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Pose Classification in Archery Sports Based on YoloV8 Using SVM and Random Forest Methods

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Abstract

This research creates a YOLOv8-based pose classification system that can analyze and classify the movements of archery athletes. The system is combined with SVM and RF methods, and utilizes YoloV8 pose detection and machine learning techniques to provide more accurate classification. Video data collection, system design and implementation, and analysis of implementation results are some of the stages passed during system development. The process includes joint feature extraction using YOLOv8 and classification for Recurve and Barebow categories using SVM and RF. The test results show the difference in performance between the two classification methods. For the Recurve category, SVM had 90% accuracy for testing, while RF had 87% accuracy for testing. For the Barebow category, SVM had 76% accuracy for testing, while RF had 75% accuracy for testing. In terms of generalization, the two methods differed, with SVM showing better stability between testing and training performance. The results show that SVM is superior when testing when compared to RF which makes an anomaly with previous studies

Keywords: Archery, Pose Classification, RF, SVM, YoloV8

I. INTRODUCTION

The development of advancements in computer vision technology in this digital era has opened up new ways to improve analysis and understanding in every aspect of life, whether it is analyzing living things or inanimate objects. Analysis on living things is not limited to general activity conditions such as walking, cooking, sleeping, and others, but also to other activities that can be carried out by these living things. These activities have movements that can be detected through pose detection. Poses that can be detected include hands, head, face, feet, and every joint [1]. Each pose when processed into the computer will be determined by each pose keypoints so that the measurements made are more precise and accurate [2]. The pose detection can also be done in sports activities. Just like the previous pose detection, the poses detected are head, hands, body, and feet. However, there are some conditions where the detection for keypoints that have been done is not read properly, therefore continuous pose detection is needed so that the results can be maximized [3]. For the development of pose detection in sports, it can be done in various types of sports, including archery.

Archery itself is a sport that is starting to attract many people, be it for entertainment alone or to compete intensely. Archery is also a sport where every athlete feels a change in motion but the change is not visible to the naked eye [2]. These changes consist of several movements such as Set-up, Draw and Aim, and Expand and

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Shoot [4]. Traditional methods involving manual analysis have been replaced with more efficient and automated computer vision approaches. In previous research that has been raised by Kawaguchi and Saptiawan [2][4], pose detection is not done using existing methods in computer vision testing. Therefore, this research seeks to find and reveal by combining YOLOv8 technology, which allows more accurate detection of human body poses from video, by considering how data is processed by Support Vector Machine (SVM) and Random Forest (RF) to produce pose classification values in archery athletes that have never been done before.

There are many types of computer vision approaches that can be used [5][6]. Approaches that can be used to test deep learning models include SVM and RF. Deep learning testing is not only focused on these two methods, but there are other algorithms that can be used such as AlexNet, LSTM, Convolutional Neural Network (CNN), and Decision Tree (DT) [6]. Each of the algorithms mentioned has its own advantages and disadvantages, as is the case with LSTM. Basically, LSTM is designed to detect images, but its implementation can also be used on videos as described by Siddiqui et al [6]. If you also look at the comparison of using SVM and RF with LSTM, the difference in the resulting value is quite significant. It can be seen in Precision, Recall, and F1 Score that the value obtained by SVM itself is 0.867, 0.846, and 0.846, respectively. Then for RF itself is at 0.998, 0.995, and 0.998. This value is very significant when compared to LSTM which is only at 0.452, 0.502, and 0.502. This can be an early indication to test both models to classify a pose.

At the same time, the SVM and RF run alongside another pose estimation algorithm, YOLOv8. YOLOv8 is a pose algorithm released in 2023 for YOLO real-time object detection with outstanding accuracy and speed. Building on the advancements from previous versions of YOLO, YOLOv8 has new features and optimizations that make it a perfect choice for a variety of object detection tasks in various applications [7]. A number of previous studies have revealed and applied deep learning and pose estimation models to sports, there are several other methods such as MoveNet, OpenPose, and MediaPipe. If explored further, each method has advantages and disadvantages, such as those in OpenPose for example. The difference can be seen in research conducted by Dong et al [8] where the OpenPose value for AP is 48.0, while for YOLO v8 itself it is 70.9. The difference in the latency produced is also quite significant, for OpenPose itself has a latency of 368 ms and for YOLO v8 itself is at 78. This difference can occur because OpenPose tends to be heavier when compared to YOLO v8 in terms of pose detection computation.

