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RESEARCH ARTICLE

Machine Learning

Machine learning methods to classify engineering students' ability to perform recreational archery activities using biomechanical data

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Abstract: Utilizing machine learning approaches to predict students' performance is a valuable tool for anticipating both low and high levels of achievement across different educational levels. In the case of engineering programmes, the students must exhibit proficient hands-on abilities that match their knowledge, to excel in their performance. When assessing the psychomotor abilities of engineering students during hands-on, practical, or laboratory tasks, the available assessment tools are limited. Utilizing both biomechanical data and observations of students' performance provides an alternate method for evaluating psychomotor skills. This study introduced a recreational archery game as a proof of concept to examine the impact of engineering students' biomechanical data-the upper-limb physical attributes, posture, and angle-on their performance as measured by the points they score in the archery activity. We recruited 104 engineering students without prior experience performing recreational archery and conducted the activity in laboratory settings. We developed a classification model combining fourteen predictors to categorize the students into two groups: those able to perform and those who are not. The model was run into three different machine learning classification algorithms including the decision tree, K-nearest neighbour, and support vector machine (SVM). Among all preset models, SVM shows the best accuracy, and then further optimization of the SVM model was conducted to achieve higher prediction model accuracy. The optimization of the SVM model increased the testing accuracy to 80 % with F1 scores of 0.75 and 0.83 in predicting the 'not able to perform' and 'able to perform' classes respectively. Thus, this study shows that a combination of biomechanical data and machine learning is a potential tool for assessing engineering students' performance involving their psychomotor abilities.

Keywords: Activity performance, biomechanical analysis, machine learning, receational archery.

INTRODUCTION

Engineering students must graduate with commendable qualities to become exceptional engineers. In engineering education, three fundamental domains of Bloom's Taxonomy must be implemented. Bloom's Taxonomy delineates the domains of learning as the cultivation of cognitive, emotional, and psychomotor skills. The majority of students' cognitive abilities are cultivated through classroom instruction. The affective skills component, which pertains to the enhancement of emotions or attitudes, is cultivated through collaborative efforts. Students' psychomotor skills, often termed manual or physical skills, are typically cultivated in a laboratory environment (Baharom *et al.*, 2015a).

This study is a critical area of investigation as it focuses on the psychomotor abilities of engineering students to provide insights into how engineering students learn and perform hands-on tasks. This is an

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innovative area where engineering education intersects with cognitive science and human factors, leading to better educational strategies and technologies to enhance learning. The motivation of the study is to investigate the hands-on skill development of the students, bridging the gap between theory and practice, and addressing diverse learning styles. Investigating psychomotor skills taps into the potential of students who may learn better by doing rather than observing, allowing for more inclusive and effective teaching approaches.

Psychomotor abilities involve fine and gross motor skills, coordination, and precise control over tools and equipment. Investigating and enhancing these abilities helps students perform real-world tasks efficiently, such as operating machinery, prototyping, and performing technical repairs. The psychomotor domain consists of four main elements to test: physical (posture), motor, fitness, and play (sports skills). The psychomotor domain in learning refers to the set of skills that include the use and coordination of skeletal muscles, such as performing, manipulating, and creating. Referring to the Kemp model, four elements of design are an integral part of course development: students, objectives, methods, and evaluation. In our study, we focus on the element of subject content identification with task analysis related to goals and purpose (Baturay, 2008; Kusrini, 2018; Birgili, 2019).

