

Smart triboelectric motion-feedback sensor for table tennis monitoring

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Nano Res., **Just Accepted Manuscript** • <https://doi.org/10.26599/NR.2026.94909149>

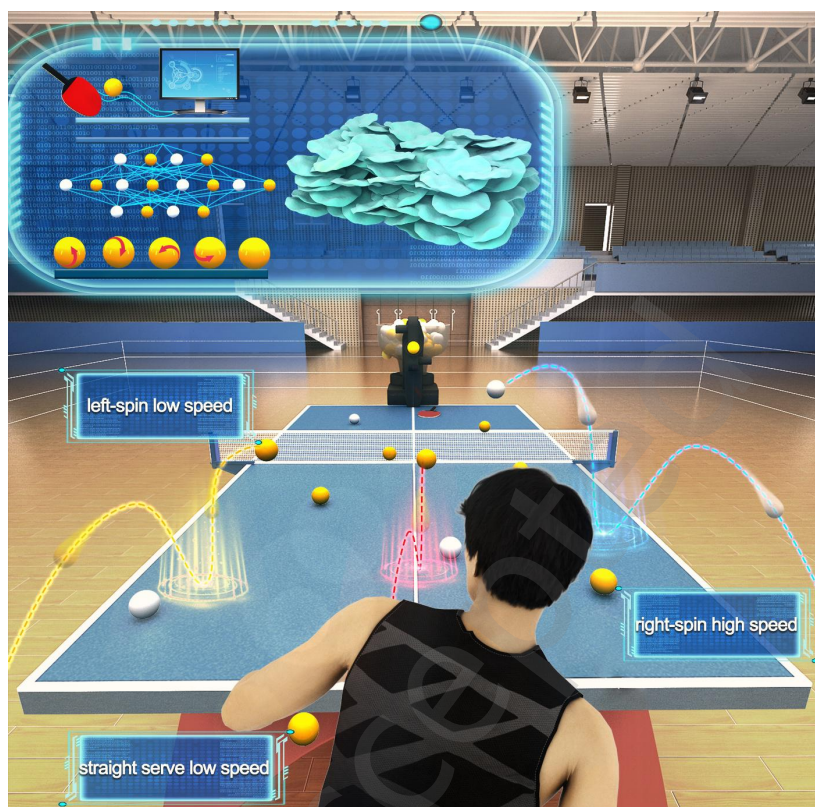
<https://www.sciopen.com/journal/1998-0124> on Aug. 27, 2026

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This work develops an MXene/bacterial cellulose triboelectric self-powered table tennis paddle sensor, whose matched LSTM-SVM model achieves 99.8% accuracy for ball rotation and speed recognition (48.5% higher than standard SVM), pioneering self-powered table tennis spin sensing for intelligent sports.

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Received: 2 May 2026; **Revised:** 21 August 2026; **Accepted:** 27 August 2026

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Cite this article: *Nano Research*, 2026, 19, 94909149 <https://doi.org/10.26599/NR.2026.94909149>

ABSTRACT: With the advancement of flexible electronics and machine learning (ML), the collection and analysis of athletic big data using self-powered sensors have become increasingly important in intelligent sports. However, accurate quantification of the rotation direction, a critical parameter in ball games, remains largely underexplored. This study proposes an ML-assisted, intelligent motion-feedback table tennis paddle integrated with a triboelectric nanogenerator (TENG) for simultaneous velocity and rotation direction sensing. By leveraging a well-intercalated MXene/bacterial cellulose (MXBC) composite thin film, the developed sensor exhibits improved tensile strength, excellent conductivity, good processability, and lightweight characteristics. Consequently, the MXBC-based TENG generates distinct and rich feature signals corresponding to rotational motions, enabling its use as a self-powered intelligent feedback sensor. To enhance detection sensitivity and accuracy, a hybrid long short-term memory network–support vector machine (LSTM–SVM) model is constructed, coupled with effective denoising technique. Using the optimized LSTM–SVM modal, the proposed sensor achieves table tennis ball rotation direction and velocity recognition with an accuracy of 99.8%, representing a 48.5% improvement over the conventional SVM method. This study is the first to achieve self-powered rotation direction detection in table tennis, demonstrating significant potential for ball sports training and opening new avenues for the advancement of intelligent sports.