This research uses YOLO V8 to extract features from each pose with a high level of detail. Then the application of SVM and Random Forest is used for motion analysis and classification. SVM's capacity to manage high dimensional data and generate ideal judgment margins led to its selection, making it suitable for classifying complex movement patterns. On the other hand, Random Forest is used because of its reliability in handling data with non-linear characteristics, sensitivity to important features and its ability to reduce the risk of overfitting through an ensemble approach. This is relevant in archery, where joint movements across different phases often exhibit complex, non-linear patterns. This combination has not been widely done or thoroughly explored in terms of archery movement analysis. The expected output of this research is that the system used can detect movements in archery accurately and can classify each movement tested

II. LITERATURE REVIEW

A. *Literature Review*

Exploring the Human Activity Recognition (HAR) side is a challenge in itself from data processing. In pose estimation, feature extraction involves recognizing important joints or landmarks on the human body that can accurately determine the player's pose during the game [9]. According to Jaouedi et al [10] the challenge itself occurs when doing a scene that is complex and demands high speed. Then according to Munea et al [11] the challenge itself can occur on how to determine the keypoints used where the determination must be appropriate at the test point in order to get the desired results. The determination of keypoints is done in YOLO v8.

When compared to other versions of YOLO, YOLO v8 produces qualified values. Research conducted by Muhammad Husain [12] can run effectively when compared to the previous generation YOLO. The use of YOLO v8 in pose detection itself has been carried out by Tan et al [13] which has described how to use each feature in YOLO v8. In this study, a robot was used as a representation of a human being whose pose was detected.

Then SVM and Random Forest themselves are testing algorithms commonly used in other studies, such as Avci et al [14]. In this study, it shows that RF produces better values than SVM itself. This is also in line with research conducted by Siddiqui et al [6] where RF results are better when compared to SVM itself. On the other hand, detection in archery has a very crucial role in this research. The crucial determination is based on research conducted by Kawaguchi et al [2] which shows how the optimal point in taking test images and what techniques will be a reference in this test. Then in the study conducted by Saptiawan et al [4] shows which points are possible to be used as tests in this research.

B. YoloV8

YOLOv8 is an advanced development carried out by ultralytic in 2023 with five scale versions, namely nano, small, medium, large, and extra-large [15]. YOLOv8 itself is a highly regarded object detection model due to offers outstanding precision and real-time performance balance [13]. Various studies have been conducted to test how effective and precise the use of YOLOv8 is.

C. Random Forest (RF)

A supervised learning technique called RF blends multiple decision trees to reduce errors in the data [16]. A number of trees make up the RF classifier, and each tree uses randomization in some way[17]. RF is arguably one of the best methods in handling complex and large data and can overcome the problem of overfitting data. Broadly speaking, Random Forest builds multiple decision trees that are trained independently using randomly selected subsets of data. Random Forest changes the way classification or regression is built. In a standard tree, each separate node has the best separation from all variables, whereas in RF, each separate node has the best separation from all variables [17].

D. Support Vector Machine (SVM)

SVM is a method used to solve data classification problems. In its use, this SVM model can be interpreted as an algorithm that aims to get the most optimal hyperplane margin value [18]. The margin value is useful for measuring how far the hyperplane is from the closest points of each class. Broadly speaking.

III. RESEARCH METHOD

A. Dataset Video

Collecting movement videos of twenty recurve and barebow archery athletes was conducted. Each recurve and barebow archer performed the movements naturally, including Setup, Draw, and Aim, and Expand and Shoot movements. The dataset is divided into three output classes, each containing Setup, Draw, and Aim, and Expand and Shoot. A trimming process was performed on each video, resulting in a short video with a length of approximately two seconds per output class. In the recurve category, there is a place to aim at the target, so the setup movement can take longer than in the barebow category. In addition, the Expand and Shoot movements of the two groups differed in the amount of time it took to release the bullet to aim at the target.