Particularly because of the remote learning environment during the COVID-19 crisis, there has been a growing focus on students‘ psychomotor skills, primarily due to the absence of hands-on activities in practical courses during that period. Due to the practice-oriented components of the accreditation standards and to meet industry demands, the graduate engineers must have strong psychomotor skills in sync with their knowledge level. The evaluation and measurement of psychomotor skills is an important assessment for engineering courses, technical courses, practical courses, hands-on courses, and laboratory courses. Conventional assessment methods, such as reports, observation, and tests, are still being used to assess student's practical and hands-on skills. However, these methods heavily emphasize evaluating the student‘s cognitive skills (Weidner & Popp, 2007; Salim *et al.*, 2012; Baharom *et al.*, 2015b; Viscione *et al.*, 2017; Isa *et al.*, 2019). The assessment tools are limited, particularly when it comes to accessing technical and engineering students‘ psychomotor skills during hands-on, practical, or laboratory work. Many previous studies that worked on engineering students‘ psychomotor skills still relied on rubrics assessment. Assessing the motor performance during the hands-on, biomechanical assessment of the student‘s posture and limb angles when performing the task is important to determine the effectiveness of learning to produce good outcomes.

This study identified skills-related activities and analyzed the coordination aspects of how engineering students use their senses and body parts to perform a motor activity or task smoothly and produce accurate outcomes. We designed a recreational archery activity to analyze the biomechanical parameters of the students, which are the upper limb physical posture and angles, thereby determining the performance level of the engineering students performing the task. Through the activity, the study aims to integrate an alternative to provide supporting quantitative data of effective learning on the engineering student's performance during recreational archery.

The posture and angle analysis during the hands-on recreational archery were performed by capturing the student‘s 2D motion using video recording and proceeding to analyses using a video annotation tool designed for sport analysis called Kinovea. The said software was chosen as it was an easily accessible tool that can be used free without subscription by educators, especially in engineering, to investigate more inclusive and effective learning methods. Kinovea is also a very simple and easily operated tool, and thus has been used in many fields before, especially sports science. The advantage of using Kinovea in this study when analysing the motor performance of the students is that it can be done in a class setting rather than conducting the activity in a laboratory with a fixed camera setting such as the Vicon system. This method is more convenient for educators as they can set up the camera settings according to their preferences and suitability to the activity they have chosen to observe (Nor Adnan *et al.*, 2018; Lau *et al.*, 2023).

Besides using a 2D motion analysis for motor performance, the study also applied the usage of educational data mining (EDM) in machine learning such as prediction models that have capabilities to inform and guide instructional practices, examine the efficiency and effectiveness of learning, provide meaningful feedback for teachers and learners, and formulate strategies for the evaluation of students, modifying learning environments to improve students‘ learning outcomes based on the early prediction of their performance. Through EDM, students' data will be analyzed to determine significant patterns that can improve students' knowledge, skills and overall institutional performance in general (Lee &

Kang, 2024; Pillitteri *et al.*, 2024). Lastly, this technique can provide early identification of future challenges or industry demand for special skills especially for engineering graduates (Ofori *et al.*, 2020; Albreiki *et al.*, 2021).

The decision tree (Rotgans & Schmidt) machine learning method operates by systematically partitioning a dataset into subsets based on a specific number of splits. At each stage of the decision-making process, the algorithm selects the most discriminative feature to split the dataset, aiming to maximize the homogeneity of the resulting subsets in terms of performance levels (Song & Ying, 2015; Charbuty & Abdulazeez, 2021; Panigrahi *et al.*, 2021). KNN classifiers provide a nuanced and intuitive framework for assessing subjects' performance levels by drawing on the concept of similarity among individuals. The K-nearest neigbour (KNN) algorithm operates on the premise that subjects with similar attributes are likely to exhibit comparable performance. KNN is particularly appealing in various research, as it has simplicity and flexibility (Johnson & Yadav, 2018; Ahmed *et al.*, 2020). This technique of classification can be applied to different types of distance metrics such as Euclidean, Cosine, Cubic, and Minkowski. Whereas support vector machine (SVM) is particularly popular for solving classification problems due to its ability to find a clear decision boundary between classes, especially in this study we want to classify the students into two different levels of performance, which are 'Not able to perform' and 'Able to perform'(Naicker *et al.*, 2020; Zulfiker *et al.*, 2020).

