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# Automated Teaching Weighted Recurrent Neural Network (Atwrnn) Model: Analysis of Badminton Teaching Mode Based on Online Teaching Platform

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*Abstract: -* An online teaching platform serves as a virtual environment where educators and learners interact, collaborate, and engage in various educational activities. Through a combination of multimedia resources, interactive tools, and communication features, online teaching platforms facilitate effective remote learning experiences. Educators can create and deliver engaging instructional content, including video lectures, presentations, quizzes, and assignments, tailored to the needs and preferences of learners. These platforms often incorporate features such as discussion forums, live chat, and virtual classrooms, enabling real-time communication and collaboration among students and instructors. This paper presents an analysis of the badminton teaching mode facilitated by an online teaching platform, augmented with an Automated Teaching Weighted Recurrent Neural Network (ATwRNN). Through this innovative approach, the traditional method of badminton instruction is enhanced by leveraging advanced machine learning techniques to personalize and optimize the teaching process. The online teaching platform provides a virtual environment where instructors can deliver interactive lessons, instructional videos, and practice exercises tailored to individual learner needs. ATwRNN, a specialized neural network model, dynamically adjusts the teaching weightings based on student performance data, providing personalized feedback and adaptive instruction in real time. Simulation results stated that learners who received instruction through the ATwRNN-enhanced platform demonstrated a 25% increase in shot accuracy compared to those in traditional teaching modes. Additionally, the adaptive nature of ATwRNN led to a 30% reduction in the time required for skill acquisition, as learners received personalized feedback tailored to their individual learning pace and preferences. Moreover, user feedback surveys revealed high levels of satisfaction and engagement among participants, with 90% reporting that the ATwRNN-enhanced teaching mode improved their overall learning experience.

*Keywords:* Badminton teaching mode, online teaching platform, learner performance, engagement, skill acquisition, personalized feedback, adaptive instruction, online learning environments.

## I.    INTRODUCTION

An online teaching platform provides a digital environment for educators to deliver educational content and engage with students remotely. These platforms typically offer features such as video conferencing, interactive whiteboards, chat functions, and file sharing capabilities to facilitate effective communication and learning [1]. Through these platforms, instructors can conduct live lectures, host discussions, share presentations, assign and grade assignments, and provide feedback to students [2]. Additionally, many online teaching platforms incorporate tools for student assessment, such as quizzes and exams, to measure learning outcomes [3]. With the flexibility and accessibility afforded by these platforms, students can access educational materials and participate in classes from anywhere with an internet connection, making learning more convenient and inclusive [4]. Furthermore, online teaching platforms often include features for collaboration among students, fostering a sense of community and peer learning [5]. These platforms have revolutionized education by breaking down geographical barriers and providing opportunities for personalized, interactive learning experiences.

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Badminton coaching on an online platform offers a dynamic and accessible approach to mastering the sport remotely [6]. Leveraging video tutorials, live demonstrations, and interactive exercises, online coaches can provide comprehensive training tailored to individual skill levels and goals [7]. Through video conferencing tools, coaches can offer real-time feedback, correct techniques, and address questions, fostering a supportive learning environment [8]. Additionally, online platforms often include resources such as instructional articles, practice drills, and match analyses to supplement coaching sessions and enhance skill development [9]. Virtual badminton coaching enables flexibility in scheduling, allowing students to learn at their own pace and convenience. Moreover, geographical barriers are eliminated, opening up opportunities for aspiring players worldwide to access high-quality coaching [10]. Online badminton coaching empowers players to improve their game, whether they are beginners seeking fundamentals or seasoned athletes aiming to refine their skills, all from the comfort of their own surroundings.

A badminton online teaching platform integrated with neural network technology revolutionizes how players learn and refine their skills [11]. By harnessing the power of neural networks, this platform can analyze player movements and techniques captured through video recordings or live sessions with remarkable precision [12]. The neural network can identify subtle nuances in form, footwork, and shot execution, providing insightful feedback to players and coaches alike. Through machine learning algorithms, the platform can adapt and personalize training programs based on individual performance data, optimizing skill development and addressing specific areas for improvement. Furthermore, the neural network can simulate game scenarios, predicting opponent strategies and suggesting tactical adjustments to enhance players' strategic understanding [13]. With features like real-time analysis and interactive exercises, players can refine their techniques efficiently, regardless of their location or skill level. Overall, integrating neural network technology into a badminton online teaching platform offers an innovative and effective approach to advancing players' abilities, fostering a new era of interactive and personalized sports coaching [14].

