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Predictive Decision Analytics for Membership Retention and Expansion in Martial Arts Organisations

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ABSTRACT

A martial arts organisation that effectively retains its existing members while simultaneously attracting new ones is more likely to experience sustainable growth. Recent studies indicate that Artificial Intelligence (AI)-driven predictive decision analytics can significantly enhance member retention by evaluating training performance and movement precision. The system assesses martial arts competencies through the application of Kernel Principal Component Analysis (KPCA) for reducing spatial-temporal dimensions of contour features, in conjunction with Time Series Analysis (TSA) and human action recognition (HAR) methodologies. This assessment framework employs a hybrid classification model that integrates Convolutional Neural Networks (CNN) with Bidirectional Long Short-Term Memory (BiLSTM) networks. The BiLSTM component interprets temporal sequences, while the CNN performs spatial analysis, facilitating a comprehensive evaluation of training movements. The operational structure comprises two sequential stages: initially, it detects standardised movements from expert demonstrations; subsequently, it evaluates learner performance through practical tests, establishing benchmarks for comparison. By monitoring patterns in skill progression, student dedication, and dropout risks, the system enables the provision of personalised training interventions aimed at improving retention rates. The empirical outcomes demonstrate that the model not only enhances training quality and member engagement but also leverages data insights to inform strategic decisions for expanding membership. Developers of this approach employ AI and predictive analytics to innovate martial arts training processes, thereby reducing short-term enrolments while fostering long-term organisational stability.

1. Introduction

The effectiveness of martial arts organisations is commonly evaluated by their capacity to retain current members while attracting new enrolments. However, many martial arts academies face

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persistent issues such as high dropout rates, inconsistent class attendance, and inefficient promotional strategies [1]. Conventional membership management practices, which often rely on intuition or traditional marketing approaches, tend to overlook the critical factors contributing to member attrition. In today's data-centric landscape, it is essential for such organisations to embrace innovative methodologies that support continuous, long-term development. One such solution lies in predictive decision analytics—a convergence of data science, machine learning, and artificial intelligence—designed to anticipate trends and inform actionable strategies for retention and growth [2]. By forecasting member behaviour, this approach enables institutions to cultivate a more engaged and committed student base.

Predictive analytics processes vast datasets including attendance records, frequency of class participation, payment compliance, activity levels, and demographic information. Through analysing these variables, martial arts organisations can uncover patterns that predict the likelihood of member disengagement [3]. For example, members who consecutively attend classes but fail to make timely payments may present a higher risk of withdrawal [4]. Proactively identifying such trends enables academies to intervene early—offering personalised solutions such as one-on-one check-ins, exclusive discounts, or tailored class recommendations [5]. This method not only enhances student satisfaction by demonstrating care and responsiveness during their martial arts journey but also boosts ongoing motivation, thus encouraging long-term participation.

In addition, AI technologies facilitate operational efficiencies by streamlining class structures, optimising instructor assignments, and customising training programmes to meet the specific needs of students [6]. Predictive analytics also extends the strategic capabilities of martial arts organisations by uncovering new avenues for expansion [7]. This is achieved through the analysis of demographic profiles, social media behaviour, and regional market dynamics [8]. For instance, data-driven insights can reveal areas of high demand, allowing academies to strategically determine new school locations. Furthermore, marketing effectiveness can be significantly enhanced by identifying the most impactful advertising platforms and tailoring campaigns to specific audience segments [9]. The integration of martial arts focus groups can support more accurate budgeting and targeted outreach, increasing the likelihood of attracting and retaining the most suitable members.

Predictive analytics also empowers organisations with tools for dynamic pricing, personalised member experiences, and strategic positioning within the broader fitness sector [10]. By monitoring macroeconomic indicators and consumer preferences, schools can adjust pricing strategies in accordance with demand fluctuations, seasonal trends, and user expectations [11]. For instance, flexible membership models, tiered pricing systems, and loyalty rewards can be developed to cater to distinct customer segments [12], thereby enhancing inclusivity and extending member engagement [13]. Similarly, class scheduling can be optimised using predictive models, ensuring high-demand sessions are offered at optimal times to maximise participation.

The integration of predictive decision analytics gives martial arts organisations a significant competitive edge [14]. These tools facilitate pre-emptive retention strategies, resolve recruitment bottlenecks, support optimal pricing, and enhance overall member satisfaction [15]. To improve predictive accuracy, a hybrid model incorporating CNN and BiLSTM can be employed. While CNN excels at identifying key features within complex data sets, BiLSTM is adept at capturing sequential behavioural trends related to attendance and participation. Together, these models yield nuanced insights that inform strategic recommendations, extending their utility beyond martial arts into broader educational and organisational contexts [10]. By leveraging such advanced techniques, martial arts academies are better equipped to make data-informed decisions that ensure resilience, sustained growth, and long-term success in an increasingly competitive environment.

2. Related Works

Data Analyticsof predictive decision analytics, incorporating AI, Machine Learning, and Big Data Analytics, plays a pivotal role in enhancing member acquisition and retention within martial arts institutions. Through examining attendance records, payment habits, and activity data, these systems can forecast member attrition and recommend preventive actions to mitigate loss. Additionally, they support data-driven decisions in areas such as marketing, strategic expansion, and pricing structures, ensuring both consistent growth and economic viability. Enhanced class scheduling, more effective instructor deployment, and tailored programme offerings further contribute to stronger community engagement. This approach confers a competitive advantage through automation and improved member satisfaction. Table 1 summarises the strengths and weaknesses of these data-centric solutions.

