ChatPPG: Computational Analysis and Statistics of Table Tennis Games

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***Abstract*— This paper presents ChatPPG prototype, which is an innovative system that combines large language models (LLMs) fine-tuned with Low-Rank Adaptation (LoRA) and computer vision for real-time data analysis and coaching for table tennis games. By integrating multi-camera 3D reconstruction, visual object detection and object tracking, ChatPPG processes match data such as player speed, ball trajectories, and service legality, transforming raw metrics into actionable insights. The fine-tuned model achieved a Q/A accuracy 92.3%, surpassing the baseline model 83.7%, with sub-second response times enabled by 8-bit quantization. Practical applications demonstrated its ability to deliver personalized training plans and tactical recommendations tailored to individual player profiles. User feedback from professional coaches and athletes rated tactical suggestions at 9.3/10 and training recommendations at 8.9/10. Integrating structured CV outputs with LLM capabilities enhanced transparency and interpretability, allowing users to trace recommendations to data-driven decisions. Despite dataset limitations and the need for advanced query handling, ChatPPG bridges the gap between data analysis and decision-making, setting a new standard for integrating LLMs and CV technologies in fast-paced sports analytics.**

Keywords—Large Language Models, Computer Vision, Table Tennis, Low-Rank Adaptation , Function Calling, Model Quantization

I. INTRODUCTION

With the rapid development of artificial intelligence (AI), particularly large language models (LLMs), the capability of understanding and generating language has reached unprecedented levels. LLMs have gradually permeated various fields, from general-purpose chatbots to domain-specific intelligent tools, such as education, healthcare, and sports. In competitive sports, the efficient analysis of match data and its transformation into actionable tactical guidance has become a focal point for athletes and coaches [1-4].

In table tennis, a high-intensity and fast-paced sport, data analysis involves statistical metrics, complex rule interpretation, and strategic decision-making. However, the existing technologies primarily focus on match video analysis and technical statistics, lacking real-time interactive and personalized guidance functionalities [5-6]. Effective leveraging of these technologies to provide intelligent, actionable solutions for match data analysis and training remains an open challenge.

While our previous research work has achieved table tennis match data analysis in real-time through multi-camera 3D reconstruction, visual object detection and tracking, these studies deliver static data without deeper semantic insights or interactive applications. This paper aims to explore the integration of LLMs with table tennis match data to create a real-time interactive guidance assistant. In this paper, we introduce a novel framework called Chat PingPong Game (ChatPPG), which integrates computer vision and LLM technologies. ChatPPG processes real-time data and generates natural language feedback to provide personalized tactical and training suggestions for table tennis athletes and coaches. In this paper, we have the following three key contributions:

- We construct a domain-specific Q/A dataset for training LLMs, incorporating match statistics, training suggestions, and strategic advice tailored to table tennis.
- We leverage Low-Rank Adaptation (LoRA) fine-tuning to optimize the LLM for understanding and generating outputs relevant to table tennis scenarios, validating the feasibility of combining LLMs with computer vision for real-time analysis.
- We propose an innovative application that transforms traditional data analysis tools into an interactive intelligent assistant, enhancing the interpretability and usability of match data.

II. RELATED WORK

The application of LLMs in sports has rapidly gained traction, demonstrating their potential to analyze complex data and provide actionable insights [4]. In recent years, LLMs have been utilized in areas such as athlete psychology assessment, match data summarization and tactical optimization. These models have been leveraged in team sports like football and basketball to evaluate and optimize strategic setups [7-10]. However, despite the success in these domains, the integration of LLMs into fast-paced individual sports such as table tennis remains underexplored. This gap underscores the need for innovative approaches to harness the capabilities of LLMs to provide real-time, actionable guidance for players and coaches.