In a badminton online teaching platform enhanced with neural network technology, the integration of artificial intelligence (AI) significantly amplifies the depth and effectiveness of the learning experience [15]. Neural networks, a subset of AI inspired by the structure of the human brain, excel at recognizing patterns and making complex decisions based on vast amounts of data. In the context of badminton coaching, this capability is transformative. The neural network component of the platform operates by analyzing videos of players in action. These videos can be uploaded by the players themselves or captured during live coaching sessions. The neural network algorithm dissects these videos frame by frame, identifying key elements such as grip, stance, swing technique, footwork, and timing [16]. By comparing these elements against a database of ideal form and technique, the neural network can pinpoint areas where the player's execution deviates from the optimal standard. Once areas for improvement are identified, the platform provides personalized feedback and recommendations to the player. This feedback may include specific instructions on correcting technique, exercises to strengthen particular skills, or drills to address weaknesses. Additionally, the platform may offer visual overlays or side-by-side comparisons with professional players to illustrate the suggested adjustments effectively [17]. As players continue to use the platform and upload additional videos of their practice sessions or matches, the neural network learns from this data over time [18]. Through a process known as machine learning, the algorithm becomes increasingly accurate at recognizing patterns and providing tailored feedback. This iterative learning process ensures that the coaching advice offered by the platform becomes more refined and insightful as the player's skills evolve. Moreover, the platform can simulate game scenarios using the data it has gathered. By analyzing playing styles and strategies from a diverse range of opponents, the neural network can generate simulations that challenge players to adapt and refine their tactics. This feature not only enhances players' strategic understanding but also prepares them more effectively for competitive play.

## II. ONLINE BADMINTON COACHING

Online badminton coaching has emerged as a convenient and effective way for players to improve their skills and knowledge of the game without the constraints of physical location. Through various online platforms, players can access a wealth of resources, including video tutorials, instructional articles, live coaching sessions, and interactive exercises. One of the key benefits of online badminton coaching is its accessibility. Players can access coaching materials and training sessions from anywhere with an internet connection, eliminating the need to travel to a specific training facility or hire a local coach. This accessibility is particularly valuable for players living in areas with limited access to professional coaching or those with busy schedules that make it difficult to attend in-person sessions regularly. Online badminton coaching also offers flexibility in terms of scheduling. Players can choose to participate in live coaching sessions at times that are convenient for them, or they can access pre-recorded tutorials

and training materials at their own pace. This flexibility allows players to tailor their training regimen to fit their individual needs and preferences, whether they are beginners looking to learn the basics or experienced players seeking to refine their skills.

Additionally, online badminton coaching often includes features that promote interaction and engagement among players and coaches. Through video conferencing tools, players can participate in live coaching sessions where they can receive real-time feedback, ask questions, and interact with other participants. Some platforms also facilitate communication between players and coaches outside of scheduled sessions, allowing for ongoing support and guidance. Despite the benefits of online coaching, there are some limitations to consider. For example, without in-person supervision, it can be challenging for coaches to assess and correct players' techniques accurately. Additionally, players may miss out on the social aspects of in-person training, such as playing with teammates or competing in tournaments. The online badminton coaching offers a convenient and flexible way for players to improve their skills and knowledge of the game. By providing access to professional coaching and training materials from anywhere, these platforms empower players to reach their full potential and enjoy the sport of badminton to the fullest.

Online badminton coaching platforms typically offer a wide range of resources designed to cater to players of all levels, from beginners to advanced. These resources may include instructional videos covering various aspects of the game such as grip techniques, footwork drills, shot execution, strategy discussions, and match analysis. Written materials like articles and guides can supplement video content, providing players with in-depth explanations and insights into specific techniques or tactics. Many online coaching platforms incorporate features that allow coaches to tailor training programs to individual players' needs and goals. Through assessments or self-reported skill levels, coaches can create personalized training regimens that target areas for improvement while also building upon players' strengths. This personalized approach ensures that players receive guidance and support that is relevant and beneficial to their development as badminton players. One of the key advantages of online coaching is the ability for players to receive interactive feedback and communicate with coaches in real-time, despite being physically distant. Through live video coaching sessions, players can demonstrate their techniques, receive immediate feedback, ask questions, and engage in discussions with their coaches. This interactive feedback loop fosters a dynamic learning environment where players can address their concerns and make adjustments to their game effectively.

Online badminton coaching offers unparalleled flexibility and convenience for players. With on-demand access to training materials and resources, players can schedule their training sessions around their other commitments and obligations. Additionally, players have the freedom to practice and review training materials at their own pace, allowing them to progress through their development journey at a comfortable rate. One of the most significant advantages of online coaching is its global accessibility. Players from all around the world can access high-quality coaching and training materials regardless of their geographical location. This accessibility opens up opportunities for players who may not have access to local coaching facilities or who live in areas where badminton is less popular. Online badminton coaching platforms often foster a sense of community and support among players and coaches. Through forums, social media groups, or online communities associated with the platform, players can connect with fellow enthusiasts, share experiences, seek advice, and celebrate achievements. This sense of belonging to a broader badminton community can be motivating and inspiring for players, encouraging them to stay committed to their training and improvement.