Wu and Zhou [16] applied deep learning, particularly CNN, to detect martial arts actions and body positions from video input. The model effectively identified movement patterns and achieved high accuracy in recognising combat techniques. However, misclassification occasionally occurred when visually similar actions were confusing. Despite this, their system proved beneficial in automating action analysis during martial arts instruction. Li [17] utilised keyframe extraction to pinpoint incorrect movements in martial arts routines. The system enabled real-time error detection, significantly boosting training efficiency. However, it faced computational challenges, and its accuracy was heavily influenced by the quality of keyframe selection. Continued development was identified as necessary to enhance its recognition precision. Chen [18] introduced a composite object modelling method for simulating martial arts movements, driven by machine learning for refined motion representation. This model enabled detailed, interpretable analysis suitable for teaching and learning applications, although it required extensive annotated datasets and computational power. Despite these constraints, the research enriched the understanding of motion modelling and classification in martial arts.

Yao et al. [1] proposed a multimodal robotic martial arts system capable of leg pose recognition using Graph Convolutional Neural Networks (GCNN). Although the system achieved high accuracy in robotic control contexts, it fell short in mimicking complex human-like movements, thus limiting real-world applicability. Nevertheless, this works advanced AI-based robotics for martial arts training scenarios. Rodrigo et al. [19] developed an automatic highlight detection system for martial arts tricking videos using computer vision techniques. Their approach successfully identified key moments to support better video summarisation and analysis. However, the model occasionally failed to capture nuanced yet critical highlights, impacting the completeness of event detection. Still, it contributed meaningfully to automated video processing within martial arts.

Table 1:
Research Gap Validation

Author(s)	Techniques Involved	Advantages	Disadvantages
Wu and Zhou [16]	CNNs, Deep Learning	Accurate Combat Action Recognition	Struggles with Similar Movement Variations
Li [17]	Key Frame Extraction	Enhances Training Efficiency	High Computational Complexity
Chen [18]	CNN & GRU, Big Data, Machine Learning	Interpretable Motion Analysis	Requires Large Labelled Datasets
Yao et al. [1]	GCNs, Multi-Modal Pose Recognition	Effective in Robotic Motion Control	Limited Handling of Complex Movements
Rodrigo et al. [19]	Computer Vision, Highlight Detection	Efficient Tricking Video Summarization	Neglects Subtle Key Moments

Existing methods in martial arts motion recognition face several limitations, including difficulties in finding similar motions, high computational complexity, dependence on large, labelled datasets, poor adaptability to complex movements, and suboptimal video analysis capabilities. This paper introduces a new approach based on a hybrid BiLSTM-CNN model. The model first extracts temporal motion features through BiLSTM, and then uses CNN to extract spatial features [20]. This model enhances recognition accuracy, reduces computational complexity, improves flexibility for handling complex martial arts motions, and facilitates more effective automatic highlight detection. By leveraging cutting-edge deep learning techniques, the proposed solution provides a more efficient, precise, and scalable approach to motion recognition in martial arts.

3. Proposed System Model

The prevalence of traditional martial arts among young people is significantly low, which exacerbates issues related to its inheritance and cultivation. Furthermore, the integration of modern science and technology into martial arts training has introduced unavoidable challenges. In sports programs, such as Olympic swimming and figure skating, techniques for detecting human movements have been employed, enabling coaches to monitor and guide athletes' progress. These methods assist in correcting non-repetitive movements and enhancing the effectiveness of learning, while also serving as electronic referees to ensure fairness and accuracy during competitions. Time series validation involves analysing data generated by phenomena at specific points in time, which is dynamic in nature. This process focuses on understanding the relationships between phenomena and their corresponding changes, thereby improving predictive models. Figure 1 illustrates the overall framework for recognising human actions in video data.

