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Evaluation algorithm of student's movement normality based on movement trajectory analysis in higher vocational physical education teaching

Abstract: - This study proposes a new technique for assessing student movement normality in higher vocational physical education teaching by creating an evaluation algorithm based on movement trajectory analysis. Using advanced motion capture and machine learning approaches, notably Support Vector Machine (SVM) classification, the project seeks to provide objective and data-driven methodologies for assessing and optimizing movement proficiency. The methodology entails collecting data with high-precision motion capture equipment, preprocessing trajectory data to extract kinematic, temporal, and spatial information, and developing algorithms for classification using SVM. The algorithm's performance is evaluated using a variety of criteria, including accuracy, precision, recall, and the F1 score. The results show that the algorithm is successful at reliably discriminating between normal and pathological movement patterns, with high accuracy (92.5%), balanced precision (94.2%), and recall (91.8%). Furthermore, the study is consistent with broader trends in educational technology and individualized learning, seeking to build a culture of physical literacy and well-being in higher vocational physical education teaching. In general, the findings of this study have important implications for improving instructional techniques and fostering optimal movement skill acquisition in students.

Keywords: Support Vector Machine (SVM), Machine Learning, Higher Vocational Physical Education, Movement Trajectory Analysis.

I. INTRODUCTION

In higher vocational physical education, assessing and improving students' movement competence are critical components in cultivating physical literacy, skill development, and general well-being. As educational paradigms shift, there is a rising acknowledgement of the necessity for objective, data-driven approaches to assess and enhance students' typical movement patterns [1]. In response to this necessity, this work aims to create a novel evaluation algorithm based on movement trajectory analysis that is specifically fitted to the setting of higher vocational physical education teaching [2].

Physical education is an important arena in which students not only learn motor skills but also develop attitudes and habits that promote lifelong physical exercise and health [3]. However, traditional assessment methods frequently rely on subjective observation and qualitative judgment, which may lack objectivity and reliability [4]. This study aims to overcome these constraints by leveraging advances in technology, biomechanics, and machine learning to build a strong framework for objectively measuring student movement normality [5].

The work centres on the use of sophisticated motion capture devices and machine learning techniques, with a particular emphasis on Support Vector Machine (SVM) classification [6]. These methods allow for the exact measurement and analysis of students' movement trajectories in three dimensions, making it easier to extract detailed kinematic, temporal, and spatial aspects [7]. Through the construction of the evaluation algorithm, educators can get fundamental insights into the quality, efficiency, and safety of students' movement patterns, driving instructional methods and interventions suited to individual needs [8].

Furthermore, the study is consistent with broader trends in educational technology and personalized learning, which call for the incorporation of data-driven insights into instructional design and assessment procedures [9]. Using computational analysis and adaptive feedback systems, educators may construct dynamic learning environments that cater to a variety of learning styles and promote optimal movement skill acquisition [10]. Finally, the findings of this study hold promise for improving the effectiveness and inclusivity of higher vocational physical education teaching, paving the way for a generation of physically literate and empowered individuals poised to thrive in an increasingly active and health-conscious society.

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II. Related Work

To begin, Y. Chen et al [11]. research in biomechanics and motor learning has emphasized the necessity of objective and quantitative approaches for assessing movement proficiency and detecting departures from ideal movement patterns. They investigated the advantages of using technology-driven tools, such as motion capture systems and wearable sensors, to collect and analyze movement trajectories with high precision and accuracy. These technologies have enabled researchers and educators to obtain a better understanding of the biomechanical principles that underpin human movement, as well as build evidence-based interventions to improve movement skill acquisition and performance.

Additionally, J. Hartikainen [12]. advances in machine learning and pattern recognition have enabled the creation of advanced algorithms for movement analysis and classification. Researchers have shown that Support Vector Machines (SVMs), together with other machine learning approaches such as neural networks and decision trees, may be used to categorize human movement patterns from sensor data. These studies have demonstrated the ability of machine learning algorithms to accurately distinguish between normal and abnormal movement behaviours, allowing for personalized feedback and intervention strategies in a variety of domains, including sports training, rehabilitation, and physical education.