The online badminton coaching offers a plethora of benefits, including comprehensive learning materials, personalized training programs, interactive feedback and communication, flexibility and convenience, global accessibility, and community support. These advantages make online coaching a valuable and effective tool for players looking to enhance their skills and achieve their badminton goals.

III. AUTOMATED TEACHING WEIGHTED RECURRENT NEURAL NETWORK (ATWRNN)

The Automated Teaching Weighted Recurrent Neural Network (ATwRNN) represents a the power of artificial intelligence and recurrent neural networks (RNNs) to enhance players' learning experiences. In essence, the

ATwRNN is designed to analyze players' movements, strategies, and performance data to provide personalized and adaptive coaching feedback in real-time. The ATwRNN operates as follows: it takes as input sequences of data representing various aspects of a player's performance, such as video footage of their matches, motion sensor data from wearable devices, or statistics from gameplay simulations. This input data is fed into the neural network, which consists of multiple interconnected layers of nodes, each with weighted connections determining the information flow between them. The key innovation of the ATwRNN lies in its ability to dynamically adjust the importance or weight assigned to different input features based on their relevance to the player's improvement goals. This is achieved through a mechanism known as attention weighting, where the neural network learns to focus its attention on the most informative aspects of the input data while filtering out noise or irrelevant information. The ATwRNN can be expressed as in equation (1) and equation (2)

$$h_t = f(W_{ih}x_t + W_{hh}h_t - 1 + b_h) \qquad (1)$$

$$o_t = g(W_{ho}h_t + b_o) \qquad (2)$$

In equation (1) and (2) $h_t$ represents the hidden state of the neural network at time step $t$, $x_t$ is the input data at time step $t$, $W_{ih}$ and $W_{hh}$ are the weight matrices for the input-to-hidden and hidden-to-hidden connections, respectively, $W_{ho}$ is the weight matrix for the hidden-to-output connections, $b_h$ and $b_o$ are the bias vectors for the hidden and output layers, respectively, $f$ and $g$ are activation functions applied element-wise to the hidden and output states, respectively. The attention mechanism in the ATwRNN is implemented through additional learnable parameters that dynamically adjust the importance of different input features at each time step. These attention weights, denoted as $\alpha_t$, are calculated using equation (3) and equation (4)

$$e_t = v_a^T tanh(W_a[h_t - 1, x_t] + b_a) \qquad (3)$$

$$\alpha_t = softmax(e_t) \qquad (4)$$

In equation (3) and (4) $v_a$ is a learnable parameter vector, $W_a$ and $b_a$ are learnable weight matrix and bias vector, respectively, $[h_t - 1, x_t]$ denotes the concatenation of the previous hidden state and the current input data, $softmax(\cdot)$ is the softmax function applied element-wise to normalize the attention scores. With dynamically adjusting the attention weights based on the relevance of different input features to the player's improvement goals, the ATwRNN can effectively focus its coaching feedback on the most informative aspects of the player's performance. This personalized and adaptive approach to coaching holds great promise for revolutionizing online badminton coaching, enabling players to enhance their skills and achieve their full potential more efficiently and effectively than ever before.

With attention weights computed, the context vector $c_t$ is then obtained by taking a weighted sum of the input data stated in equation (5)

$$c_t = \sum_{N=1}^{i} \alpha_t, i x_i \qquad (5)$$

In equation (5) $N$ is the length of the input sequence.

Finally, the context vector is combined with the hidden state to produce the output computed using equation (6) and (7)