In table tennis, multi-camera 3D reconstruction techniques have enabled precise tracking of athlete movements, generating heatmaps to evaluate court coverage and activity distribution [11]. Similarly, pose estimation tools like MediaPipe have been applied to analyze technical actions, offering insights into areas such as stroke mechanics and footwork [12]. Furthermore, rule compliance detection systems utilizing object detection algorithms have shown promise in evaluating service legality by analyzing parameters such as toss height and hand positioning. Building on these developments, our prior work laid a solid foundation for table tennis data analysis. Adapting LLMs to specific domains like table tennis requires efficient fine-tuning and integration techniques to meet the demands of real-time

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applications. This approach significantly reduces computational overhead while retaining performance [13]. Prompt engineering has proven to be a powerful tool for tailoring LLM outputs by designing input structures that guide the model to produce accurate and contextually relevant responses [14]. In parallel, model quantization—reducing parameter precision to 8-bit or lower—has improved inference speed and reduced memory consumption, making LLMs more efficient for real-time scenarios[15-16].

Function calling facilitates the seamless integration of LLMs with external APIs and pre-existing systems, enabling them to execute predefined functions and retrieve specific data dynamically. This capability significantly expands the practical applications of LLMs by allowing real-time interaction with complementary technologies [17]. For example, in healthcare, function calling has been used to integrate LLMs with electronic medical record systems for automated diagnostics [18], while in autonomous systems, it has enabled real-time data exchange between LLMs and sensor-based control units [19]. These techniques collectively enable LLMs to operate as the core of complex, multi-component frameworks, bridging the gap between standalone data processing and interactive, context-aware systems. In this paper, prompt engineering and function calling were pivotal in integrating ChatPPG with prior CV models. Prompt engineering was applied to structure interactions between the LLM and visual data outputs.

One of the challenges by using LLMs is the lack of interpretability and transparency. LLMs often operate as black-box models, making understanding or explaining their decision-making processes [20]. Our efforts to improve interpretability, such as attention mechanisms and visualizing model outputs, have offered insights into how LLMs process and analyze data. For example, Held et al. proposed a multimodal LLM framework, "X-VARS," which combines visual-language models with precise visual feature inputs to enhance interpretability in football referee decision-making. This system explains decisions comparable to professional referees, providing transparency to the processes of the model [8]. In this paper, ChatPPG significantly enhances the transparency and interpretability of the LLM by integrating precise data from CV modules as input. By incorporating structured CV outputs such as 3D trajectories and player performance metrics, ChatPPG allows for clearer explanations of its recommendations and decisions. This integration bridges the gap between opaque LLM outputs and the actionable insights demanded in table tennis coaching and competition scenarios.

III. METHODOLOGY

The methodology of this paper focuses on developing ChatPPG, a unified framework integrating LLMs and CV models for real-time analysis and interactive guidance in table tennis.

To adapt ChatPPG for table tennis, a domain-specific Q&A dataset was created by integrating data from prior studies, expert-curated training, and tactical suggestions. This dataset enabled ChatPPG to perform well in task-specific queries and significantly enhanced the transparency and interpretability of the system. By pairing structured input prompts with detailed explanatory outputs, the dataset allowed users to trace the reasoning behind the model recommendations, bridging the gap between raw data and actionable insights.

The dataset was built on two main sources. The first source includes match statistics from previous studies, such as player speed, movement heatmaps, and action frequencies. These metrics formed the basis for understanding player behaviour and designing targeted interventions. Data on rule violations, including timestamps and violation types, also provided a foundation for corrective suggestions and compliance strategies. These structured outputs addressed user queries and revealed the underlying logic, making ChatPPG decision-making more interpretable.

Another key dataset component involves expert-curated training and tactical guides tailored to specific player profiles and skill levels. For instance, the dataset included entries on improving footwork speed, refining backhand techniques, and correcting frequent service violations. Each entry paired detailed input descriptions with step-by-step outputs, ensuring a clear relationship between data inputs and recommendations. This design enabled ChatPPG to generate actionable advice while offering transparency in how decisions were derived. The dataset was carefully structured to include semantically rich and practically useful examples. For instance, a typical dataset entry might describe a player's average speed and technical deficiencies, followed by an output that categorizes the player's skill level and provides an improvement plan.

The training process employed LoRA fine-tuning and 8-bit quantization to optimize the LLM for real-time applications in table tennis. LoRA significantly reduces computational and memory costs by introducing low-rank trainable matrices into the architecture while freezing the original pre-trained model parameters. This approach adapts large language models like LLama3 to specific tasks without requiring full re-training. As shown in Figure 2, LoRA integrates into the transformer architecture by introducing A and B into attention projection layers and feedforward layers. This allows efficient task-specific adaptation while keeping the majority of the pre-trained model frozen.