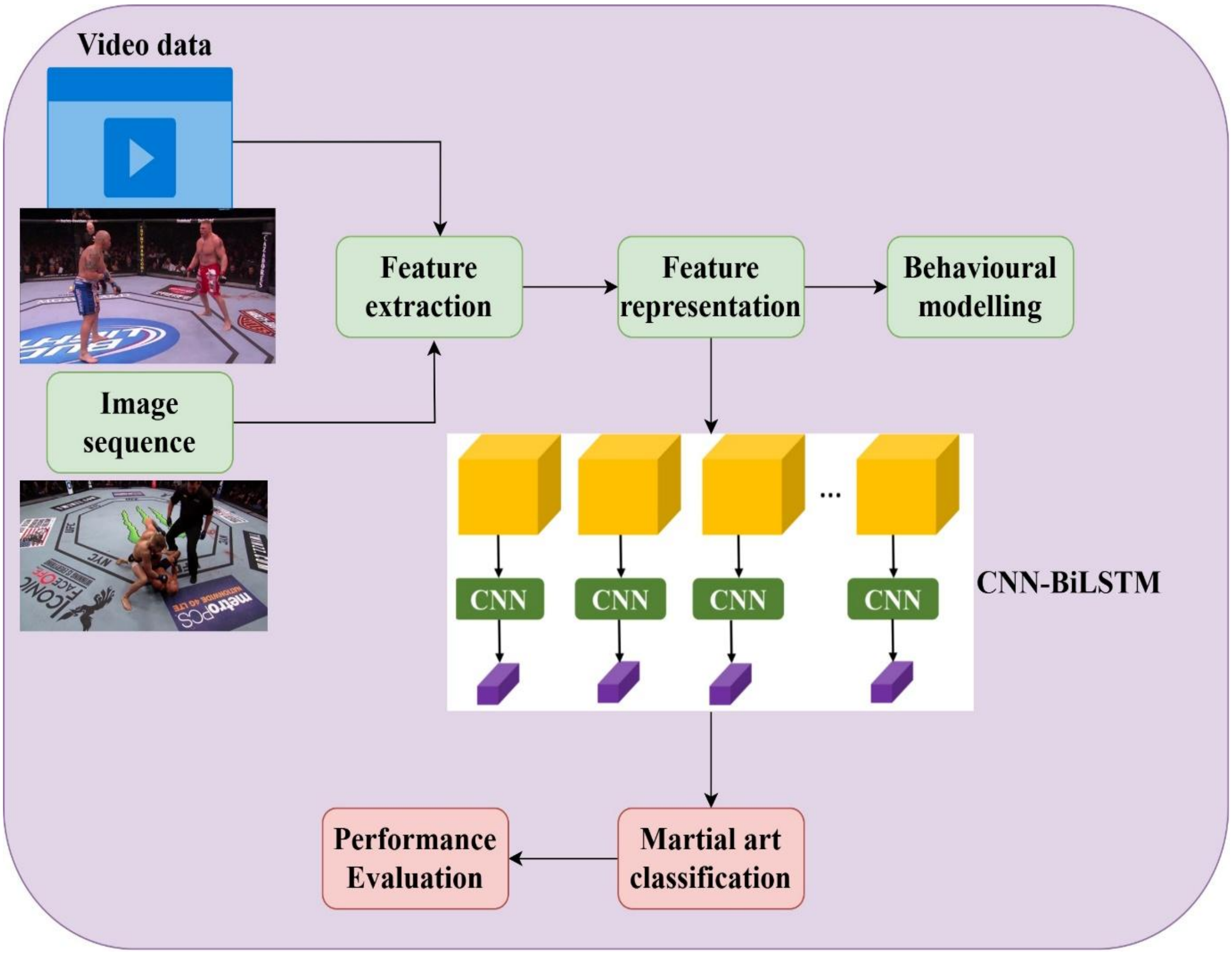

Fig.1. Block Diagram of the Martial Arts (Human Action) Recognition

The input consists of image sequences or video data. The challenge in video feature extraction is to identify and extract various attributes of the object to be detected, such as position, joint angles, wave motion, colour, texture, contour, and speed, through the image sequence. Feature definition involves processing the extracted data and converting it into a format that is easily expressible and identifiable, often through histograms, vectors, etc., to statistically verify the variables, and then presenting the target data for identification [21]. Behaviour design involves gathering the required data, learning the relationships and variations among them, and producing a simplified and normalised representation. An optimal classifier can then be applied to classify the characteristics and assist in identifying the detection result.

3.1 Architecture of a Time Series Related Martial Arts Movement Recognition System

For feature extraction, the selection of a colour map is crucial for identifying the features of martial arts actions. The construction of a feature vector for martial arts actions is based on a time series feature vector, and a classifier is then employed for classification. The architecture is divided into four modules, each dedicated to a specific function: feature extraction, representation, characteristics modelling, and action classification. During processing, the data are split into two types: time series and image data. The architecture compiles and processes this information, gradually transforming the image space into the space of time series data [12]. The time series data theory of martial arts movement is applied in the classification process by extracting statistical features from the time series. The entire architecture is divided into two phases: the normal movement detection phase and the practice test phase. In the normal movement detection phase, actions demonstrated by a skilled practitioner are collected to produce feature representations and perform feature extraction. In the practice test phase, the student’s martial arts movements are collected, followed by feature representation, extraction, and classification. Finally, the outputs are compared to the normal movements [22].

3.2 Feature Extraction

This section describes the feature extraction process, which includes recognising martial arts actions from video, extracting contour features, and processing time series data derived from contour sequences [23]. Among these, the feature extraction module plays a critical role in calculating the final characteristic, and optimising feature extraction enhances the detection results. The methods for human behaviour detection feature extraction are divided into global and local features, such as motion history maps, optical flow, contour, spatio-temporal body, motion history image, grid-based, third-dimensional time scale sift, HOF, and HOG. In this work, spatio-temporal wheel templates are employed to characterise martial arts movements, while the KPCA method is utilised to condense part of the spatio-temporal contour map data, which contains a large volume of information, and subsequently transforms it into time series data [24]. The silhouette conveys information only about the shape and boundary of the target, and an explicit description of the human body's shape indicates the target's form, specifying the orientation of local information and the general scale of the image. To detect objects that belong to the same category, silhouettes can be considered. Spatio-temporal contours are responsible not only for the content of the image but also for globally 'preserving' the data in an optimal way, in contrast to place-oriented spatio-temporal points of interest that focus on local data. When the video background remains unchanged, processing the contours is more efficient than processing spatio-temporal points of interest [15]. This process incurs high computational costs for direct detection and classification, resulting in features with a high dimension. To address this, dimensionality reduction is applied, often using kernel function-based principal component analysis, as represented in equation (1).

$$\emptyset : S^N \rightarrow f, X_1 \rightarrow X \quad (1)$$

Here, f is a feature map, $\emptyset$ is a mapping function, X_1 is an input function. After performing the substitution computation, the principal component is calculated. Let X represent a test sample point, which, after transformation, is expressed in equation (2) and equation (3).

$$(v_J)^t \emptyset(X) = \sum_{I=1}^{M} \alpha_I^J \, \emptyset(X_I)^T \emptyset(X) \quad (2)$$
$$= \sum_{I=1}^{M} \alpha_I \, K(X_I, X) \quad (3)$$

There, $K(X_I, X)$ is a kernel function and the kernel function is to compensate for the mercy theorem. In this section, the feature representation module transforms the interval sequence information into feature vectors. The time series information is validated to extract various features that define martial arts movements and their representation methods. Deterministic validation techniques for time series are enhanced, including seasonality, periodicity, and self-similarity validations, which help determine the pattern of variation in martial arts movements over time [21]. The cycle computation technique is applied in this study to validate the cycle of the extracted time series of the wheelhouse aspect ratio, which is used as one of the features for action detection. In the process of feature extraction, transforming the video into time series enables the calculation of patterns from multiple time series of the same martial arts movements, facilitating the identification of new movements [12]. The period validation is based on the variation between adjacent maxima in the sequence autocorrelation, with the aspect ratio sequence being smoothed initially.