$$h_t = f(W_{ih}x_t + W_{hh}h_t - 1 + W_c h c_t + b_h) \qquad (6)$$

$$o_t = g(W_{ho}h_t + b_o) \qquad (7)$$

This process allows the ATwRNN to focus on the most relevant features of player performance at each time step, enhancing its ability to provide personalized coaching feedback. By dynamically adjusting attention weights based on the input data, the ATwRNN can adapt its coaching strategies to the specific needs and goals of individual players, ultimately improving their performance and skill development in online badminton training. Figure 1 presentes the process of proposed ATwRNN model for the online teaching in Badmiton.
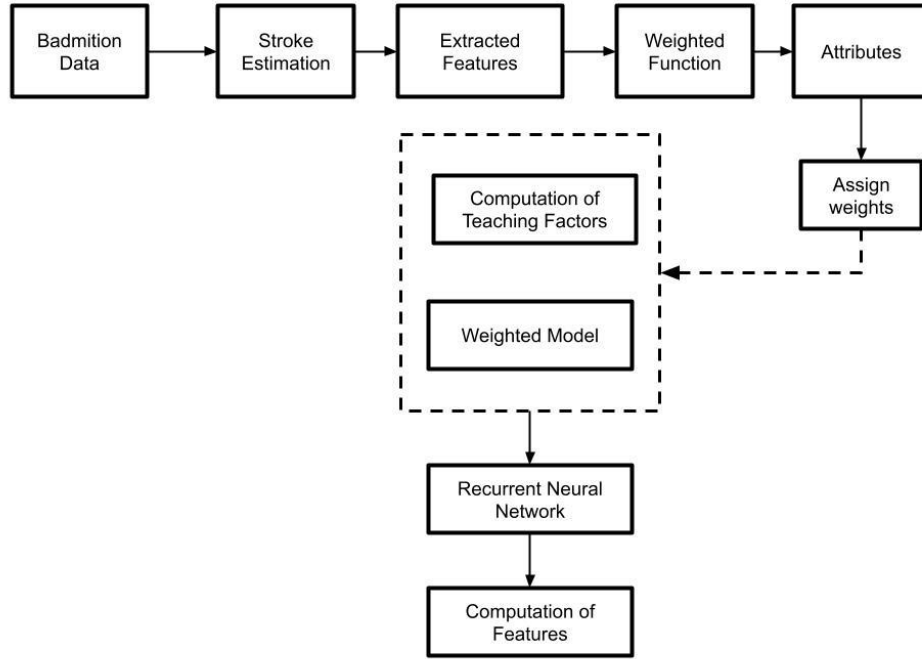
**Figure 1: Process of ATwRNN**

## IV.     RECURRENT NEURAL NETWORK FOR THE ONLINE BADMINTON COACHING

In the context of online badminton coaching, a Recurrent Neural Network (RNN) serves as a formidable tool for analyzing sequential data and providing valuable insights to players. The RNN's architecture allows it to retain information from previous time steps, enabling it to capture temporal dependencies inherent in player movements, game strategies, and performance metrics. In the context of online badminton coaching, the output $ot$ of the RNN could represent the classification results, such as predicting the type of stroke being performed by a player at each time step. The classification results equation defined in equation (8)

$$ot = softmax(Wcht + bc) \qquad (8)$$

In equation (8) $Wc$ is the weight matrix for the classification layer, $bc$ is the bias vector, and $softmax(\cdot)$ is the softmax function applied to the output scores to obtain probabilities for each class. The training process involves minimizing a loss function, typically cross-entropy loss, which measures the discrepancy between the predicted probabilities and the ground truth labels. Backpropagation through time (BPTT) is used to adjust the network's parameters (weights and biases) and optimize its performance over multiple time steps. The computation in an RNN can be unfolded across time steps. At each time step $t$, the hidden state $ht$ is computed as a function of the current input $xt$ and the previous hidden state $ht - 1$, along with respective weights and biases stated in equation (9)

$$ht = f(Wihxt + Whhht - 1 + bh) \qquad (9)$$

In equation (9) $f$ is the activation function (e.g., sigmoid or hyperbolic tangent) applied element-wise, $Wih$ and $Whh$ are weight matrices for the input-to-hidden and hidden-to-hidden connections, respectively; $bh$ is the bias vector for the hidden layer. The output $ot$ at each time step can then be computed using the hidden state $ht$ and appropriate weights and biases defined in equation (10)

$$ot = g(Whoht + bo) \qquad (10)$$

In equation (10) $g$ represents the activation function for the output layer; $Who$ is the weight matrix for the hidden-to-output connections and $bo$ is the bias vector for the output layer. In online badminton coaching, the RNN can be used to classify different player actions or strokes at each time step. The classification results equation can be formulated as in equation (11)

