993 at a 0.5 threshold reflects excellent aggregate performance across all classes at this threshold. This result impacts the detection of Likurai dance movements by showing the model's strong capability in detecting movements with high precision and recall. High precision indicates that the model rarely makes false detections of the correct movements, while high recall means the model successfully captures nearly all movements present. The consistency across classes also shows that this model is reliable for detecting various types of movements with similar accuracy, enhancing confidence in detecting movements across different variations of the Likurai dance.

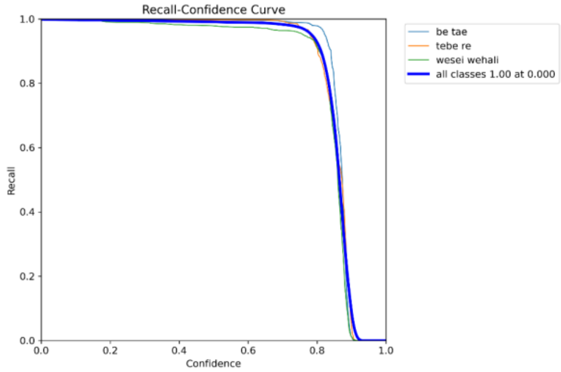

Figure 8 Recall-Confidence Curve

The model in Figure 9 demonstrates optimal performance with recall nearing 1.0 across the entire confidence range. The consistency among classes is evident from the similar curves, indicating stable performance across different classes. A recall value of 1.00 at a confidence level of 0.000 shows excellent recall performance across all classes at this confidence level. The model's results in detecting Likurai dance movements indicate very strong performance with both high precision and recall. With this performance, the model can be relied upon to accurately identify various variations of Likurai dance movements, supporting further analysis or practical applications that require precise movement detection.

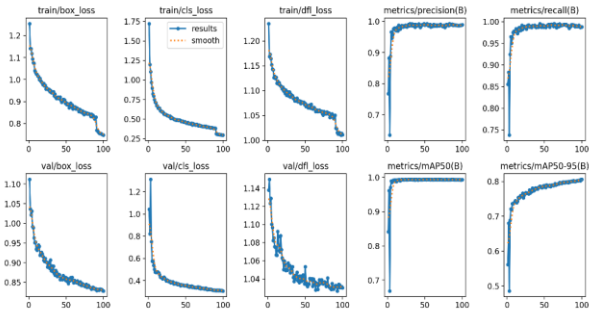

Figure 9 Performance Metrics Graph

The graphs in Figure 10 show that the model consistently improves its performance during training and validation. All losses decrease, while precision, recall, and mAP metrics increase, indicating that the model not only becomes more accurate in detecting and classifying objects but also more stable across different thresholds. The results suggest that, although the Likurai dance movement detection model performs well overall, some misclassifications still occur. Factors such as the similarity between movements, data imbalance, and movement complexity can affect the model's accuracy. These errors can lead to inaccuracies in the automatic recognition of dance movements, which is crucial in real-world applications like training or cultural documentation. Therefore, model improvements or additional data may be needed to enhance the reliability of movement detection.

Figure 10 Model Training

Figure 11 illustrates the results of the model training. Each frame displays various positions and movements of the dancers. The red bounding boxes surrounding each dancer indicate that object detection technology is used to identify and track their movements. This image conveys that the technology is employed to observe or analyze movement patterns within the context of traditional dance.

Figure 11 Model Prediction Validation

Figure 12 shows the results of model prediction validation. Each frame displays orange bounding boxes around the dancers, which represent the outcomes of the object detection process. Above these boxes, there are labels such as "wessi wehali" and confidence values (e.g., 0.98), indicating the model's level of certainty in detecting and classifying the objects. This process utilizes machine learning or computer vision techniques to recognize the movements and positions of the dancers in each video frame.