3.3 Marital Art Movement Classification using CNN-BiLSTM

In comparison to CNNs, RNNs are better suited for time series tasks, while CNNs excel at feature extraction from high-dimensional, complex databases. The primary function of CNNs is to search for spatial characteristics within a single data input. Additionally, video processing tasks, such as detecting motion and directional changes from sequential images, require a series of images [25]. The image classification problem in this context is like wildfire spread identification. The theory of an image pyramid was developed to improve the classification process. To assess the efficacy of LSTM networks in capturing long-term temporal dependencies, two key parameters are considered: first, a memory cell that can retain state over time, and second, a gating mechanism that controls the flow of data. The LSTM design includes three gates—input, output, and forget. For time series data, the LSTM unit is enhanced according to equations (4), (5), (6), (7), and (8).

$$F_T = \sigma(w_f [H_{T-1}; X_T] + B_F) \quad (4)$$
$$I_T = \sigma(w_I [H_{T-1}; X_T] + B_I) \quad (5)$$
$$O_T = \sigma(w_O [H_{T-1}; X_T] + B_O) \quad (6)$$
$$\tilde{C}_T = w_C [H_{T-1}; X_T] + B_C \quad (7)$$
$$H_T = \tanh(C_T) \times O_T \quad (8)$$

The forget gate, output gate and input gate F_T, O_T, I_T are defined here. The weight matrices include w_C, w_O, w_f, w_I and each define hidden stage at time T, such that H_T defines hidden stage at time T. The integral components are defined as B_F, B_I, B_O, B_C, σ is defined as activation function.

BiLSTM is an enhancement over the conventional LSTM architecture, enabling the model to effectively mine temporal dependencies in the input sequence by processing the input in both forward and reverse directions. In traditional LSTM, information flows only from the past to the future [26]. BiLSTM, being bidirectional, is designed to incorporate both future and past context simultaneously. In a BiLSTM, the structure is divided into two parts: the first processes the input sequence in the forward direction, and the second processes it in the reverse direction. Each part has its own memory cells and gates [27]. After the forward and backward hidden states are concatenated, they provide a more comprehensive understanding of the input sequence, which is then fed into the neural network for encoding.

The proposed CNN-BiLSTM model Gonçalves et al. [28] is applied at each time step using a 50x50x17 tensor as input. The model includes two convolutional layers with different filter sizes, followed by a DCNN module with a uniform filter. The concatenated features are generated by combining CNN functions with max-pooling operations and various filter kernel sizes, allowing further concatenation along the channel axis. Subsequently, three Bi-LSTM layers with different numbers of neurons are generated, utilizing features created in the batch normalization layer. The output from the last Bi-LSTM layer at the final time step is passed through a dense layer with 32 neurons, controlled by the final layer and a sigmoid activation function, which calculates the probability of a burn event for each pixel in the subsequent time period [29]. A flatten layer reshapes the output vector into a 2D map. In both the CNN and dense layers, the rectified linear unit (ReLU) activation function is used, except in the last dense layer, where the sigmoid activation function is applied.

Before behavioural classification, the system better captures changes in gestures over time to distinguish between different types of expressions. The time data is best represented using a sparse, multi-dimensional time series modelling approach, leveraging the period relationship among sequences. The action classification module transforms feature vectors into classification results via CNN-BiLSTM. A post-processing threshold parameter is applied to convert the probability output into a binary parameter for experimental purposes. Martial arts movements and human body design often result in actions of varying complexity, which can be difficult to capture. In this research, the CNN-BiLSTM model is employed to achieve semi-automatic action detection. This classification method is commonly used to compare one sample to another in a database.

4. Performance Evaluation

The predictive decision analytics framework, integrated with artificial intelligence, leverages input imagery alongside segmented images and confusion matrix assessments to enhance membership retention and foster growth through improved training quality, engagement, and personalized programs. By segmenting martial arts movement images, the system offers comprehensive feedback to members, enabling them to assess their performance and identify areas for improvement. This visual feedback boosts motivation, leading to more rewarding training sessions for participants. Using confusion matrix analysis, the retention strategy is refined by detecting common mislabelling patterns, such as when members confuse the Left Lunge Punch with the Back Horse Stance Punch, which could lead to frustration. Instructors who recognise these recurring errors can devise tailored correction methods, offering appropriate guidance to prevent members from losing interest. The segmented image analysis generates data points that allow trainers to continuously adjust performance, ensuring movement consistency among members. The system evaluates movements by identifying deviations exceeding 12%, which helps instructors understand when members may be at risk of disengaging from their training. Martial arts organisations can enhance their training programs with these insights, improving skill acquisition and designing personalised experiences that foster long-term member commitment. This approach also attracts new participants through coach evaluations driven by data.