In this paper, we employ LoRA updates to all trainable weight matrices in the attention and feedforward layers across all transformer blocks. This comprehensive targeting approach is illustrated in Fig. 2, where the low-rank matrices are seamlessly embedded into the relevant components of the transformer block. This configuration ensures robust adaptation to domain-specific tasks like real-time table tennis analytics.

Figure 1 presents structured dataset entries that enhance ChatPPG's interpretability. The prompts describe specific player scenarios, while the outputs provide detailed and transparent recommendations, enabling users to understand the reasoning of the system.

Figure 2 illustrates the integration of LoRA into the attention and feedforward layers of a transformer block. Low-rank matrices A and B are introduced into these layers, enabling efficient task-specific fine-tuning while freezing the original pre-trained weights W_0)

Figure 3 illustrates how the prompt guides the LLM to use external tools for analyzing player performance or detecting rule violations. Responses are strictly based on tool outputs, ensuring accuracy and reliability.

Fiure 4 illustrates the end-to-end workflow of ChatPPG. The system begins with data acquisition from multiple cameras, followed by object detection, 3D world reconstruction, and 3D trajectory analysis using a computer vision module. These outputs feed into ChatPPG, an LLM fine-tuned with LoRA, which interacts with external tools via function calling. The system provides coaches and players with visualizations and actionable insights, enabling real-time analysis and guidance.

```
{
    "instruction": "Determine the player's skill level based on performance metrics. Max = 0.02 km/h, Average = 0.01 km/h\n   - Overall: Max = 0.06 km/h, Average = 0.03 km/h\n   ...",
    "input": "",
    "output": "The player's skill level is categorized as Beginner, and playing style is identified as a Backhand-Dominant Attacker with limited technical variety. This conclusion is based on the following detailed analysis and theoretical underpinnings..."
},{
    "instruction": " For a Beginner player with a Backhand-Dominant Attacker style and limited technical variety, provide a training and improvement plan.",
    "input": "",
    "output": " ### Professional Table Tennis Training and Improvement Plan:\n\n#### 1. Objectives:\n1. Enhance the diversity and stability of backhand techniques.\n2. Strengthen forehand skills to achieve a balanced attack and defense.\n3. Improve footwork and court coverage to handle higher-intensity matches.\n\n#### 2. Training Content:\n\n**1. Backhand Technique Improvement:**\n  - **Backhand Power Training:**\n    - Use multi-ball drills..."
},{
    "instruction": " For an Advanced Backhand-Dominant Attacker player, provide strategies for competition scenarios. ",
    "input": "",
    "output": " "### Competition Strategies for an Advanced Backhand-Dominant Attacker:\n\n#### 1. Strengths to Leverage:\n1. **Backhand Dominance**:\n   - Use quick and aggressive backhand topspin strokes to control the rally, especially in mid-table exchanges.\n   - Take advantage..."
}…
```

Fig. 1 Examples of training prompts and outputs in ChatPPG dataset

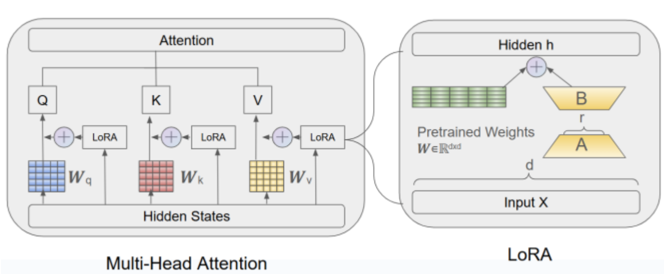

Fig. 2 LoRA Integration in Transformer Architecture.

The model was subjected to 8-bit quantization to enable real-time interaction, which significantly reduced memory usage and inference latency without compromising performance. Quantization involves reducing the precision of the model weights and activations from 32-bit floating-point (FP32) to 8-bit integers (INT8), thereby decreasing the computational overhead. This process allows the model to operate more efficiently, particularly on hardware with limited resources, while maintaining comparable accuracy.