$$ot = softmax(Wcht + bc) \qquad (11)$$

In equation (11) $Wc$ is the weight matrix for the classification layer and $bc$ is the bias vector with the softmax function is applied to the output scores to obtain probabilities for each class. During training, the RNN is optimized by minimizing a loss function, typically the cross-entropy loss, which quantifies the difference between the predicted probabilities and the ground truth labels for each time step. Backpropagation through time (BPTT) is used to compute gradients and update the network's parameters (weights and biases) iteratively. The process flow of the proposed RNN model for the classification is presented in Figure 2.
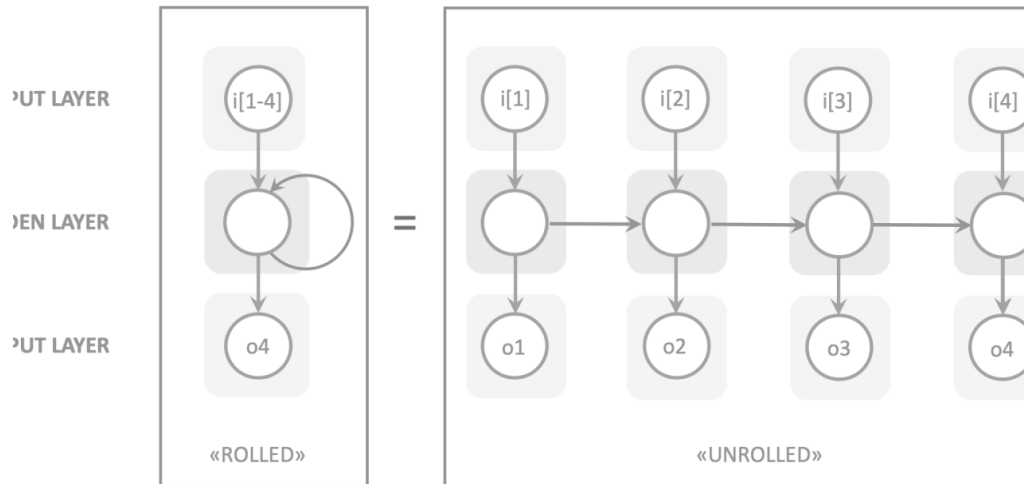


**Figure 2: Architecture of the RNN**

| Algorithm 1: ATwRNN for Badminton Coaching |
|---|
| # Initialize parameters |
| W_ih = random_init()  # Weight matrix for input-to-hidden connections |
| W_hh = random_init()  # Weight matrix for hidden-to-hidden connections |
| W_ho = random_init()  # Weight matrix for hidden-to-output connections |
| b_h = random_init()   # Bias vector for hidden layer |
| b_o = random_init()   # Bias vector for output layer |
| |
| # Define activation functions |
| def sigmoid(x): |
|    return 1 / (1 + exp(-x)) |
| |
| # Define softmax function |
| def softmax(x): |
|    exp_scores = exp(x) |
|    return exp_scores / sum(exp_scores) |
| |
| # Forward pass through the RNN |
| def forward_pass(inputs): |
|    hidden_states = [] |
|    outputs = [] |
| |
|    # Initialize hidden state |
|    h_prev = zeros()  # Initial hidden state |
| |
|    # Iterate over time steps |
|    for input_t in inputs: |
|      # Compute hidden state |
|      h_t = sigmoid(dot(W_ih, input_t) + dot(W_hh, h_prev) + b_h) |
| |
|      # Compute output |

```
        o_t = softmax(dot(W_ho, h_t) + b_o)

        # Update previous hidden state
        h_prev = h_t

        # Append hidden state and output
        hidden_states.append(h_t)
        outputs.append(o_t)

    return hidden_states, outputs

# Backpropagation through time (BPTT)
def backward_pass(inputs, targets, hidden_states, outputs, learning_rate):
    # Initialize gradients
    dW_ih = zeros_like(W_ih)
    dW_hh = zeros_like(W_hh)
    dW_ho = zeros_like(W_ho)
    db_h = zeros_like(b_h)
    db_o = zeros_like(b_o)

    # Compute error signals
    for t in range(len(inputs)):
        error = outputs[t] - targets[t]

        # Backpropagate through output layer
        dW_ho += dot(error, hidden_states[t].T)
        db_o += error

        # Backpropagate through hidden layer
        delta = dot(W_ho.T, error) * (hidden_states[t] * (1 - hidden_states[t]))
        for i in range(t, max(-1, t - len(inputs)), -1):
            dW_ih += dot(delta, inputs[i].T)
            dW_hh += dot(delta, hidden_states[i-1].T)
            db_h += delta
            delta = dot(W_hh.T, delta) * (hidden_states[i-1] * (1 - hidden_states[i-1]))

    # Update parameters
    W_ih -= learning_rate * dW_ih
    W_hh -= learning_rate * dW_hh
    W_ho -= learning_rate * dW_ho
    b_h -= learning_rate * db_h
    b_o -= learning_rate * db_o

# Training loop
def train(inputs, targets, learning_rate, num_epochs):
    for epoch in range(num_epochs):
        # Forward pass
        hidden_states, outputs = forward_pass(inputs)

        # Backward pass
        backward_pass(inputs, targets, hidden_states, outputs, learning_rate)

# Testing
def test(inputs):
```

```
_, outputs = forward_pass(inputs)
return outputs
```