Decision Making: Applications in Management and Engineering
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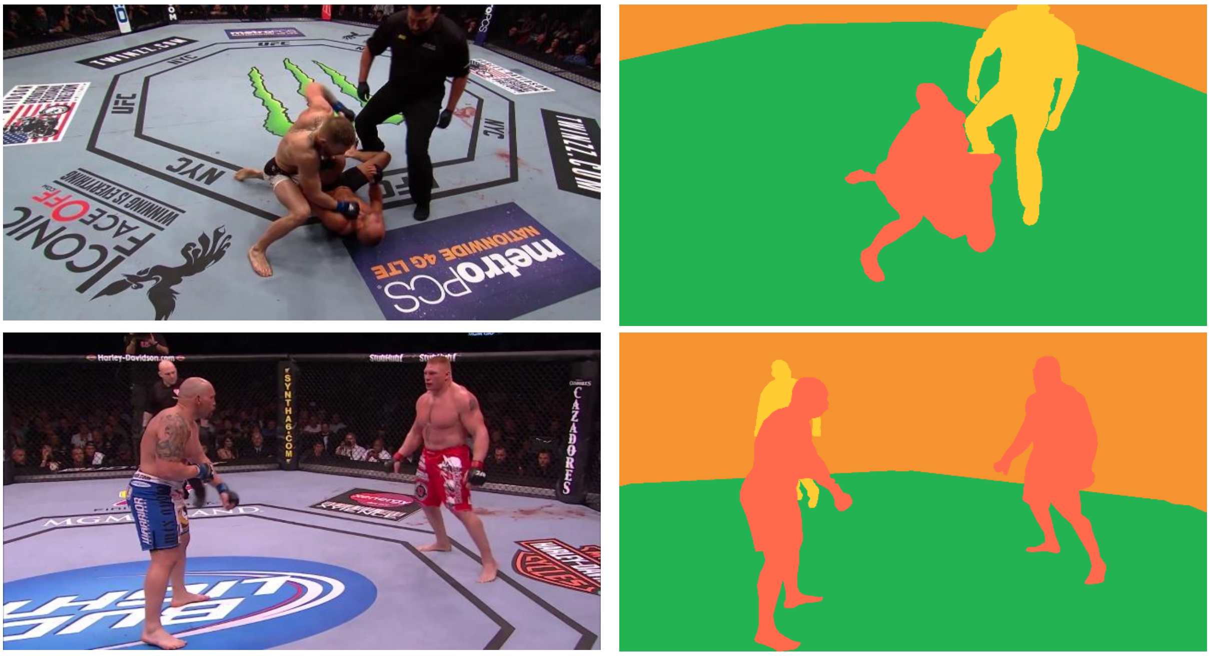

Fig.2. Input Images with Segmentation Techniques

Figure 2 shows the input image along with its segmentation results, while Figure 3 illustrates the confusion matrix.

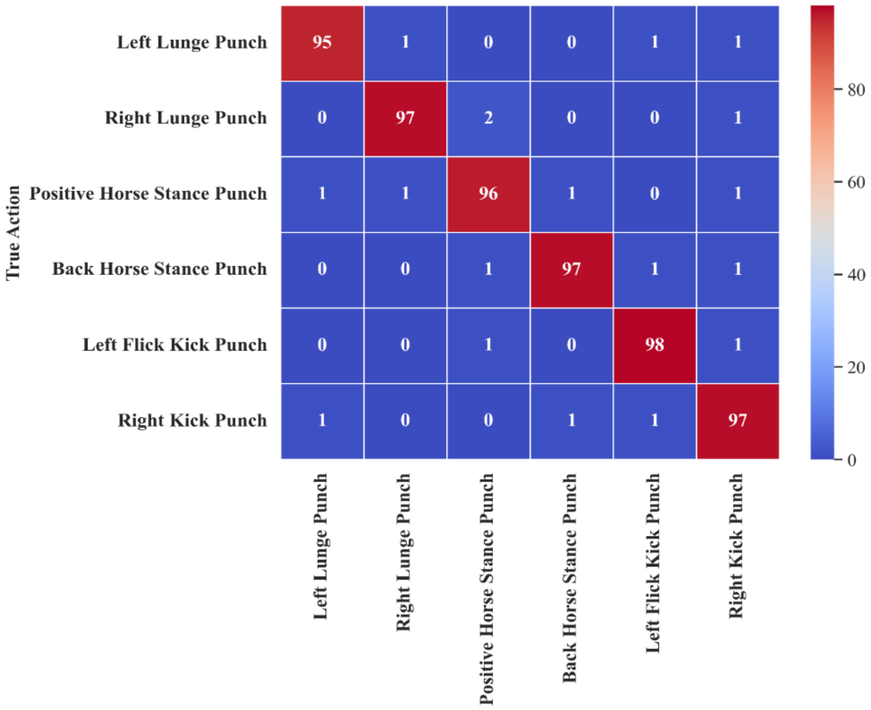

Fig.3. Confusion Matrix

Figure 4 illustrates a comparison of the FPR and FNR for the SVM, LSTM, CNN, and the Proposed Model. The SVM model yields the highest error rates, with an FPR of 8.7% and an FNR of 8.1%, indicating a significant number of misclassifications. The LSTM model performs better by reducing errors, achieving an FPR of 6.2% and an FNR of 5.8%, although misclassifications remain. The CNN model offers further improvement, lowering the FPR to 4.3% and the FNR to 3.9%, thanks to its enhanced ability to extract features from complex patterns. The Proposed Model outperforms the others, demonstrating the lowest misclassification rates with an FPR of approximately 1.2% and an FNR of around 1.0%. This model proves highly effective in reducing false classifications, showcasing superior predictive accuracy and reliability in executing the task.