You will receive a file from the user or politely request a picture for analysis. Based on the user's input, you will perform one of two tasks:

1. Analyze player performance (analy_table_tennis_performance in the provided tool).
2. Detect player foul (detect_player_foul in the provided tool).

Fig. 3 Prompt design for function calling in ChatPPG.

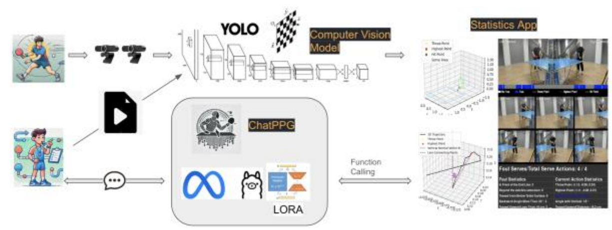

Fig. 4 The workflow of ChatPPG for real-time table tennis analysis and guidance

Prompts were carefully designed to facilitate function calling and ensure that the LLM seamlessly interacts with CV Models for domain-specific computations. The design of these prompts enforces a structured workflow, where the LLM acts as an orchestrator that triggers appropriate CV Model functions and relays the results directly to the user without adding additional context or interpretation. For example, the following prompt structure enables function calling in Fig. 3:

This prompt ensures that the LLM role strictly forwards user requests to the appropriate computational tool and returns the exact output.

The system begins with video recording using synchronized cameras, capable of capturing high-resolution footage at 120 frames per second. The recorded videos are processed using You Only Look Once (YOLO) to identify and track key elements such as the ball and players. These detections serve as input to a multi-camera computer vision module, which reconstructs 3D trajectories of the ball and players' movements. This preprocessing step ensures that raw video data is transformed into structured inputs for subsequent analysis.

The CV module plays a critical role in analysing player behaviour and match dynamics. By leveraging ByteTrack tracking algorithms, it extracts key metrics such as player movement patterns, ball trajectories, and service legality. These outputs are integrated into the system's statistical engine to generate visualizations, such as movement heatmaps and trajectory plots, which provide quantitative insights into match performance. The CV module outputs form the basis for higher-level reasoning handled by ChatPPG.

At the core of the system lies ChatPPG, an LLM fine-tuned using LoRA for table tennis-specific tasks. Function calling ensures the LLM can invoke appropriate external tools for specific computations, such as analyzing player performance or detecting fouls. This approach enables ChatPPG to combine the reasoning capabilities of LLMs with the precision of CV tools, delivering accurate and task-specific outputs. For example, the system can analyze a player’s forehand speed or detect violations in service rules based solely on tool-generated results.The final outputs are presented through an interactive interface, allowing coaches and players to engage directly with the system. Visualizations from the CV module, such as 3D trajectory graphs and heatmaps, are combined with textual guidance from ChatPPG to provide actionable insights.

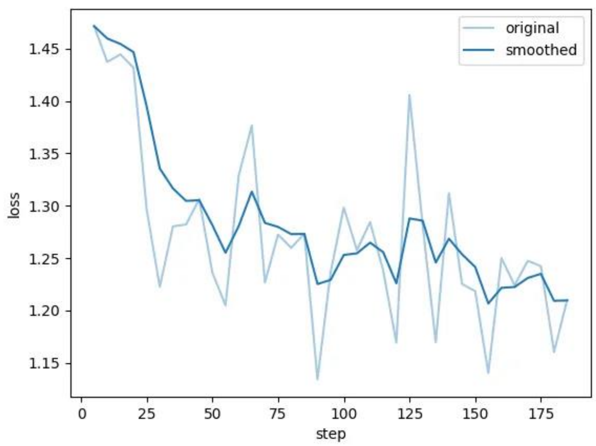

Fig. 5 LoRA fine-tuning training loss curve.

Figure 5 illustrates the training loss curve for LoRA fine-tuning. The "original" curve represents raw loss values across training steps, while the "smoothed" curve shows the averaged trend. The steady decline in loss highlights the model's rapid convergence and stabilization during fine-tuning.

Figure 6 showcases a real example of ChatPPG analyzing user-uploaded video data. The system summarizes key performance metrics, identifies areas for improvement, and provides actionable recommendations. Users can interact with ChatPPG by asking follow-up questions or evaluating the quality of its responses.