SVM can effectively handle large and complex datasets with many features, such as those collected from student performance and engagement tracking systems. With the kernel function, SVM can capture nonlinear relationships between input features and output performance levels. SVM models tend to generalize well to new, unseen data, which is important when predicting the future performance of students. In some cases, student datasets may be small, and SVM can still perform well when trained on limited samples (Bhavsar & Panchal, 2012; Cervantes *et al.,* 2020; Naicker *et al.*, 2020). SVM can be used to predict student performance based on historical data. In this study, a binary classification of whether a student is able or not able to perform can serve as the target labels, while features like demographic data such as gender, anthropometric measurements, and upper limb's joint angle were used as inputs.

Thus, this study aims to provide classification models on the engineering student's performance during recreational archery activity using 2D motion analysis and machine learning.

MATERIALS AND METHODS

Subject recruitment and study procedure

The study recruited a total of 104 subjects (N = 104; 42 males and 62 females. The criteria for recruiting subjects included their enrolment as engineering students, their age between 18 and 22 years, their ability to participate in physical activities in class and no prior experience in performing archery games. We collected written consent from each subject and conducted a briefing on the study procedure before the activity. There is no restriction on any of the subjects requesting to withdraw while the study is still ongoing.

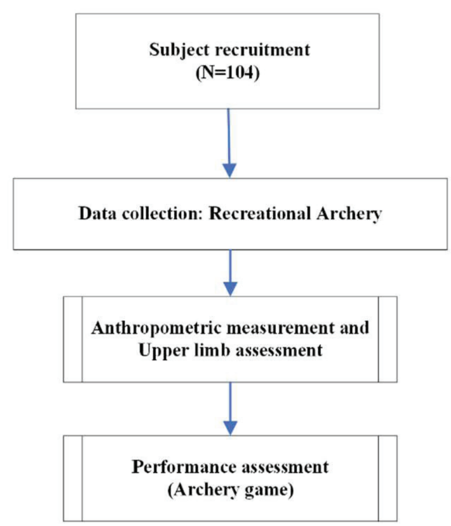

Figure 1: Flow of the study data collection.

Figure 1 shows the flow of the study. The data collection was conducted with 1st and 2nd-year students from the biomedical engineering department. In this study, the archery game was selected as it can provide wide upper limb movement and immediate performance outcomes based on their scores on the archery target. Each subject was tasked with shooting nine arrows at a distance of 3 m. This task was recorded with a video camera. The setup of the camera is shown in Figure 2. Further analysis of the motion of the upper limb of the subjects during shooting was done in Kinovea (version 0.9.5, 2021).

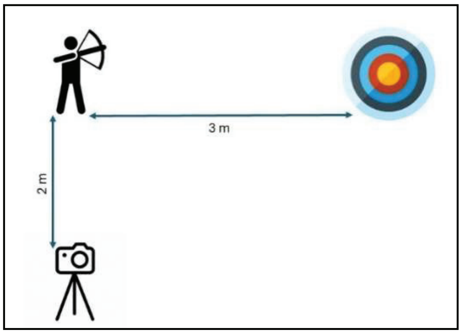

Figure 2: Schematic diagram of archery activity settings in Human Centric Laboratory.

Anthropometric measurements and upper limb assessment

Each subject underwent anthropometric measurements to determine their weight, height, body mass index (BMI), and arm muscle grade. Their upper limb length was also measured, such as shoulder to elbow, elbow to wrist, arm, hand, and trunk (shoulder to waist) length. The measurements were repeated three times, and the average was recorded on the anthropometric measurement form. The strength of the upper limbs of the students was also evaluated using the Oxford Scale (AKA Medical Research Council Manual Muscle Testing Scale). This method involves testing key muscles from the upper extremities against the examiner's resistance and grading the subject's strength on a 0 to 5 scale accordingly: 1) flicker of movement; 2) through full range actively with gravity counterbalanced; 3) through full range actively against gravity; 4) through full range actively against some resistance; and 5) through full range actively against strong resistance.