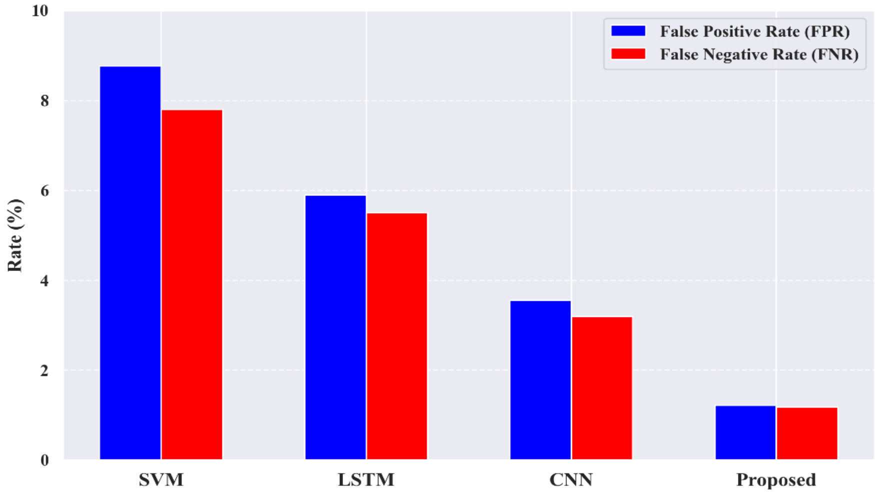

Fig.4. FPR and FNR

Figure 5 presents the AUC-ROC measurement (%) for the SVM model, along with the LSTM, CNN, and proposed model solutions. The SVM model achieves an AUC-ROC value of 89.80%, indicating its performance is inferior to that of the other models. The LSTM model shows an improvement in classification performance with an AUC-ROC value of 92.50%. The CNN model surpasses the LSTM, achieving a higher AUC-ROC value of 95.20%. However, the proposed model excels, achieving an outstanding AUC-ROC value of 98.40%, which demonstrates its superior ability to accurately distinguish between classes and attain optimal classification results. This highlights the proposed model's effectiveness in predicting membership decisions for martial arts organizations through its enhanced performance metrics.

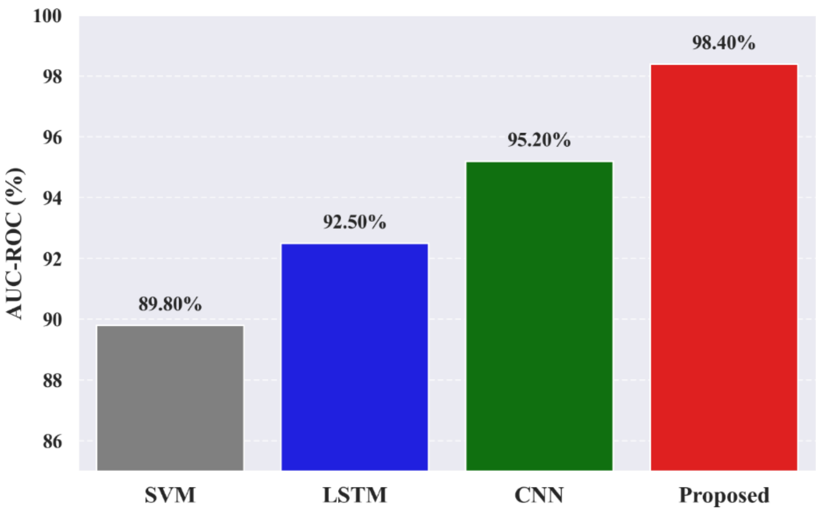

Fig.5. AUC-ROC Validation

Figure 6 illustrates performance metrics, including accuracy, precision, and recall, for various action classes in martial arts movement classification. The recall for the Left Lunge Punch is high, with a value of 0.8, while its precision and accuracy levels are moderate. The Right Lunge Punch yields comparable results across all metrics. The Positive Horse Stance Punch exhibits stable accuracy and precision but shows a slightly lower recall value. The Back-Horse Stance Punch demonstrates competitive recall performance, although its precision is only moderately competitive. The Left Flick Kick Punch excels in precision, reaching up to 0.8, while maintaining competitive recall and accuracy rates. Right Kick Punch, however, performs the lowest across all three metrics, indicating that it is the most challenging action to identify correctly. The predictive model's performance varies in distinguishing different martial arts movements, with each action exhibiting different levels of capability.

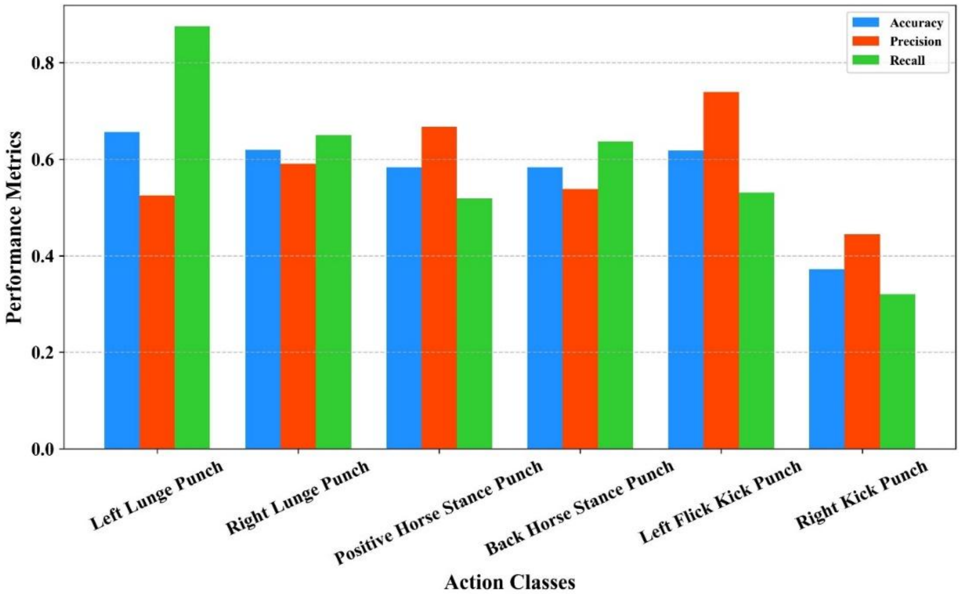

Fig.6. Performance Validation

Figure 7 illustrates the training and validation loss across 100 epochs, demonstrating the model's learning progression. Initially, both loss metrics decrease rapidly from 0.8 to reach their lowest points before epoch 20. As the training progresses, the losses continue to reduce gradually, eventually approaching near-zero values in the training loss. Between epoch 40 and 100, the validation loss shows sporadic fluctuations but generally decreases. Towards the final epoch, the validation loss stabilizes at a slightly higher level than the training loss, which can be attributed to minor overfitting effects. Both reduced loss values indicate effective learning, resulting in strong performance with an acceptable generalization gap.