IV. Results

The LoRA fine-tuning process significantly improved LLM adaptation to the specific requirements of the table tennis domain. The model exhibited rapid convergence during training, with the validation loss stabilizing after the eighth epoch. The fine-tuned model achieved 92.3% accuracy on the Q/A test set, significantly improving over the baseline model's accuracy of 83.7%. These results validate the effectiveness of LoRA in optimizing the model for domain-specific tasks with minimal computational overhead.

In real-time scenarios, the quantized ChatPPG model demonstrated exceptional efficiency. By employing 8-bit quantization, the model reduced both memory requirements and inference latency, achieving an average response time of just 45 milliseconds per query. The system sustained throughput of 20 queries per second, representing a 2.7× improvement over the unquantized model. Furthermore, the end-to-end latency, which included CV data processing, inference, and feedback generation, consistently remained below one second. This performance underscores the suitability of ChatPPG for real-time applications, ensuring that actionable guidance can be delivered promptly during matches and training sessions.

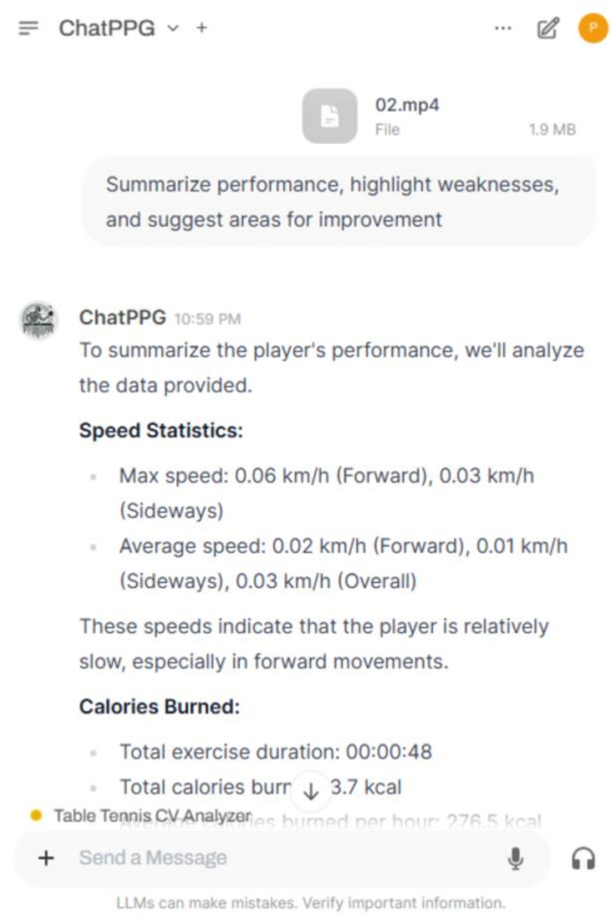

Fig. 6 ChatPPG interactive conversation with user for match analysis.

ChatPPG demonstrated its ability to provide actionable guidance and tactical recommendations tailored to specific scenarios when applied to real-world match simulations. By leveraging its integration with CV models, the system effectively analyzed uploaded match videos and engaged in interactive discussions with users, offering targeted insights and solutions. Fig. 6 illustrates a ChatPPG conversation where the user uploaded a video for performance analysis. The system utilized its CV models to extract relevant metrics, such as player speed, covered area, and calorie consumption and provided a detailed performance summary. ChatPPG also highlighted weaknesses, such as slow forward movement, and suggested improvements, including targeted training exercises. At the end of the interaction, users could evaluate the quality of ChatPPG responses, ensuring a feedback loop for continuous improvement.