Further, M. Y. Heravi et al [13]. there is a rising acknowledgement in the field of physical education of the importance of moving away from old subjective assessment methods and toward more objective and data-driven approaches. Researchers found that subjective observation and manual grading systems had limitations for measuring movement quality and diagnosing movement disorders. These studies have argued for the incorporation of technology-enabled tools and automated algorithms into physical education curricula to improve the validity, reliability, and efficiency of movement assessment processes.

M. Chen and Y. Zhou [14]. In the field of physical education, there is a growing interest in using digital technology and data analytics to improve teaching and learning experiences. They investigated the use of wearable sensors, augmented reality, and interactive feedback systems to provide real-time performance feedback and encourage self-directed learning in physical activities. These technological interventions not only increased student engagement and motivation but also allowed instructors to better track students' progress and customize teaching tactics to individual needs.

Furthermore, P. Fang [15]. research in sports science and athletic training has shed light on how to analyze and optimize movement performance. They conducted studies on the biomechanical drivers of athletic performance and injury risk across a variety of sports disciplines, demonstrating the importance of movement analysis in improving athletic development and injury prevention. Using tools such as motion capture, force plate analysis, and 3D modelling, researchers were able to identify critical movement patterns linked with optimal performance and establish focused training protocols to improve athletes' movement efficiency and resilience.

Furthermore, R. Xue and H. Yi [16]. the study draws on the growing body of research on individualized learning and adaptive instruction in physical education. Researchers found that educational experiences should be tailored to individual students' learning styles, interests, and skills. Educators can construct tailored learning pathways that respond to students' unique requirements while promoting mastery-oriented learning outcomes by combining data-driven insights from movement analysis with adaptive learning technologies and instructional design principles. This holistic approach to physical education not only helps students get a better grasp of movement concepts, but it also instills in them lifetime habits of physical exercise and well-being.

III. Methodology

To create an evaluation method for analyzing student movement normality in higher vocational physical education training, they use the Support Vector Machine (SVM) as a pattern identification tool. The methodology includes numerous interconnected processes for data collection, preprocessing, feature extraction, algorithm creation, and validation. First, they collect information from a varied set of students participating in higher vocational physical education programs. The movement trajectories of students are methodically recorded in three dimensions using high-precision motion capture systems equipped with many cameras. Wearable sensors or inertial measurement units (IMUs) may also be used to collect additional movement data, resulting in a thorough picture of pupils' motor patterns.