3. 1 Comparison of Split Ratio Results from 10%/10%/80% to 80%/10%/10%

In this section, the researcher will discuss the results of three key metrics across various split ratios. The focus will be on evaluating the model's performance in terms of precision, recall, and mAP (mean Average Precision). The researcher will then calculate the average values based on these results.

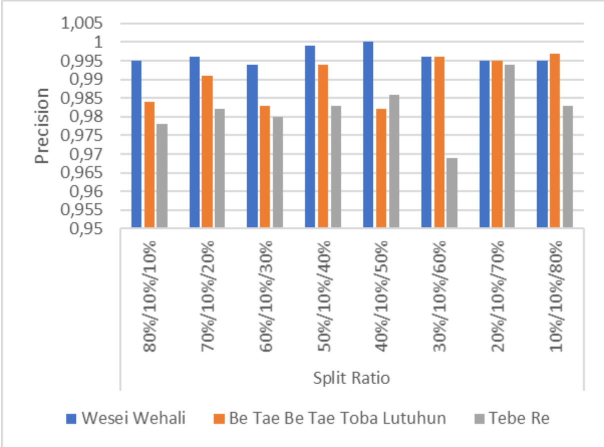

Figure 12 Precision Value Comparison Graph

The graph in Figure 13 displays the precision of the machine learning model for three labels: "Wesei Wehali," "Be Tae Be Tae Toba Lutuhun," and "Tebe Re," with various data split ratios (training/validation/testing) ranging from 10%/10%/80% to 80%/10%/10%. The X-axis represents the data split ratios, while the Y-axis shows precision values ranging from 0 to 1. Each set of ratios includes three bars representing each label. The results indicate that the precision for "Wesei Wehali" is generally very high, approaching 1, while "Be Tae Be Tae Toba Lutuhun" and "Tebe Re" have slightly lower but still high values. Overall, the model demonstrates consistent and reliable performance in identifying the three labels, with average precision values of 0.996, 0.990, and 0.982, respectively.

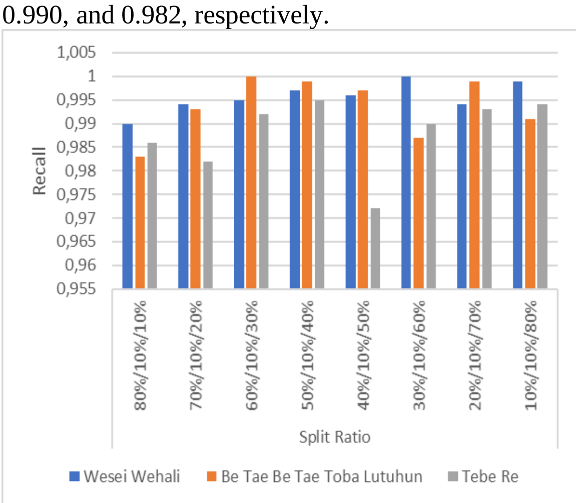

Figure 13 Comparison chart of Recall values

The graph in Figure 14 illustrates the recall of the machine learning model for three labels: "Wesei Wehali," "Be Tae Be Tae Toba Lutuhun," and "Tebe Re," with various data split ratios (training/validation/testing) ranging from 10%/10%/80% to 80%/10%/10%. The X-axis represents the data split ratios, while the Y-axis shows recall values ranging from 0 to 1. Each set of ratios includes three bars representing each label. The results show that recall for "Wesei Wehali" is generally very high, approaching 1, while "Be Tae Be Tae Toba

Lutuhun" and "Tebe Re" have slightly lower but still high values. Overall, the model demonstrates consistent and reliable performance in identifying the three labels, with average recall values of 0.996, 0.994, and 0.988, respectively.