B. Pre-Processing

1) FPS Adjustment: Videos that have gone through the trimming process enter a phase of decreasing FPS, also known as frames per second. Since the videos came from three different sources, namely Instagram, YouTube and field recordings, their FPS was different at the time of data collection. This FPS reduction is done to ensure that the size is the same for each video.

2) Frame Extraction: To equalize the number of frames used, as each video has a different duration, the size-adjusted FPS videos were extracted into frames with a maximum number of 50 frames per video. To ensure that each video can receive all the existing movements without losing data, the extraction process has been anticipated at the FPS customization stage. Next, the extracted results are stored in a folder with a name that corresponds to the predefined class. The results of the recurve and barebow category frame extraction can be seen in Fig. 1 and Fig. 2.

(A) (B) (C)

Fig. 1. Frame Extraction in the Recurve Category, (A) Setup (B) Draw and Aim (C) Expand and Shoot

(A) (B) (C)

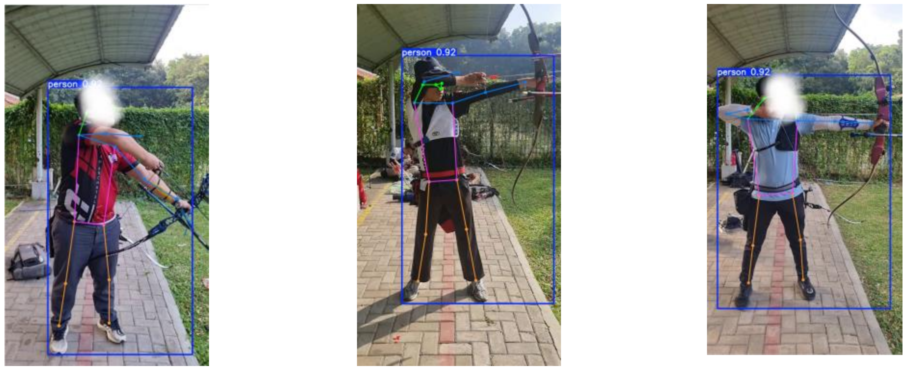
Fig. 2. Frame Extraction in the Barebow Category, (A) Setup (B) Draw and Aim (C) Expand and Shoot

3) Pose Detection: After the frames are extracted in the previous stage, each key point is identified in each frame based on YoloV8, which serves as the basis for pose extraction in this test. Keypoints themselves are features that can detect any unique or salient points in an image or video, which can be used to identify, describe, or match existing objects or features. The available points for YoloV8 can be seen in Table 1.

TABLE I
KEYPOINTS

No	Keypoints Name	No	Keypoints Name
1.	*Nose*	10.	*Left Wrist*
2.	*Left Eye*	11.	*Right wrist*
3.	*Right Eye*	12.	*Left Hip*
4.	*Left ear*	13	*Right Hip*
5.	*Right ear*	14	*Left Knee*
6.	*Left Shoulder*	15	*Right Knee*
7.	*Right Shoulder*	16	*Left Ankle*
8.	*Left Elbow*	17	*Right Ankle*
9.	*Right Elbow*		

In this study, the left, right, left, and left knee keypoints were not used. No movement occurred during the exercise, so there was no need for additional detection. Also, the left ear button was not included because each athlete had been aiming at a target where the button was not visible. This happened in the existing video. Fig. 3 and 4 show the results of the frames found for the recurve and barebow categories.



(A) (B) (C)

Fig 3. Keypoints Extraction in the Recurve Category, (A) Setup (B) Draw and Aim (C) Expand and Shoot

(A) (B) (C)

Fig 4. Keypoints Extraction in the Barebow Category, (A) Setup (B) Draw and Aim (C) Expand and Shoot

C. Labeling and Data Split

After pose detection is complete, the next step is labeling. Each data point that has been determined is then numbered 1 for the Configuration class, number 2 for the Draw and Aim class, and number 3 for the Expand and Shoot class. The numbered data is then divided into two, which means 75% is included in the training data and 25% is included in the testing data. This applies to both barebow and recurve. The data contains each keypoint in the form of x and y coordinates, and for ease of testing, the values are stored in .csv format.