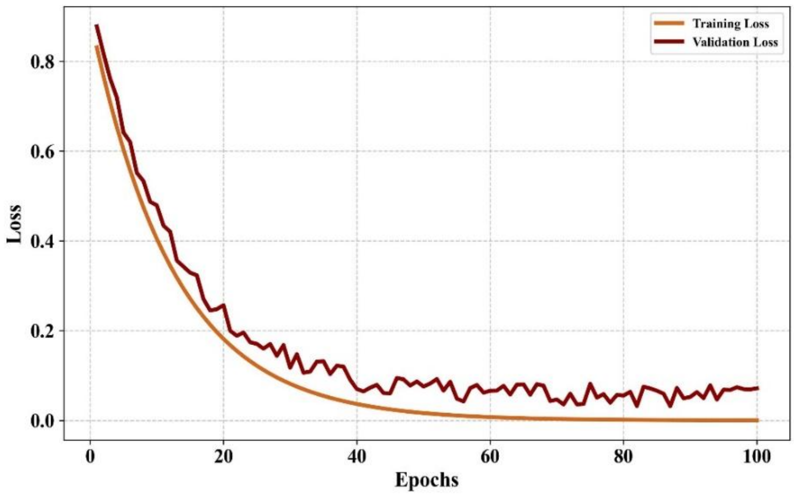

Fig.7. Loss Validation

Figure 8 shows the development of training and validation accuracy throughout the 100 epochs as the model processes the data. Initially, both training and validation accuracies are nearly equal at 0.970, followed by a rapid increase between epochs 1 and 20, signalling significant learning progress. The training accuracy steadily increases, reaching nearly 0.980, suggesting that the model has thoroughly learned the training dataset. The validation accuracy follows a similar trend, with slight fluctuations that levelled off at 0.978 after epoch 40. The small deviations in accuracy readings reflect slight variability in generalization performance on validation samples. The testing accuracy demonstrates high levels of accuracy, with minimal discrepancies between training and validation performance, indicating that the model has achieved robust generalization and minimal overfitting.

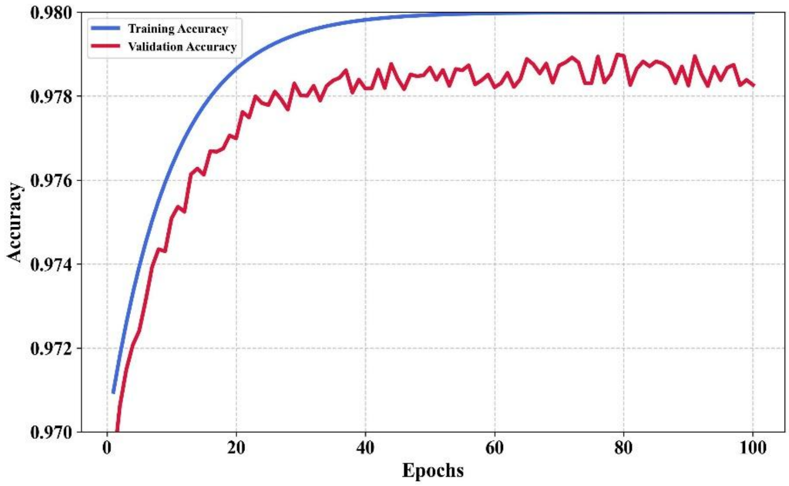

Fig.8. Accuracy

Figure 9 illustrates the classification performance of various models through Receiver Operating Characteristic (ROC) curves, with the False Positive Rate (FPR) plotted on the x-axis representing negative sample misclassifications and the True Positive Rate (TPR) plotted on the y-axis for positive sample accuracy. The AUC-ROC values displayed in the legend indicate that the proposed model achieves an exceptional AUC score of 0.99, outperforming other models, including CNN (0.93), LSTM (0.96), and SVM (0.98). This demonstrates that the proposed model provides superior classification performance compared to standard techniques, as it exhibits the highest AUC value. The dashed baseline represents random classification performance, and the proposed models show better discrimination by being further from this reference, highlighting their enhanced ability to accurately classify positive and negative samples.

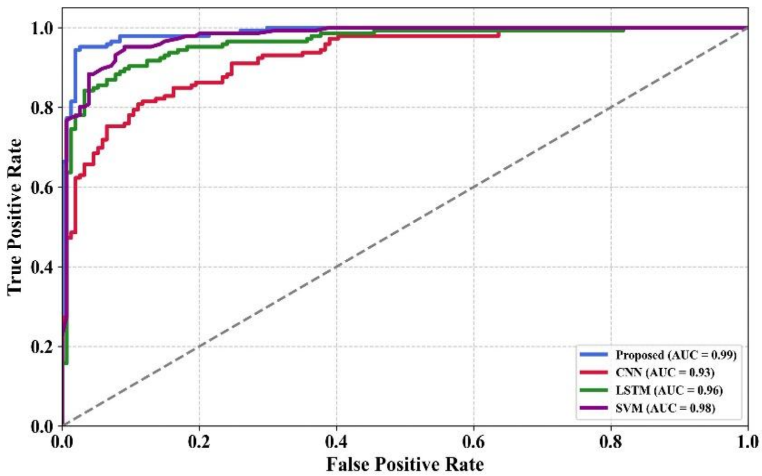

Fig.9. AUC Validation

Figure 10 illustrates the success rates of identifying various action types across five different testing conditions. The action classes are displayed on the x-axis, including "Left Bow Step Punch," "Right Lunge Punch," "Frontal Horse Step Punch," "Back Horse Step Punch," "Left Bounce Kick Punch," and "Right Bounce Kick Punch." The recognition rate measurements are shown on the vertical axis, ranging from 50% to 100%. A distinct line represents the results from each test run (Test 1 through Test 5), as indicated in the legend. The tests reveal varying performance trends, with recognition rates fluctuating depending on the action type being observed. Some action classes achieve recognition rates above 90%, while others fall below 70%, indicating differences in the difficulty of testing each action. Moreover, Figure 10 allows users to assess and compare the recognition accuracy for distinct action classes within the system.