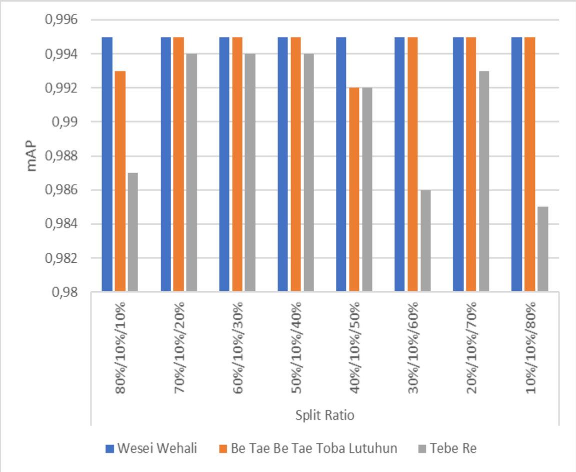

Figure 14 Comparison chart of Accuracy values

The graph in Figure 15 displays the mean Average Precision (mAP) of the machine learning model for three labels: "Wesei Wehali," "Be Tae Be Tae Toba Lutuhun," and "Tebe Re," with various data split ratios (training/validation/testing) ranging from 10%/10%/80% to 80%/10%/10%. The X-axis represents the data split ratios, while the Y-axis shows mAP values ranging from 0 to 100%. Each set of ratios includes three bars representing each label. The results indicate that mAP for "Wesei Wehali" is generally very high, around 99.5%, while "Be Tae Be Tae Toba Lutuhun" and "Tebe Re" have slightly lower but still high values. Overall, the model demonstrates consistent and reliable performance in identifying the three labels, with average mAP values of 99.5%, 99.4%, and 99.1%, respectively.

Table 2 Split Ratio Precision Results

Split Ratio	Precision (%)		
	Wesei Wehali	**Be Tae Be Tae Toba Lutuhun**	**Tebe Re**
10%/10%/80%	99,5	98,4	**97,8**
20%/10%/70%	99,6	99,1	98,2
30%/10%/60%	**99,4**	98,3	98
40%/10%/50%	99,9	99,4	98,3
50%/10%/40%	**100**	**98,2**	98,6
60%/10%/30%	99,6	99,6	96,9
70%/10%/20%	99,5	99,5	**99,4**
80%/10%/10%	99,5	**99,7**	98,3
Average	**99,6**	**99**	**98,2**

Table 2 shows the results of the split ratio for precision, as well as the average values for the three classes. For the "Wesei Wehali" class, the minimum precision value is 99.4%, the maximum is 100%, and the average precision is 99.6%. The "Be Tae Be Tae Toba Lutuhun" class has a minimum precision of 98.2%, a maximum of 99.7%, and an average precision of 99%. The "Tebe Re" class shows a minimum precision of 97.8%, a maximum of 99.4%, and an average precision of 98.2%.

Table 3 Table of Split Ratio Recall Results

Split Ratio	Recall (%)		
	Wesei Wehali	Be Tae Be Tae Toba Lutuhun	Tebe Re
10%/10%/80%	99	**98,3**	98,6
20%/10%/70%	**99,4**	99,3	98,2
30%/10%/60%	99,5	**100**	99,2
40%/10%/50%	99,7	99,9	99,5
50%/10%/40%	99,6	99,7	**97,2**
60%/10%/30%	**100**	98,7	99
70%/10%/20%	99,4	99,9	99,3
80%/10%/10%	99,9	99,1	**99,4**
Average	**99,6**	**99,4**	**98,8**

Table 3 displays the results of the split ratio for recall, along with the average values for the three classes. For the "Wesei Wehali" class, the minimum recall value is 99.4%, the maximum is 100%, and the average recall is 99.6%. The "Be Tae Be Tae Toba Lutuhun" class has a minimum recall of 98.3%, a maximum of 100%, and an average recall of 99.4%. The "Tebe Re" class shows a minimum recall of 97.2%, a maximum of 99.4%, and an average recall of 98.8%.