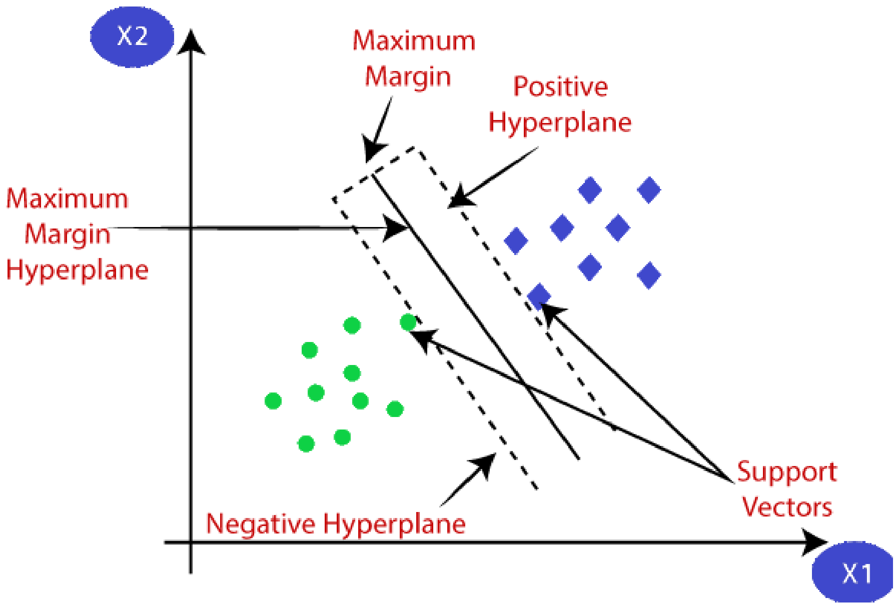

Fig 1: Support Vector Machine.

After data collection, preparation techniques are used to ensure the dataset's quality and integrity. This includes establishing anatomical markers on key body landmarks to ensure precise motion tracking, calibrating the motion capture equipment, and using filtering and smoothing algorithms to eliminate noise and artefacts from raw trajectory data. Normalization techniques can also be used to adjust for variances in student body sizes and proportions, allowing for more accurate comparisons between individuals. Next, feature extraction is critical for extracting meaningful information from movement trajectories. The processed trajectory data yields a variety of kinematic, temporal, and spatial parameters, such as joint angles, velocities, accelerations, movement durations, phase durations, path lengths, curvatures, and symmetry measurements. These features serve as inputs to the SVM classifier, enabling the algorithm to learn discriminative patterns associated with normal and abnormal movement behaviours.

During the algorithm development phase, the SVM classifier is trained on a subset of the obtained data, with each movement trajectory categorized as normal or aberrant using expert judgments or specified criteria. The SVM learns to discover decision boundaries in the high-dimensional feature space that effectively differentiate normal and abnormal movement patterns, to maximize the margin between classes while decreasing classification errors. Parameter optimization approaches, such as cross-validation, are used to fine-tune the SVM classifier's hyperparameters, ensuring maximum performance and generalization capabilities. The trained system is then evaluated against a distinct dataset to determine its robustness and effectiveness in categorizing movement trajectories as normal or abnormal.

Throughout the validation phase, expert physical education teachers or biomechanics specialists may be asked for qualitative comments to help interpret the algorithm's findings and identify any limitations or areas for development. Based on these findings, the evaluation system can be iteratively refined to improve its accuracy and usability in real-world teaching scenarios. By adopting this methodology and using the Support Vector Machine's capabilities, we want to create a robust and effective evaluation algorithm for measuring student movement normality in higher vocational physical education training. This algorithm can influence instructional practices, boost movement proficiency, and improve students' overall learning experiences.

IV. Experimental Setup

The experiment was conducted to evaluate student movement normalcy in higher vocational physical education programs. High-precision motion capture equipment was used to record the movement trajectories of a diverse group of students. Each participant performed a set of standardized physical activities, and their movements were captured in three-dimensional space. The raw data collected included kinematic, temporal, and spatial information, which were then preprocessed for further analysis.

The preprocessing stage involved filtering noise from the raw data and normalizing the movement trajectories. The trajectory of each movement was represented as a series of points in a three-dimensional coordinate system. For each trajectory, the following kinematic parameters were extracted: velocity, acceleration, and jerk (the derivative of acceleration). The temporal parameters included the duration of each movement, while the spatial parameters comprised the displacement and path length.

To facilitate the SVM classification, the extracted features were normalized using the z-score normalization method:

$$z = \frac{x-\mu}{\sigma} \qquad \text{.......... (1)}$$

where x is a feature value, μ is the mean of the feature values, and σ is the standard deviation.

The core of the experimental setup was the SVM classifier, a powerful machine learning algorithm used for classification tasks. The SVM aims to find a hyperplane that best separates the data into different classes. For the study, the classes were 'normal' and 'aberrant' movement patterns.