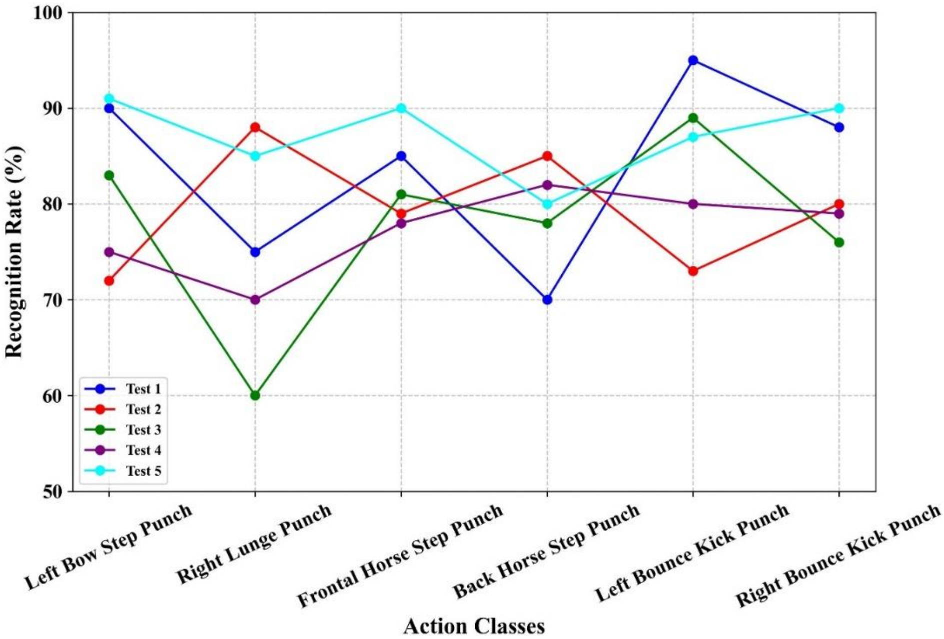

Fig.10. Recognition Rate

Figure 11 presents a comparison of the accuracy of various traditional methods against the proposed model. The methods referenced in [17] to [21] encompass a range of deep learning and computer vision techniques, including keyframe extraction, CNN-based recognition, and multi-modal pose detection. The accuracy rates of these methods fall between 0.75 and 0.80, demonstrating their efficiency, albeit with certain limitations. In contrast, the proposed approach achieves an accuracy of 0.85, outperforming all the traditional methods in terms of precision and stability. This notable improvement highlights the superior learning mechanisms, enhanced feature extraction, and refined processing techniques integrated into the proposed model. The graphical representation of accuracy further emphasises that the proposed approach provides a more consistent and precise system for the intended application, making it a promising candidate for real-world implementation.

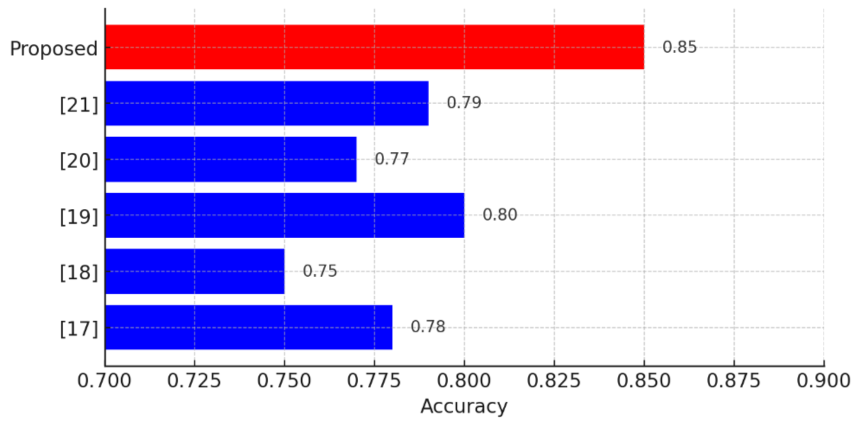

Fig.11. Comparison Validation

5. Conclusion

This research introduces a predictive analytics framework underpinned by artificial intelligence technology, designed to assist martial arts organisations in retaining their members by accurately assessing movement quality and the effectiveness of training programmes. By combining human action recognition with time series analysis, the system enables effective performance evaluation through spatio-temporal contour-based feature extraction and dimensionality reduction techniques. The CNN-BiLSTM hybrid model enhances the system's ability to detect and classify movements, enabling precise evaluation of skills. The two-step approach, which incorporates expert movement benchmarking alongside the assessment of student performance, facilitates clear tracking of skill development and engagement levels. Predictive analytics further strengthens retention strategies by identifying students at risk of disengagement, allowing trainers to tailor training recommendations accordingly. The experimental results demonstrate that the system not only improves training quality and student involvement but also supports sustained educational participation. Ultimately, the integration of AI and predictive analytics in this study advances modern martial arts training by enabling data-driven decisions that promote membership growth and organisational development.

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