Table 4 Table of Split Ratio mAP Results

Split Ratio	mAP (%)		
	Wesei Wehali	Be Tae Be Tae Toba Lutuhun	Tebe Re
10%/10%/80%	**99,5**	99,3	98,7
20%/10%/70%	99,5	99,5	99,4
30%/10%/60%	99,5	**99,5**	**99,4**
40%/10%/50%	99,5	99,5	99,4
50%/10%/40%	99,5	**99,2**	99,2
60%/10%/30%	99,5	99,5	98,6
70%/10%/20%	99,5	99,5	99,3
80%/10%/10%	99,5	99,5	**98,5**
Average	**99,5**	**99,4**	**99,1**

Table 4 shows the results of the split ratio for mean Average Precision (mAP), along with the average values for the three classes. For the "Wesei Wehali" class, the mAP value is stable at 99.5%, so the average is also 99.5%. The "Be Tae Be Tae Toba Lutuhun" class has a minimum mAP of 99.2%, a maximum of 99.5%, and an average of 99.4%. The "Tebe Re" class shows a minimum mAP of 98.5%, a maximum of 99.4%, and an average of 99.1%.

Table 5 Comparison of Previous Research Methods with the Proposed Method Results

Researcher	Objek Detection	Evaluation
YOLOv8 [11]	Multi-Person Dance Posture Recognition	The result shows that this approach achieved a mean Average Precision (mAP) of 75.7%.

saraf self-organizing mapping (SOM) [12]	Dance Movement Recognition	The simulation results show an accuracy of 9.34%.
frame difference [13]	Motion Detection	The values are: Precision 88%, Recall 88%, and Accuracy 80%.
YOLOv8 Our Proposed (Average Split Ratio)	Detection of Wesei Wehali Movement from NTT	The mean Average Precision (mAP) is 99.5%, with Precision at 99.1% and Recall at 99.6%.
	Detection of Be Tae Be Tae Toba Lutuhun Movement from NTT	The mean Average Precision (mAP) is 99.4%, with Precision at 99.1% and Recall at 99.4%.
	Detection of Tebe Re Movement from NTT	The mean Average Precision (mAP) is 99.1%, with Precision at 98.2% and Recall at 98.8%.

Table 5 compares various dance movement recognition methods. The study by Kao (2024) using YOLOv8 for multi-person dance posture recognition highlights the need for systems capable of identifying postures or movements of multiple individuals within a single frame with high accuracy. This is particularly important for applications such as dance training, performance analysis, and security. Pang and Niu (2023) used self-organizing mapping (SOM) in dance movement recognition, showcasing innovations in non-conventional methods that may be more effective under certain conditions or for specific data types. Yovi Apridiansyah et al. (2024) employed frame difference for motion detection, presenting a simpler, potentially computationally lighter method that remains effective for real-time applications and on resource-constrained devices.

This research employs the YOLOv8 model, achieving exceptionally high mAP levels: 99.5% for Wesei Wehali, 99.4% for Be Tae Be Tae, and 99.1% for Tebe Re. These results demonstrate the model's highly accurate detection capabilities, with precision and recall rates also exceeding 98%. The study contributes to cultural preservation by utilizing artificial intelligence technology to document and recognize traditional dance movements with high precision, aiding in efforts for preservation and cultural education.

4. CONCLUSION

Based on the comparison of the machine learning model's performance with various data split ratios (training/validation/testing) ranging from 10%/10%/80% to 80%/10%/10%, the model exhibits excellent performance in terms of precision, recall, and mean Average Precision (mAP) for the labels "Wesei Wehali," "Be Tae Be Tae Toba Lutuhun," and "Tebe Re." The average precision values for the three labels are 99.6%, 99.0%, and 98.2%, respectively. The average recall values are 99.6%, 99.4%, and 98.8%, while the average mAP values are 99.5%, 99.4%, and 99.1%. This research contributes to cultural preservation through technology, particularly in documenting and analyzing traditional dance movements using artificial intelligence. The technology not only aids in preserving traditional dances but also provides an effective tool for education and enhancing cultural appreciation among younger generations.

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