Recreational archery performance

The activity setting was set where the archery target was put on the wall, and a 3-meter marker was determined to fix the distance between the subject and the target. Video cameras (Samsung Galaxy Tab S5e, 1080p HD Webcam) were positioned as in Figure 2, where the height was fixed perpendicular to the subject's centre and lateral to the subject's right-side position to capture their movement during the archery shooting. The right shoulder, elbow, wrist, and midsection of the participant was marked with tape prior to the commencement of the task as in Figure 3. This is important for later steps in analyzing the angles of the archer's wrist, elbow, shoulder, and trunk while performing archery. Throughout the task, the camera recorded footage of the archer.

Figure 3: Image view on the recording camera. Markers were placed on the shoulder, elbow, wrist and waist. Additional markers were placed during Kinovea analysis on the neck and knee. In the study, all participants were required to draw the bowstrings using their right arm.

The archery activity requires shooting in three separate sets of trials. During the task, each subject must draw a total of nine bows at a distance of three meters. The study used a bow and arrow playset (material: plastic, bow size: 64 cm x 21 cm x 3.5 cm, arrow length: 56 cm, target diameter: 20 cm, range distance: about 5 m). The target area has marks on it ranging from miss as '0' to '10' points. The subjects' scores for each attempt were recorded and calculated, and the maximum total score of the three sets was 90 points. The total marks for those three sets will be the outcome of the performance assessment. Table 1 lists the indicators for the subjects' performance levels.

Table 1: Performance level of subjects based on their total archery score (Response).

Performance indicators	Total archery score
Able to perform	≥ 10
Not able to perform	0 – 9

In supporting the recreational archery performance scores, the upper limb angles were analyzed. For this analysis, the study uses Kinovea software, as it is easier to observe frame-by-frame motion and capture 2-dimensional kinematic angles at a specific frame. The software was feasible to use and a low-cost technology used often by researchers in biomechanics research

(Fernández-González *et al.*, 2020; Hisham *et al.*, 2017; Sharifnezhad *et al.*, 2021). The angles of the wrist (blue), elbow (red), shoulder (turquoise), and trunk (green) of the subject when they flexed or extended from each attempt were analyzed and recorded. Figure 4 shows four angles captured during the phase when the subjects were about to release the bow's arrow.

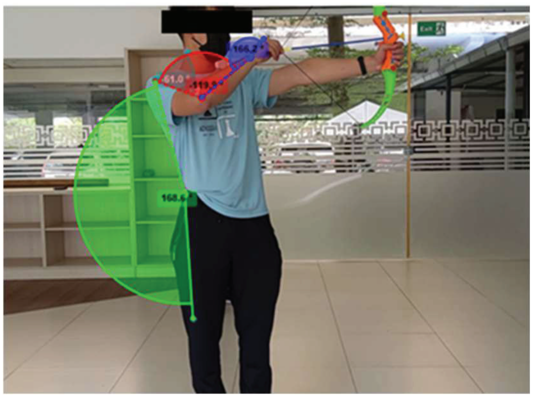

Figure 4: The image from Kinovea software where the video was imported and analysed to get the angles of the trunk, shoulder, elbow and wrist of their right hand when performing the task.

Table 2: Input predictors and response for the classification analysis.

Classification items	Details
Input predictor	Gender, weight, height, BMI, shoulder to elbow, elbow to wrist, hand, trunk and arm lengths, arm muscle grade, trunk, shoulder, elbow and wrist angles.
Response classes	2
Response class Names (Table 1)	Not able to perform (0), Able to perform (1)
Validation (Training and Testing)	10-fold cross-validation

Student performance level classification model design

Machine learning classifiers have been adapted previously by researchers for classification purposes on students' performance (Araya *et al.*, 2022; Hashim *et al.*, 2020; Martínez-Carrascal *et al.*, 2020; Pallathadka *et al.*, 2023). In this step of the analysis, we will compare and choose the best classifier that is most suitable to classify the students' performance levels using MATLAB 2024b software with the classification learner toolbox. The study chooses to compare three different classification algorithms which are DT (Rotgans & Schmidt, 2011), KNN and SVM.