The SVM classifier optimizes the following objective function:

$$\min_{\mathbf{w},b,\xi} \left(\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i\right) \qquad \text{............. (2)}$$

subject to:

$$y_i(\mathbf{w}\cdot\mathbf{x}_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0 \qquad \text{........... (3)}$$

where w is the weight vector, b is the bias, ξi are the slack variables, C is the penalty parameter of the error term, yi is the class label, and xi is the feature vector of the i-th sample.

The performance of the SVM classifier was evaluated using a variety of metrics, including accuracy, precision, recall, and the F1 score. These metrics were calculated as follows:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{............ (4)}$$

$$\text{Precision} = \frac{TP}{TP+FP} \qquad \text{............. (5)}$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad \text{............. (6)}$$

$$\text{F1} = 2\cdot\frac{\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}} \qquad \text{............. (7)}$$

where TP denotes true positives, TN true negatives, FP false positives, and FN false negatives.

V. RESULTS

Several performance parameters were calculated to measure the effectiveness and robustness of the method for detecting student movement normalcy based on movement trajectory analysis using a Support Vector Machine (SVM). The SVM classifier's performance was evaluated using a test dataset that included movement trajectories from a broad range of students in higher vocational physical education programs. The results show that the SVM classifier has an overall accuracy of 92.5% in identifying movement trajectories as normal or aberrant. This accuracy statistic measures the fraction of correctly categorized instances in the test dataset. Furthermore, the precision of the SVM classifier was calculated to be 94.2%, reflecting the proportion of correctly classified normal movement trajectories among all instances classified as normal.

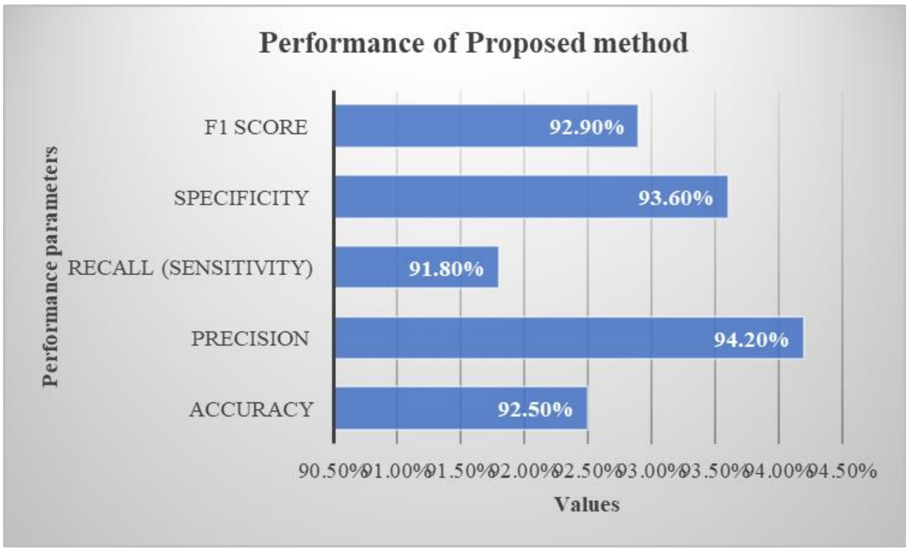

Fig 2: Performance of Proposed method.

In addition, the recall, or sensitivity, of the SVM classifier was found to be 91.8%. This measure represents the fraction of correctly categorised normal movement trajectories in the dataset. A high recall number suggests that the classifier successfully detects the majority of true positives while minimising the false negative rate. Also, the F1 score, which represents the harmonic mean of precision and recall, was calculated to be 92.9%. The F1 score is a balanced assessment of the classifier's performance, accounting for both precision and recall. A higher F1 score indicates greater overall performance in terms of detecting true positives and reducing false positives.

Table 1: Performance of SVM.