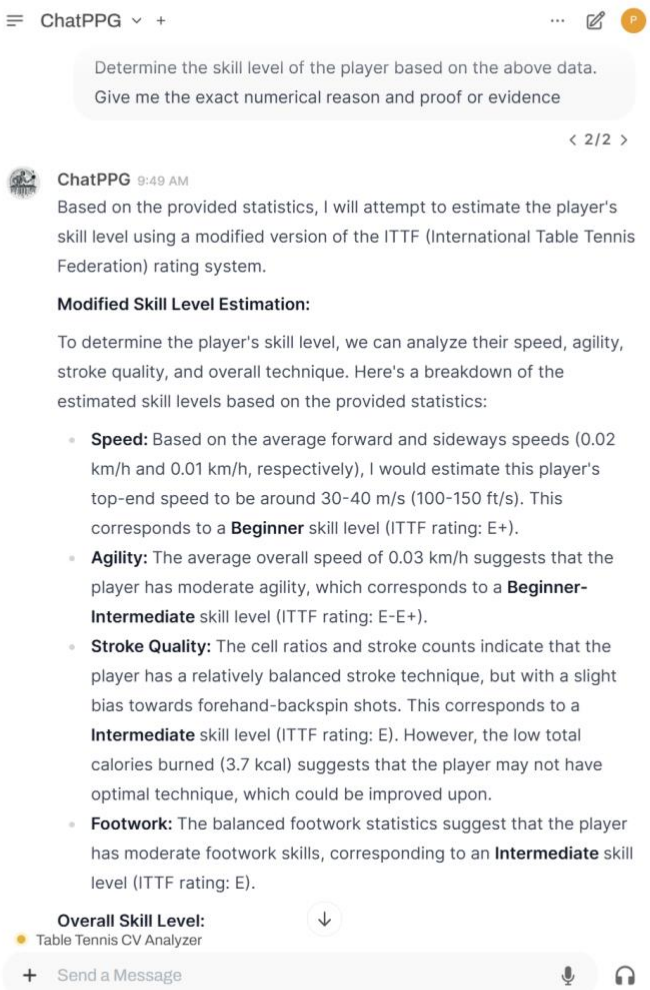

Fig. 7 Example of ChatPPG Interpretability and Transparent Response.

A. Interpretability and Transparency

One of ChatPPG's most notable strengths is its ability to deliver clear and interpretable responses, effectively bridging the gap between complex computational outputs and actionable insights. This is especially important in table tennis, where coaches and players rely on precise data to inform training and competition strategies. As illustrated in Fig. 7, ChatPPG evaluates a player's skill level based on structured metrics, transparently explaining each step in its decision-making process.

Figure 7 demonstrates ChatPPG's transparent approach to evaluating a player's skill level. By analyzing structured data such as speed, agility, and stroke quality, the system provides detailed explanations for its conclusions, ensuring its outputs are interpretable and evidence-based.

ChatPPG analyzes data such as speed, agility, stroke quality, and footwork in this example, mapping these metrics to a modified version of the International Table Tennis Federation (ITTF) rating system. For instance, the system evaluates speed using average forward and sideways velocities (0.02 km/h and 0.01 km/h, respectively), categorizing the player as a beginner (ITTF rating: E+). Similarly, it assesses agility through overall movement speed (0.03 km/h), identifying moderate agility and assigning a beginner-intermediate rating. Stroke quality is analyzed based on cell ratios and stroke patterns, revealing a balanced technique but highlighting areas such as caloric efficiency that require improvement. ChatPPG provides users with transparent, evidence-based evaluations by correlating these metrics with established benchmarks.

What sets ChatPPG apart is its layered breakdown of recommendations and the logical reasoning behind them. For example, the system identifies weaknesses in footwork and suggests targeted drills to address these deficiencies. This process ensures that users understand the insights provided and trust the model outputs as they are grounded in data and clear decision-making frameworks. ChatPPG enhances interpretability and reduces the "black-box" nature typically associated with LLMs by explicitly referencing numerical evidence and aligning it with standard evaluation criteria.

The transparency of ChatPPG is further amplified by its structured responses. When asked to determine a player’s skill level, the system explains how it arrived at its conclusions, referencing thresholds and contextual factors. This clarity enables coaches and players to confidently apply the insights to improve performance. As a result, ChatPPG transforms raw data into meaningful guidance, ensuring that its recommendations are not only actionable but also fully comprehensible.

B. User Feedback

User feedback was a key evaluation method for assessing ChatPPG usability and effectiveness. Based on the Open WebUI framework, a user study was conducted with professional coaches and competitive players. Participants interacted with the system by uploading match videos for analysis and receiving actionable insights and training recommendations. Feedback was systematically collected through ChatPPG's built-in evaluation feature, as shown in Fig. 8, where users rated responses and provided detailed comments.