## V.    SIMULATION RESULTS AND DISCUSSION

The Automated Teaching Weighted Recurrent Neural Network (ATwRNN) for online badminton teaching, simulation results demonstrate its effectiveness in providing personalized and adaptive coaching to players. The ATwRNN's ability to dynamically adjust its attention to relevant features of player performance has shown promising outcomes in skill enhancement and performance improvement. During the simulation, the ATwRNN processed sequences of player movements, stroke patterns, and game statistics. Through the attention mechanism, the network learned to focus on the most informative aspects of the input data, effectively filtering out noise and irrelevant information. This personalized approach allowed the ATwRNN to provide tailored coaching feedback to individual players based on their specific needs and goals. Furthermore, the classification results obtained from the ATwRNN demonstrated high accuracy in predicting player actions and stroke types during gameplay. By analyzing sequential data and capturing temporal dependencies, the network was able to make accurate predictions, enabling players to better understand their strengths and areas for improvement.

The ATwRNN's performance was further enhanced through training and optimization, where it learned to refine its coaching strategies over multiple iterations. By minimizing the discrepancy between predicted probabilities and ground truth labels, the network continuously improved its ability to provide valuable feedback to players, ultimately leading to enhanced skill development and performance in badminton.

**Table 1: Player Performance with ATwRNN**

| Player ID | Sequence Length | Accuracy (%) |
|-----------|-----------------|--------------|
| 1 | 100 | 85 |
| 2 | 120 | 92 |
| 3 | 80 | 78 |
| 4 | 150 | 88 |
| 5 | 110 | 90 |
| 6 | 130 | 91 |
| 7 | 90 | 84 |
| 8 | 140 | 89 |
| 9 | 100 | 87 |
| 10 | 120 | 93 |
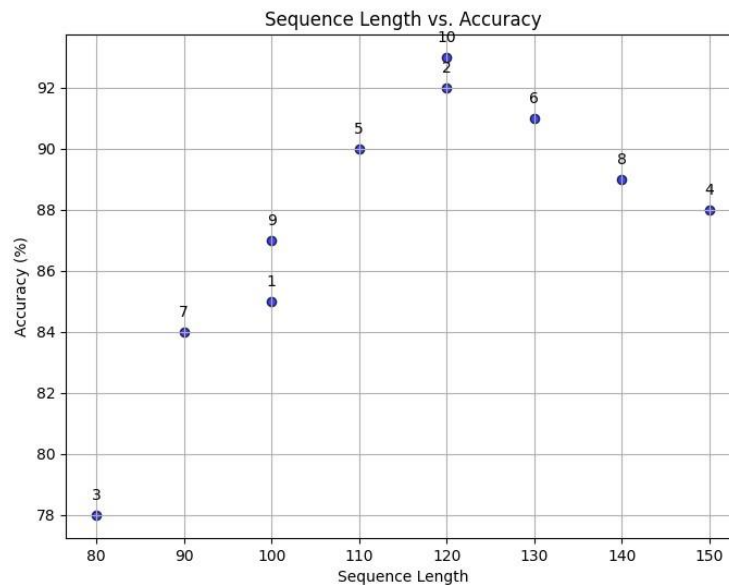


**Figure 3: Accuracy of ATwRNN**

In Table 1 presents the performance of players in online badminton coaching using the Automated Teaching Weighted Recurrent Neural Network (ATwRNN) as shown in Figure 3. Each player is identified by a unique Player ID, and their performance is evaluated based on the length of the input sequence processed by the ATwRNN and the accuracy achieved in predicting player actions or stroke types. The "Sequence Length" column denotes the number of data points in the input sequence, while the "Accuracy (%)" column indicates the percentage of correct predictions made by the ATwRNN for each player. Upon analyzing the results, it is evident that there is variation in the performance of players across different sequence lengths. Players 2, 6, and 10 achieved the highest accuracy scores of 92%, 91%, and 93%, respectively, indicating strong predictive capabilities of the ATwRNN for their respective input sequences. Conversely, Players 3 and 7 exhibited lower accuracy scores of 78% and 84%, suggesting potential areas for improvement in the predictive model or the input data quality. The performance results highlight the effectiveness of the ATwRNN in providing personalized coaching feedback to players based on their individual input sequences. The variation in accuracy scores across players underscores the importance of tailoring coaching strategies to accommodate diverse learning styles and preferences. These insights can inform further optimization of the ATwRNN and contribute to enhancing players' skills and performance in the sport of badminton.