D. Hyperparameter Tuning

Parameter optimization that is not directly learned by the model during training is known as hyperparameter tuning (HT). In this study, HT is used to find the grid for SVM and the random state for RF. This process tests every possibility until finding the most suitable parameters to give the highest score value. Table 2 displays the SVM parameters with range search and Table 3 displays the RF parameters.

E. Training and Modelling

This research uses two training models: Support Vector Machine (SVM) and Random Forest. Random Forest uses 100 estimators with 42 coincident states each. SVM also uses two parameters, the C parameter and the gamma parameter. The parameter assignments for each method are intended to provide a comprehensive overview of how each configuration affects the model's ability to classify archery sports movements.

TABLE 2
HYPERPARAMETER TUNING SVM

No	Parameter	Value
1	Kernel	‘rbf’
2	C	0.01, 0.1, 1, 10, 100, 1000
3	Gamma	'scale', 'auto', 0.001, 0.01, 0.1, 1

TABLE 3
HYPERPARAMETER TUNING RF

No	Parameter	Value
1	n_estimator	’100’
2	random_state	42

F. Prediction and Evaluating

Random Forest and SVM were tested using the training data, as was done previously with the tested training and validation data. This testing is essential to ensure that the trained models can make precise and reliable predictions to distinguish between the original videos and reliable and accurate predictions to distinguish between categories. Confusion matrix, accuracy, precision, recall, and f1 score are the metrics used to evaluate the performance of the system.

1) Accuracy: Accuracy validation is a statistical method used to evaluate how well a classification model functions by comparing correct predictions with the total number of journal predictions made [19].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2) Precision: Ratio of accurate metrics positive predictions to all of the model’s positive prediction [20].

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

3) Recall: The percentage of favorable data from metrics that are actually detected by the model [21].

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

4) F1-Score: Average harmonized metrics of precision and recall [21].

$$F1\text{-}score = 2 * \frac{Precision\ x\ Recall}{Precision+Recall} \quad (4)$$

IV. RESULTS AND DISCUSSION

A. Result

1) Random Forest: According to Table 4 and 5, the RF model training results show perfect performance with 100% accuracy, precision, recall, and F1 score for all three classes (SetUp, DrawAndAim, and ExpandAndShoot). This shows that the model can classify the training data accurately. The RF test results showed an overall accuracy of 87% for all three features, with different performances for the precision, recall, and F1 score metrics. With high precision (97%) but low recall (86%), feature 1 shows that the model is often correct in predicting the positive class but ignores some relevant examples. In contrast, feature 2 has a high recall (95%) but low precision (73%), indicating that the model tends to predict the positive class more often, although not all of them are correct. Looking at the confusion matrix, there is a difference in expand and shoot, but it is still safe for the test results.

TABLE 4
TRAINING RF RECURVE

Class	Performance			
	Accuracy	Precision	Recall	F1-Score
1	100 %	100 %	100 %	100 %
2	100 %	100 %	100 %	100 %
3	100 %	100 %	100 %	100 %

TABLE 5
TESTING RF RECURVE

Class	Performance			
	Accuracy	Precision	Recall	F1-Score
1	87 %	97 %	86 %	91 %
2	87 %	73 %	95 %	83 %
3	87 %	98 %	79 %	88 %

For the barebow category which can be seen in Table 6 and 7, the RF model showed excellent performance on the training data with 100% accuracy, perfect F1-score for each class, and confusion matrix with no prediction errors. However, the performance on the test data drops significantly, with 75% accuracy and unbalanced performance between classes (the lowest precision, recall, and F1-score on the “DrawandAim” class). The confusion matrix on the test data shows that the model has high prediction errors, especially for the class “ExpandandandShoot,” which is often mispredicted as the class “DrawandAim.”

TABLE 6
TRAINING RF BAREBOW

Class	Performance			
	Accuracy	Precision	Recall	F1-Score
1	100 %	100 %	100 %	100 %
2	100 %	100 %	100 %	100 %
3	100 %	100 %	100 %	100 %

TABLE 7
TESTING RF BAREBOW

Class	Performance			
	Accuracy	Precision	Recall	F1-Score
1	75 %	91 %	86 %	89 %
2	75 %	59 %	82 %	69 %
3	75 %	87 %	58 %	LXIX.