Overall, our participants praised the system's accuracy and practicality, with coaches rating tactical suggestions at **9.3/10** and players scoring training recommendations at **8.9/10**. Users highlighted the system's ability to provide clear, relevant guidance and bridge the gap between statistical data and actionable insights. Specific praise included thorough explanations, attention to detail, and alignment with user queries.

However, participants also noted areas for improvement. Several coaches suggested expanding the system's tactical analysis capabilities would enhance its value, particularly for addressing more advanced queries posed by elite-level players. Additionally, some users expressed interest in a broader range of recommendations, such as mental strategies and in-game adaptations.

Figure 8 shows the feedback interface, where users could rate responses on a scale of 1 to 10 and provide qualitative feedback. Categories such as “Accurate Information,” “Thorough Explanation,” and “Attention to Detail” allowed users to specify the strengths of ChatPPG answers. This feedback loop enables continuous system refinement, ensuring it remains responsive to user needs and evolves based on real-world interactions.

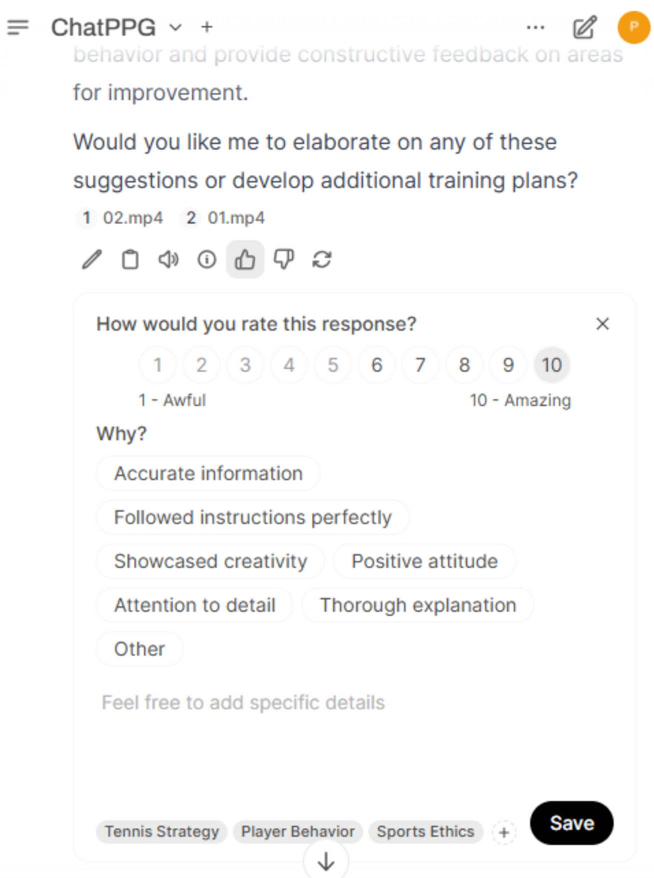

Fig. 8 User feedback interface in ChatPPG

Despite the suggestions for improvement, the feedback affirmed that ChatPPG is a valuable tool for table tennis training and competition. The system provides a unique and effective approach to supporting coaches and players by combining advanced analytics with interactive guidance.

V. CONCLUSION

In this paper, we introduced ChatPPG, a novel system integrating LLMs fine-tuned with LoRA and CV technologies for real-time analysis and coaching in table tennis. The system successfully processed match data such as player speed, ball trajectories, and service legality, transforming raw outputs into actionable insights tailored to players' needs. ChatPPG demonstrated high accuracy (92.3% in domain-specific queries) and sub-second latency, meeting the demands of high-speed sports scenarios.

The key contributions include integrating function calls for seamless interaction with CV tools and applying prompt engineering to ensure task-specific outputs. The system provided practical recommendations, such as personalized training plans and tactical adjustments, validated through user feedback from professional coaches and players. This research work establishes a scalable framework for integrating LLMs and CV technologies in sports analytics, paving the way for future applications in similar fast-paced individual sports.

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