For DT, the split criterion was set using Gini's diversity index with the respective maximum number of splits. The formula of the Gini index is as in Equation 1, where the p_i is the probability of students being classified into a particular class (1- Not able to perform, 2-Able to perform).

$$Gini\ index = 1 - \sum_{i=1}^{2}(p_i)^2 \qquad (...01)$$

For KNN, we trained the subject's data with several models with different distance metrics, such as Euclidean (actual distance between two points) and cosine (angle between two points) as displayed in Figure 5.

$$Euclidean = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2} \qquad ...(02)$$

$$Cosine\ angle = \cos\theta = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2 \sum_{i=1}^{n} B_i^2}} \qquad ...(03)$$

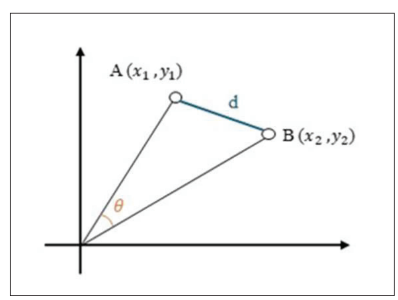

Figure 5: Example of Euclidean distance and Cosine similarity angle of two points.

The SVM classifier models of various Kernel functions, such as linear, quadratic, cubic, and Gaussian, were compared in the study. The most accurate classifiers for the students' datasets use the kernel function defined in Equation 4. SVM created a linear decision boundary called a hyperplane that separates the training subject's data sets into their respective classes. One reasonable choice as the best hyperplane is the one that represents the largest separation or margin between the two classes.

$$K(x_i, x_j) = x_i \cdot x_j \quad ...(04)$$

The quality of predictions depends heavily on the input features. The predictors classify the subjects' performance based on whether they fall into the 'perform' or 'not perform' classes. The validation is set to 10-fold cross-validation, to protect against the model overfitting. The model's performance is determined by its accuracy, confusion matrix, and F1 scores. The confusion matrix provides each model's performance with an actual and predicted output, called true positive (TP), true negative (TN), false positive (FP), and false negative (FN). This output is later used to calculate precision (the number of correct positive results divided by the number of positive results predicted by the classifier) and recall (the number of correct positive results divided by the number of all samples that should have been identified as positive). Lastly, the F1 scores that determine the harmonic mean between precision and recall is calculated using Equation 7.

$$Precision = \frac{TP}{TP + FP} \quad ...(05)$$

$$Recall = \frac{TP}{TP + FN} \quad ...(06)$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \quad ...(07)$$

To increase the model's accuracy, efficiency, and prediction ability, optimization of the classifiers was conducted, which involved fine-tuning key parameters and techniques. The optimization was run on the hyperparameters of the model and at each iteration, the model tried a different combination of hyperparameter values and plotted a graph with the minimum validation classification error observed up to that iteration. The hyperparameter of the SVM model was tuned in this study to optimize the performance of the model. The hyperparameters search range was set as follows; box constraint level: 0.001–1000, kernel scale: 0.001–1000, kernel function: linear, quadratic, cubic, and gaussian. To see whether a better result can be produced, it is advisable to run the optimization longer, therefore the iteration value was increased, in this study to 30.

Ethical considerations: The Universiti Malaya Research Ethics Committee has approved the study protocol under reference number UM.TNC2/UMREC_3264.