2) SVM: The evaluation results of the SVM models for the recurve category, shown in Table 8 and 9, show quite good performance. They show an accuracy of 90% in the test data and 94% in the training data. In the training data, the “SetUp” class showed the best performance, while the “DrawandAim” class showed worse performance with a recall of 83%. However, due to its shortcomings in precision and recall, the “DrawandAim” class remains a weakness of the model with an F1-score of only 0.83. The confusion matrix shows that the “DrawandAim” class-often mistaken for “ExpandandShoot”-makes most of the errors. The imbalance between classes can still be corrected.

TABLE 8
TRAINING SSV RECURVE

Class	Performance			
	Accuracy	Precision	Recall	F1-Score
1	94 %	97 %	100 %	98 %
2	94 %	99 %	83 %	90 %
3	94 %	88 %	99 %	93 %

TABLE 9
TESTING SVM RECURVE

Class	**Performance**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
1	90 %	97 %	100 %	98 %
2	90 %	95 %	74 %	83 %
3	90 %	81 %	96 %	88 %

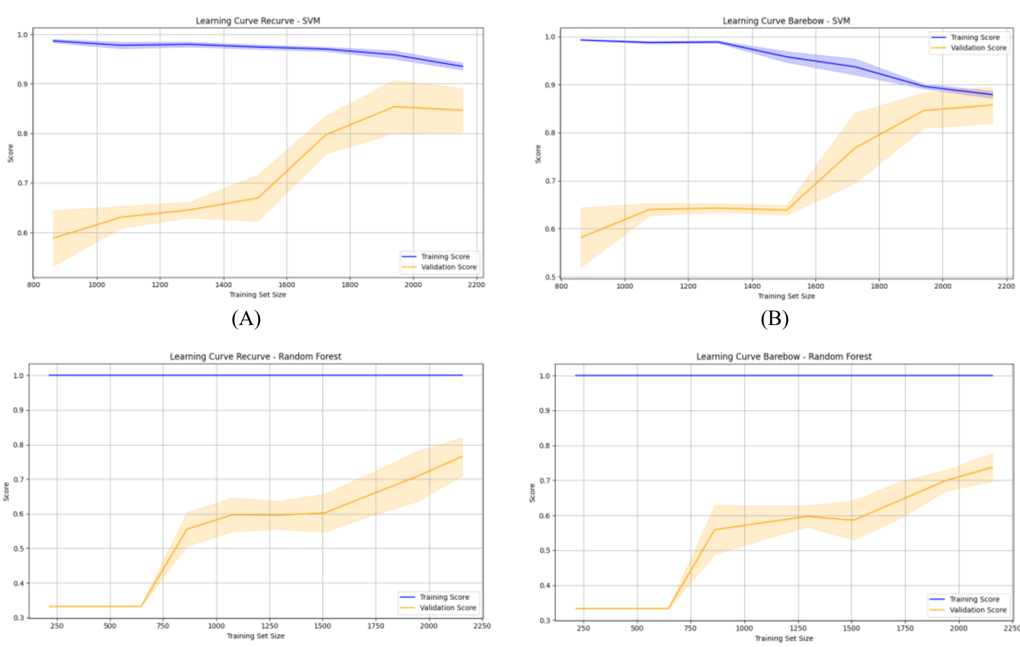
For the barebow category it can be seen in Table 10 and 11, Figure (C), and figure 6(D) that the SVM model shows excellent performance on training data with 88% accuracy, especially in the SetUp class (precision 0.98, recall 1.00). However, the performance on the testing data has decreased significantly with an accuracy of 76%. This can be seen in the confusion matrix, where the model struggles to distinguish the DrawandAim class (recall 0.39), often misclassified as SetUp or ExpandandandShoot.