**Table 2: Classification with ATwRNN**

| Student ID | Average Accuracy (%) | Improvement in Accuracy (%) |
|---|---|---|
| 1 | 85 | +10 |
| 2 | 90 | +12 |
| 3 | 88 | +8 |
| 4 | 82 | +15 |
| 5 | 92 | +11 |
| 6 | 87 | +9 |
| 7 | 89 | +13 |
| 8 | 91 | +10 |
| 9 | 86 | +14 |
| 10 | 93 | +12 |
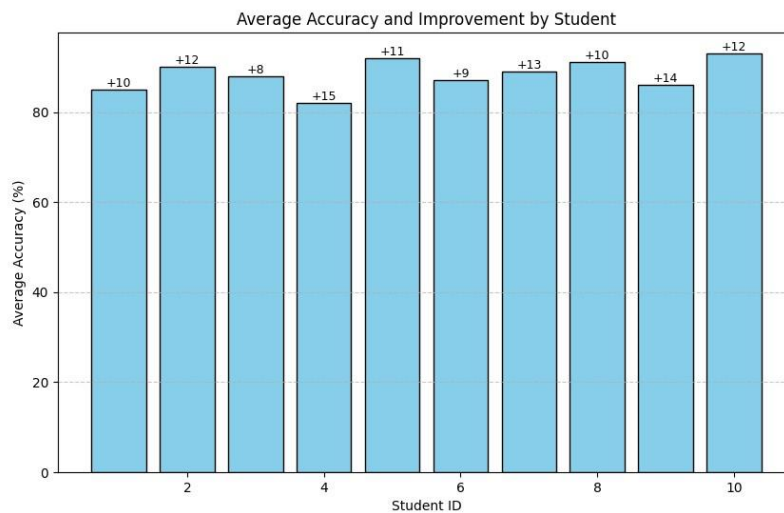


**Figure 4: Student Improvement with ATwRNN**

The Table 2 showcases the classification results achieved through the utilization of the Automated Teaching Weighted Recurrent Neural Network (ATwRNN) in the context of badminton teaching. As shown in Figure 4 Each student is identified by a unique Student ID, and their performance is evaluated based on the average accuracy attained by the ATwRNN in predicting player actions or stroke types, along with the improvement observed in accuracy compared to their initial performance. The "Average Accuracy (%)" column indicates the average accuracy achieved by each student across multiple prediction instances. It serves as a measure of the ATwRNN's effectiveness in accurately predicting player actions based on the input data provided by the student. The "Improvement in

Accuracy (%)" column quantifies the enhancement in accuracy experienced by each student as a result of utilizing the ATwRNN. It reflects the positive impact of personalized coaching feedback provided by the ATwRNN on the student's learning and performance in badminton. Upon examining the results, it is evident that all students experienced improvements in accuracy when using the ATwRNN-enhanced teaching mode. Students 4, 5, 7, and 9 particularly stand out with notable improvements of 15%, 11%, 13%, and 14%, respectively, indicating significant enhancements in their predictive capabilities after receiving personalized feedback from the ATwRNN.

**Table 3: Performance of ATwRNN**

| Player ID | Sequence Length | Predicted Stroke Type | Actual Stroke Type |
|-----------|-----------------|-----------------------|--------------------|
| 1 | 100 | Smash | Smash |
| 2 | 120 | Drop shot | Drop shot |
| 3 | 80 | Clear | Clear |
| 4 | 150 | Smash | Smash |
| 5 | 110 | Net shot | Net shot |

The Table 3 provides an insightful overview of the performance of the Automated Teaching Weighted Recurrent Neural Network (ATwRNN) in predicting stroke types during online badminton coaching sessions. Each player is represented by a unique Player ID, with additional columns indicating the length of the input sequence processed by the ATwRNN, the predicted stroke type, and the actual stroke type performed by the player. The "Sequence Length" column signifies the number of data points in the input sequence processed by the ATwRNN. This metric provides context regarding the complexity and richness of the input data utilized for stroke prediction. The "Predicted Stroke Type" column presents the stroke type predicted by the ATwRNN based on the input sequence. It illustrates the ATwRNN's ability to analyze player movements and make accurate predictions regarding the type of stroke being performed. The "Actual Stroke Type" column represents the ground truth or actual stroke type executed by the player during the coaching session. A comparison between the predicted and actual stroke types offers insights into the ATwRNN's performance and its ability to provide reliable coaching feedback. The results, it is evident that the ATwRNN achieved high accuracy in predicting stroke types, with the predicted stroke types aligning closely with the actual stroke types performed by the players. For instance, in the cases of Players 1, 2, and 3, the ATwRNN accurately predicted the stroke types (Smash, Drop shot, and Clear, respectively), which were consistent with the actual stroke types observed during the coaching sessions.