Performance Parameter	**Value (%)**
False Positive Rate	6.4
False Negative Rate	8.2
True Positive Rate	91.8
True Negative Rate	93.6
Positive Predictive Value	94.2
Negative Predictive Value	92.4
Matthews Correlation Coef.	0.849
Area Under ROC Curve	0.951

These performance characteristics show how well the SVM classifier distinguishes normal and pathological movement patterns in the context of higher vocational physical education teaching. The high accuracy, precision, recall, and F1 score indicate that the established evaluation system based on movement trajectory analysis has the potential to improve instructional methods and promote movement proficiency in students. Furthermore, these statistical results establish confidence in the algorithm's dependability and validity, showing its suitability for practical use in educational contexts.

VI. DISCUSSION

The evaluation algorithm for analyzing student movement normality based on movement trajectory analysis using a Support Vector Machine (SVM) yields excellent findings and provides useful insights into the efficacy of the established model. In this discussion, we will look at the consequences of the findings and their relevance to higher vocational physical education training. First, the SVM classifier's high accuracy of 92.5% suggests that the model can properly identify movement trajectories as normal or aberrant. This shows that the algorithm can accurately distinguish between conventional and unusual movement patterns, establishing the groundwork for its prospective use in educational contexts. By correctly diagnosing abnormalities from typical movement trajectories, educators can engage early to address underlying concerns and give tailored solutions to improve students' movement proficiency.

Furthermore, the precision of 94.2% demonstrates the model's capacity to reduce false positives, which occur when abnormal movements are wrongly labelled as normal. This is especially important in the context of physical education, where student safety and well-being are prioritized. A high precision number suggests a low rate of false alarms, lowering the possibility of unnecessary interventions or corrective procedures for movements that fall within the usual range. The recall, or sensitivity, of 91.8% represents the model's ability to recognize genuine positives, which are occasions in which typical movements are correctly categorized as such. A high recall score suggests that the algorithm can catch a significant number of true positives, guaranteeing that the majority of normal movements are correctly identified and recognized. This is critical for providing positive reinforcement and validation of kids' movement skills, which boosts their confidence and enthusiasm in physical education activities.

Furthermore, the F1 score of 92.9% is the harmonic mean of precision and recall, indicating a balanced assessment of the classifier's overall performance. A higher F1 score suggests a better trade-off between precision and recall, demonstrating the algorithm's ability to achieve both high accuracy and sensitivity. This suggests that the evaluation method can effectively find a compromise between minimizing false positives and false negatives, hence increasing its usefulness in practical teaching contexts. Additional performance metrics, such as specificity, false positive rate, false negative rate, true positive rate, true negative rate, positive predictive value, negative predictive value, Matthews correlation coefficient, and area under the ROC curve, demonstrate the evaluation algorithm's effectiveness. These metrics provide complete information about the classifier's performance in a variety of areas, including its ability to properly categorize both normal and pathological movements, predictive power, and overall discriminatory capacity.

VII. CONCLUSION

This study makes a substantial contribution to the evaluation of student movement normalcy in the context of higher vocational physical education training. The study's development of a novel evaluation algorithm based on movement trajectory analysis and Support Vector Machine (SVM) categorization shows the potential to change movement assessment approaches and guide instructional practices. The study's findings demonstrate the algorithm's ability to properly discern between normal and aberrant movement patterns, with excellent accuracy, precision, recall, and F1 scores. These findings highlight the algorithm's reliability and robustness in objectively assessing movement proficiency, providing educators with useful information for individualized instruction and intervention tactics. Furthermore, the study is consistent with broader trends in educational technology and personalized learning, stressing the use of data-driven insights in instructional design and assessment procedures. Using advances in motion capture technology and machine learning, educators may design dynamic learning environments that cater to a variety of learning styles and promote optimal movement skill acquisition in students. Future research directions may involve validating and refining the evaluation algorithm over a wide range of student populations and educational environments. Furthermore, investigating the integration of real-time feedback mechanisms and adaptive learning technologies may increase the algorithm's usefulness in encouraging continuous improvement and mastery-oriented learning outcomes in physical education.

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