TABLE 10
TRAINING SVM BAREBOW

Class	**Performance**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
1	*88%*	*98 %*	*100 %*	*99 %*
2	*88%*	*92 %*	*70 %*	*80 %*
3	*88%*	*77 %*	*94 %*	*85 %*

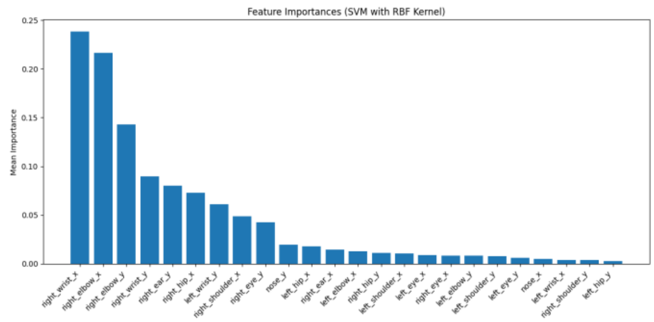
TABLE 11
TESTING SVM BAREBOW

Class	**Performance**			
	Accuracy	**Precision**	**Recall**	**F1-Score**
1	*76 %*	*84 %*	*88 %*	*86 %*
2	*76 %*	*76 %*	*39 %*	*51 %*
3	*76 %*	*70 %*	*100 %*	82 %

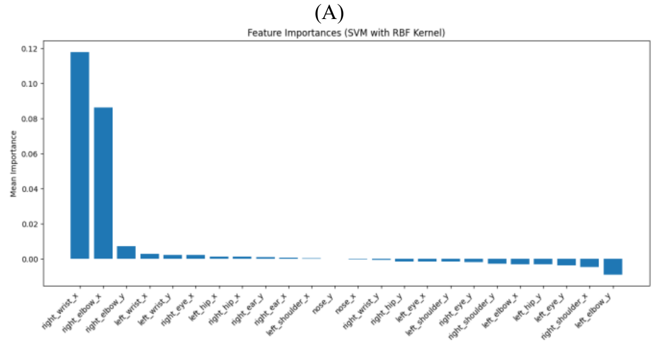


(A) (B) (C) (D)

Fig 5. Learning curve (A) SVM Recurve (B) SVM Barebow (C) RF Recurve (D) RF Barebow

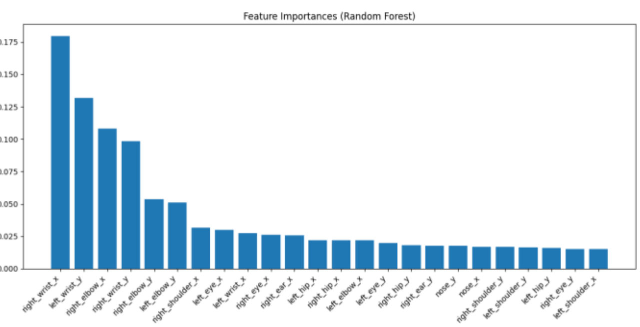


(A)

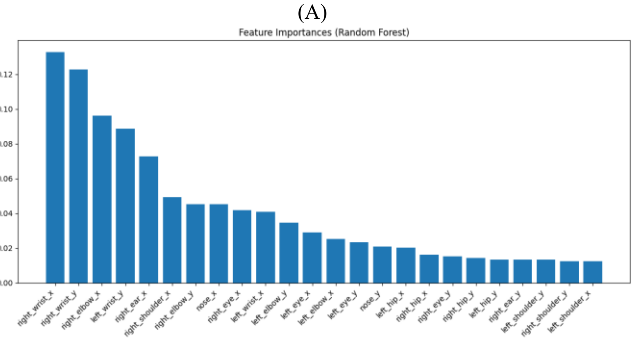


(B)

Fig 6. Feature Importance SVM, (A) Recurve (B) Barebow



(A)



(B)

Fig 7. Feature Importance RF, (A) Recurve (B) Barebow

3) Learning Curve: Fig. 5 shows the learning performed by each method; Fig. 6(A) and 6(B) show commendable convergence, with the training and testing curves remaining close. This shows that these models can avoid significant overfitting by achieving an ideal balance between bias and variance. Figures 6(C) and

6(D) show significant differences between the training and testing curves for RF Recurve and RF Barebow, indicating that the models generalize effectively to new data. The scoring performance (orange line) is far below the training performance (blue line), which indicates that the model is too focused on the training data and cannot generalize effectively.