KEYWORDS: intelligent sports, triboelectric nanogenerator, machine learning, self-powered sensing, MXene

1. Introduction

Flexible and wearable electronics have garnered considerable scientific interest owing to their applications in health monitoring[1-3], athlete training[4, 5], and intelligent sports[6, 7]. These technologies are esteemed for their excellent biocompatibility[8, 9], high sensitivity[10, 11], and superior data acquisition capabilities[12, 13]. Despite these benefits, conventional wearable electronics typically face challenges related to limited endurance, high replacement costs, and notable environmental impacts. These limitations highlight the urgent need for innovative, maintenance-free, and self-powered sensing technologies.

Triboelectric nanogenerators (TENGs), which leverage Maxwell's displacement current[14, 15], have emerged as a significant technological advancement for efficiently harvesting high-entropy energies from human motion[16, 17] and environmental vibrations[18, 19]. TENGs have been

extensively used in self-powered sensing systems[20-22] and micro/nano energy harvesting[23, 24], offering advantages such as high energy conversion efficiency[25], simplicity of construction[26], and a diverse range of material options[27, 28]. Technological innovations in TENGs include the development of novel operational principles[29-32], materials optimization[33, 34], and structural design improvements[35] that enhance electrical output and mechanical stability. TENGs directly convert mechanical stimuli into electrical signals without external power, making them critical for autonomous sensing systems. Noted for their high sensitivity, size controllability, and broad compatibility, TENG-based sensors have demonstrated high effectiveness in intelligent sports[36]. They can be integrated into sports facilities or worn on the body to analyze various sports activities[37, 38].

As intelligent sports continue to evolve, the role of athletic

big data in enhancing training quality and sports performance becomes increasingly critical. However, managing the vast amounts of data generated presents a significant computational challenge. Conventional approaches have integrated TENG-based sensors with signal processing modules to streamline data handling[39]; however, this typically results in increased system complexity, enlarged device sizes, and elevated costs. In contrast, machine learning (ML) presents a potent alternative with its advanced signal processing and data analysis capabilities[40]. Through extensive training, ML can efficiently process raw data from TENG-based sensors [41] by employing techniques such as convolutional neural networks (CNN)[42], support vector machines (SVM)[43], and long short-term memory (LSTM)[44-47] to refine sensor functionality. However, the application of ML-assisted self-powered sensors for detecting rotational parameters in sports such as table tennis remains underexplored[48-50]. In this study, we propose an ML-assisted, self-powered, and intelligent rotation motion-feedback sensor that employs a thin and durable $\text{Ti}_3\text{C}_2\text{T}_x$ MXene/bacterial cellulose (BC) composite film. In this composite film, MXene nanosheets are uniformly dispersed within a three-dimensional BC network, creating a mechanically robust structure. The MXene/BC (MXBC) film exhibits excellent mechanical properties (tensile strength of 18.8 MPa and Young's modulus of 1.5 GPa at 50wt% MXene), good conductivity (0.33 S/m), wear resistance, processability, low weight (76 mg/m²), and minimal thickness (50 μm). The unique nanostructure of the MXBC film facilitates the integration of an MXBC-based TENG onto a table tennis paddle, transforming it into a self-powered intelligent feedback sensor capable of detailed sensing of velocity and rotation direction, which are key parameters for optimizing table tennis performance. To improve sensor sensitivity and accuracy, we developed a hybrid LSTM-SVM composite model, incorporating effective noise. Consequently, the proposed sensor achieves an accuracy of 99.8% in

determining the rotation direction and velocity of a table tennis ball. This study marks the first successful application of ML-assisted self-powered sensor technology for rotation direction detection in table tennis, heralding a new era in intelligent sports. By leveraging the properties of MXBC films combined with advanced ML algorithms, the proposed sensor paves the way for improving athletic performance through an integrated approach of sensor technology, big data, and robotic innovations.