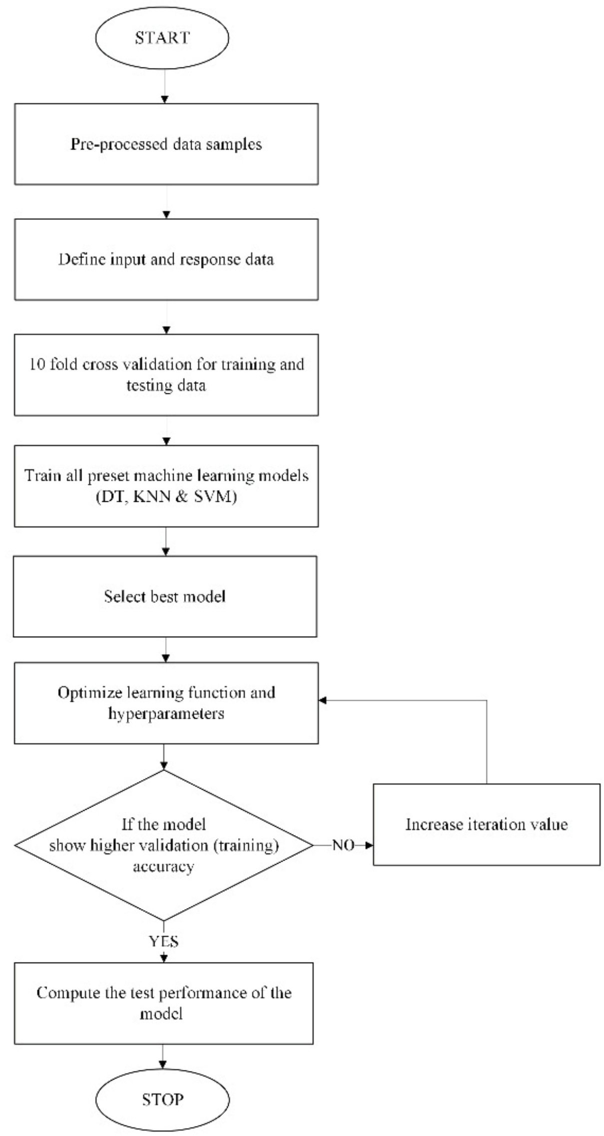

Figure 6: Flowchart of the classifications using preset models and optimization of the models.

RESULTS AND DISCUSSION

Recruited subjects consist of 40.4 % males and 61.5 % females. The demographic data of the subjects were tabulated in Table 3. The average height and weight of both male and female subjects slightly differ however their average BMI stay in the same range of healthy weight status between the value of 21 to 22. The average arm length of both genders also displays a slight difference, not exceeding 10 cm. The average trunk length of the male subjects was recorded as higher than female subjects, due to the influence of the height of male subjects. However, the average arm grade muscle recorded for both male and female subjects falls into the same range between 4 to 5 grade which suggested that all subjects supposedly could conduct activity with their arm without any difficulties.

Table 3: Demographic data consists of no. of subjects, gender, and anthropometric measurements. Results are mean ± SD (standard deviation).

Subjects' characteristics (N=104)	Mean ± SD	
Gender	Male, n = 42	Female, n = 62
Weight, kg	63.5 ± 10.4	54.38 ± 11.18
Height, cm	171 ± 6.24	159 ± 5.9
BMI, kg/m^2	21.74 ± 3.19	21.54 ± 4.25
Shoulder to elbow length, cm	31.9 ± 3.8	28.5 ± 3.0
Elbow to wrist length, cm	26.4 ± 2.1	24.4 ± 1.7
Arm length, cm	58.3 ± 5.1	52.8 ± 4.1
Hand length, cm	18.5 ± 1.1	17.4 ± 0.9
Trunk length, cm	42.5 ± 4.6	36.8 ± 3.9
Arm muscle grade (0-5)	4.88 ± 0.22	4.67 ± 0.48
Trunk angle (degrees)	168 ± 5	168 ± 5.
Shoulder angle (degrees)	66 ± 28	91 ± 25
Elbow angle (degrees)	111 ± 30	81 ± 22
Wrist angle (degrees)	157 ± 11	160 ± 11
Total Archery Scores	16.02 ± 9.65	9.31 ± 8.49

The performance level of students in recreational archery games

As stated in Table 1, the performance level of the subjects was determined by their total score in all archery sets. Table 5 tabulates the number of students who achieved the score based on their performance level. The division of the subjects into two levels resulted in 52.88% of them achieving more than 10 total points, while 47.12% were unable to perform. The data aligns with the expectation that half of the students will be able to perform archery games for the first time.