4) Feature Importance: In Fig. 6 and Fig. 7, we can see which keypoints coordinates are the most influential in this test. The higher the value of the keypoints coordinate, the more influential the keypoints coordinate is. In Fig. 7(A) and 7(B), it can be seen that right_wrist_x and right_elbow_x have the highest influence values on the SVM method. For the same images, left_hip_y and right_shoulders_y in Fig. 7(A) and left_elbow_y and right_shoulders_x in Fig. 7(B) have the lowest values. This can also be seen in Fig. 8(A) and 8(B) where right_wrist_x and right_wrist_y have the highest values. For the same figures, left_shoulder_x and right_eyes_y in Fig. 8(A) and left_shoulder_x and right_shoulders_y in Fig. 8(B) have the lowest values.

B. Analysis of Result

Based on the results in the previous point, it can be seen that the two categories in the method used produce different values in training and testing. The RF method shows the best value in training which produces a value of 100% in both categories. This does not apply to testing where in the second category the SVM shows a better value with an accuracy value of 90% in the recurve category and an accuracy value of 76% in the barebow category. When referring to the confusion matrix, there is misdetection in testing where misdetection occurs a lot in both methods in the barebow category. Misdetection occurs in class 3 for the RF method and class 2 for the SVM method. It cannot be denied that in the recurve category there are also misdetections in both methods, it's just that the misdetection that occurs is not as massive as in the barebow category.

Misdetection in the recurve category can occur due to overlap in the shooting process. As can be seen in Fig. 9, when viewed with the naked eye, there is no difference at all in Fig. 8(A) and 8(B). However, the two images are not in the same class so that misdetection can occur. Then in the barebow category misdetection can occur due to two things, namely the same overlap as explained in the previous recurve category and the different shooting styles of athletes. It can be seen in Fig. 9 where an example is used in the Expand and Shoot class, the two athletes have both released their arrows. Seen in Fig. 9(A) athlete 1 performs a shooting motion similar to the Draw and Aim movement where the hands are still around the face area, while Fig. 9(B) athlete 2 performs a shooting motion with hands behind the head. Basically, there is nothing wrong with these two techniques in barebow archery, it's just that when the detection is done on a computer, the possibility of misdetection is very large so that it affects the results of existing training and testing.

(A)

(B)

Fig 8. Example Overlap Frame (A) Draw and Aim (B) Expand and Shoot


(A)


(B)

Fig 9. An example of an athlete's shooting style (A) Athlete 1 (B) Athlete 2

At the same time, in Fig. 5, Fig. 6, and Fig. 7, the results are quite clear to the naked eye. In terms of learning performance and feature importance, there is a significant difference between the SVM and Random Forest models. While the Random Forest model shows signs of overfitting characterized by a large gap between testing and training performance, the SVM model (both Recurve and Barebow) performs better, showing good generalization ability on new data. Both models found similar patterns in the feature importance analysis, where some initial features had a dominant influence, but with different distributions. SVM showed a gradual decline in feature importance values, while Random Forest showed a sharper decline. Although the overfitting problem in Random Forest can be addressed by proper pruning techniques or hyperparameter optimization, these findings suggest that in this situation, the SVM model may be a better choice. In addition, it is important to note that both models consistently show that performance metrics and firing technique features are the factors that most influence prediction making.

IV. CONCLUSION

Based on the analysis results, the full study shows that the SVM model shows superior and consistent performance compared to the RF model in classifying archery movements for both recurve and barebow categories. Although Random Forest achieved perfect training accuracy (100%) for both categories, RF showed considerable overfitting, as evidenced by its degraded testing performance. In contrast, SVM showed better balance, with a testing accuracy of 90% for the recurve category and 76% for the barebow category.

The determining factors that affect detection accuracy are mainly related to the complexity of the archery movement itself. Detection errors can be attributed to two main factors: firstly, the overlap of movements between classes that show significant visual similarities, and secondly, differences in shooting methods among athletes, particularly in the barebow category. This is most evident in the Expand and Shoot class, where variations in individual athletes' techniques can lead to widely varying postures, even within the same phase of technique.

Learning Curve and Feature Importance supports the conclusion that SVM offers superior generalization, as evidenced by the narrower difference between training and testing performance. This data suggests that for archery skill classification systems, SVM is the superior choice, especially in handling the many movements and complexities inherent to the sport of archery.

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