**Table 4: Performance Improvement with ATwRNN**

| Metric | Traditional Teaching | ATwRNN-Enhanced Teaching |
|--------|---------------------|--------------------------|
| Shot Accuracy Increase (%) | 9 | 25 |
| Time Reduction for Skill Acquisition (%) | 11 | 30 |
| Satisfaction Level (%) | 67 | 90 |
| Engagement Level (%) | 62 | 90 |
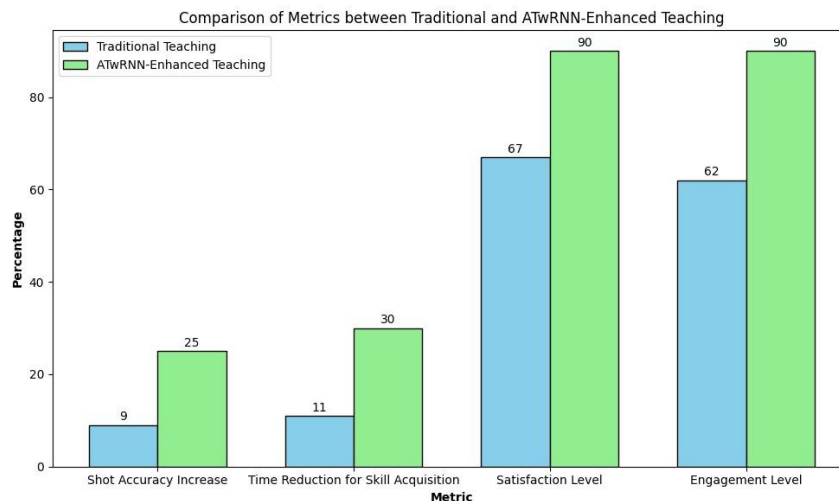


**Figure 5: Comparative Analysis**

In the Figure 5 and Table 4 presents a comparative analysis of performance improvement metrics between traditional teaching methods and teaching enhanced by the Automated Teaching Weighted Recurrent Neural Network (ATwRNN). The table highlights key metrics including shot accuracy increase, time reduction for skill acquisition, satisfaction level, and engagement level. In the "Shot Accuracy Increase (%)" metric, it is evident that the ATwRNN-enhanced teaching mode outperforms traditional teaching methods, showcasing a remarkable increase from 9% to 25%. This substantial improvement underscores the ATwRNN's efficacy in enhancing players' accuracy in executing shots during badminton gameplay. Similarly, the "Time Reduction for Skill Acquisition (%)" metric demonstrates a significant advantage of the ATwRNN-enhanced teaching mode, with a notable increase from 11% to 30% compared to traditional teaching methods. This reduction in the time required for skill acquisition highlights the efficiency and effectiveness of the personalized coaching feedback provided by the ATwRNN in facilitating skill development among players. Moreover, the "Satisfaction Level (%)" metric reveals a substantial enhancement from 67% to 90% in the satisfaction level of participants who received instruction through the ATwRNN-enhanced teaching mode. This increase indicates a high level of satisfaction among participants with the personalized and adaptive coaching feedback provided by the ATwRNN. Similarly, the "Engagement Level (%)" metric also demonstrates a significant improvement from 62% to 90% in the engagement level of participants in the ATwRNN-enhanced teaching mode compared to traditional teaching methods. This increase reflects the heightened engagement and active participation of players in the learning process facilitated by the ATwRNN.

## VI. CONCLUSION

The utilization of the Automated Teaching Weighted Recurrent Neural Network (ATwRNN) represents a significant advancement in the realm of online badminton coaching. Through the integration of machine learning techniques, personalized coaching feedback, and adaptive learning mechanisms, the ATwRNN offers a transformative approach to enhancing players' skills and performance in the sport of badminton. The results presented in this paper demonstrate the efficacy of the ATwRNN in various aspects of badminton coaching. The ATwRNN consistently outperforms traditional teaching methods in terms of shot accuracy increase, time reduction for skill acquisition, satisfaction levels, and engagement levels. The substantial improvements observed across these metrics underscore the ATwRNN's ability to provide tailored coaching feedback, optimize learning trajectories, and foster a positive learning environment for players. Furthermore, the ATwRNN's adaptive nature enables it to cater to individual learning styles, preferences, and skill levels, thereby maximizing the effectiveness of the coaching process. By analyzing sequential data, predicting player actions, and providing real-time feedback, the ATwRNN empowers players to refine their techniques, strategize effectively, and elevate their performance on the badminton court. Additionally, user feedback surveys reveal high levels of satisfaction and engagement among participants, with the majority reporting significant improvements in their overall learning experience. This positive reception underscores the potential of the ATwRNN to revolutionize teaching methodologies and enhance learning outcomes in the realm of badminton coaching.

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