Table 4: The subjects' performance is based on the total archery score of all three sets.

Performance level indicators	Total archery score	No. of subjects achieving the score	Percentages, %
Able to perform	≥ 10	55	52.88 %
Not able to perform	0 – 9	49	47.12 %

The analysis of the subjects' upper limb angles supported their performance in the archery activity. The angles of the trunk, shoulder, elbow, and wrist of the subjects' right hand were analyzed at the frame where they released the arrow. As the subjects quote that their posture and handling of the tools might be affecting their scores, Table 5 shows the average upper limb angles of different levels of performance. Table 5 shows that the posture of the body, indicated by referring to the trunk and upper limb angle, might suggest differences in their performance (Sarro *et al.*, 2021). The closer the trunk angle to 180 degrees (straight body posture), the higher the average total score achieved by the subjects. The shoulder must be angled within the range of 70 to 80 degrees when pulling the bowstring to achieve a favourable score on the target. Increasing the elbow angle and flexing the wrist inwards produced better total scores during the archery. A short-term coaching session may contribute positively to increasing their chances of getting better total scores thus improving their performance level (Beyaz *et al.*, 2024).

Table 5: Upper limb angles of different levels of performance

Subjects	Performance level	Angles (˚)				Average total score
		Trunk	Shoulder	Elbow	Wrist	
n = 55	Able to Perform	169.08	75.41	103.09	157.27	19.50
n = 49	Not able to Perform	167.64	86.08	83.38	160.15	4.02

It is debatable whether gender affects the performance of the subjects as a previous study mentioned that gender does not influence determining one's archery skills (Destriani *et al.*, 2024). However, there was also a suggestion that females might perform poorly under pressure and there have been recent failures compared to males in archery games (Li & Zhao, 2024). In this study, the performance of male subjects was also better compared to female referring to their average total score achieved during the recreational archery activity. Therefore, we are considering gender as one of the predictors affecting their performance in our study. Besides that, several parameters such as arm length, trunk angle, and shoulder angle were determined by previous researchers to be affecting the scores of the archers. Previous studies by Noor and by Setiakarnawijaya *et al.* reported that, in addition to the arm muscle grade and strength, arm length significantly affected the accuracy of the archers' scores with a p-value of less than 0.05 (Setiakarnawijaya *et al.*, 2021; Noor, 2023). As both studies were investigating athletes, the athlete's anatomy is also very important; in their case, the arm length is very important for archery athletes. Their studies were focused on highlighting the importance of the physical aspect's contribution to determining archery achievement. Another parameter that appears significant in previous studies was postural sway during shooting archery. This parameter was closely related to the position of the trunk during the phases of aiming and releasing the bow. A study by Zawi & Mohamed (2013) reported that the shooting score performance of skilled archers was significantly affected by the postural sway during the release phase at a p-value of less than 0.001. Reduction in postural sway meaning that the body trunk should be positioned towards the centre line suggesting an increasing trend of shooting scores. As archery mainly uses the upper limb to operate, a suitable shoulder position is important to minimize fluctuations in high-strength muscle performance. Several studies have shown that towards the releasing phase of archery, the position of the arm shoulder is the main key to achieving favourable results (Lin *et al.*, 2010; Kolayiş & Ertan, 2016; Vendrame *et al.*, 2022).

Students' performance on classification models

Classification with all fourteen measured parameters as input predictors was run in the preset DT, KNN and SVM models. The best of each classification algorithm was tabulated in Table 6.

Table 6: Comparison of the best models of each classification algorithm.

Models	Models performance				Model properties
	Training accuracy (Validation) (%)	F1 score	Error rate (%)	Test accuracy (%)	Algorithm & hyperparameters
Model 1	50	0.50	50.0	70	• Coarse DT • Maximum no of splits = 4 • Split Criterion = Gini's diversity index
Model 2	68.1	0.67	31.9	70	• Medium KNN • No of neighbours = 10 • Distance metric = Euclidean • Distance weight = Equal
Model 3	69.2	0.69	30.9	70	• Medium Gaussian SVM • Kernel function = Gaussian • Kernel scale = 3.7 • Box constraint level = 1

Out of all the algorithms compared, the SVM model produced the highest accuracy on validation and testing. To increase the performance of the SVM model, the optimization was run on the hyperparameters of the model and at each iteration, the model tried a different combination of hyperparameter values and plotted a graph with the minimum validation classification error observed up to that iteration. To see whether a better result can be produced, it is advisable to run the optimization longer, therefore the iteration value was increased to 30.

From the SVM optimization, Model 4 gives a training (validation) accuracy of 72.3% and a test accuracy of 80%, where the best point hyperparameter was observed in Figure 7 at the red square point with minimum classification error at 0.279, with kernel function: cubic and box constraint level at 0.00269.

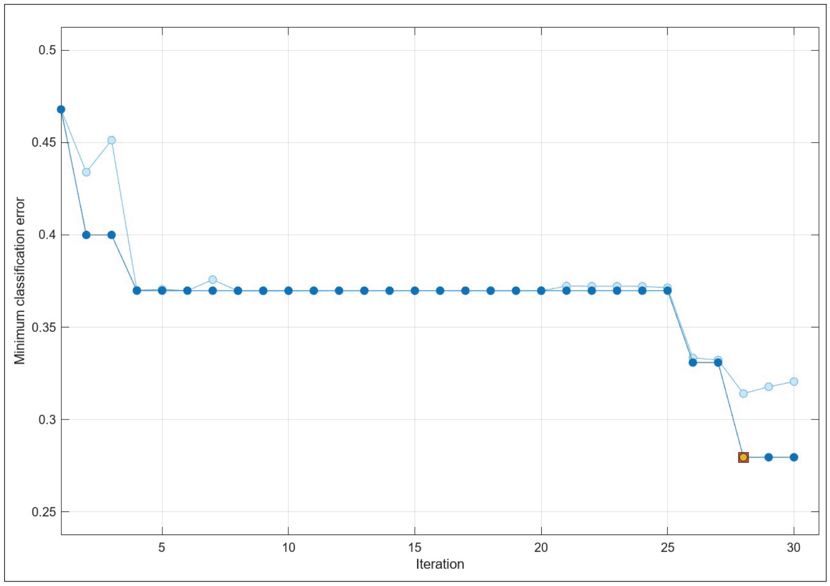

Figure 7: Minimum classification error plot of Model 4 (Optimize SVM model).

Table 7: Per-class metrics of training (validation) and test sets of optimized SVM Model 4.

	Model 4 (Optimize SVM)					
Per-class metrics	Not able to perform class			Able to perform class		
	Precision	Recall	F1 score	Precision	Recall	F1 score
Training (Validation)	0.73	0.63	0.68	0.71	0.80	0.75
Test	1.00	0.60	0.75	0.71	1.00	0.83

As the training and testing accuracy of Model 4 increases after optimization, the performance in the ability to correctly classify the student's performance also increases. Table 7 tabulates the results of per-class metrics for Model 4. The F1 scores of Model 4 recorded the highest among all investigated models thus depicting the precision of the model in correctly classifying the students into their respective classes based on all fourteen predictors.

CONCLUSION

The study's hypotheses lead to the conclusion that a student's biomechanical data, including physical and posture components like gender, arm muscle grade, arm length, shoulder angle, elbow angle, and trunk angle, influences their ability to perform a physical task, specifically the recreational archery activity. Based on these parameters, the selected classifiers were able to classify the students into 'able to perform' and 'not able to perform' classes. In this study, after optimization, SVM classifiers displayed superior performance when applied to the student's data, with the highest accuracy and precise classification. Therefore, our study demonstrates that the integration of biomechanical data and machine learning has the potential to be a valuable tool for evaluating psychomotor abilities, particularly in the context of engineering students. Soon, to strengthen the assessment of engineering students' skills, we will further work on combining these parameters with the self-assessment of students' confidence levels before they perform the recreational archery task.

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