2. Results and Discussion

2.1 General Design

Ball rotation is not merely a physical characteristic, more importantly, it is a core technical means for athletes to control gameplay, deceive opponents, create opportunities, and improve performance. Although rotation plays an essential role in ball sports, particularly in table tennis, our ability to accurately measure it has not kept pace with its growing importance in modern sports. We address this issue through a combination of innovations in material synthesis, device fabrication, and algorithm optimization, enabling high-accuracy rotation sensing of table tennis (Figure 1). This study is the first realization of smart triboelectric motion-feedback sensor for table tennis monitoring. The developed smart triboelectric motion-feedback sensor comprises an MXBC thin film designed to be mechanically flexible and conformable to the table tennis paddle. The MXBC thin film exhibits excellent mechanical properties, good conductivity, and measurable electrical signals upon impact with the tennis ball. The generated electrical signals contain comprehensive data, including velocity and rotation direction. Using optimized ML algorithms, we perform feature extraction and data noise reduction, enabling effective discrimination between velocity and rotation direction signals.

The following sections detail the material synthesis and device fabrication of the key TENG sensor element.

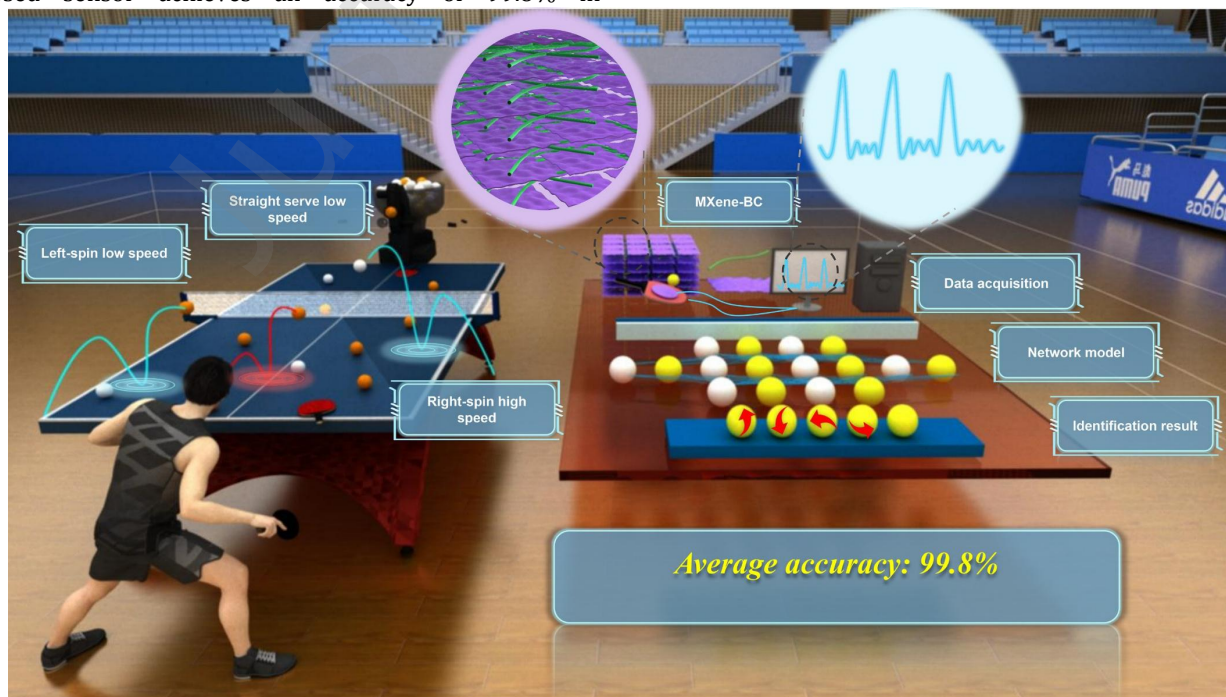


Figure 1 General principle of the proposed ML-assisted, self-powered intelligent rotation motion-feedback sensor.

2.2 Device Fabrication

Figure 2a shows the fabrication process and the morphological and structural characterizations of the BC, MXene, and MXBC composite film. MXene is derived by etching Ti_3AlC_2 under specific conditions to produce a high-concentration solution. Subsequently, MXBC is obtained by cross-blending and intercalating this high-concentration solution and BC via extraction and filtration. The resulting MXene/BC film features a well-intercalated structure, ensuring optimal performance characteristics.

Figures 2b-d show scanning electron microscopy images, revealing distinct planar and cross-sectional views of each material. The layered integration of nanofibrous BC and MXene flakes yields a well-intercalated MXBC composite structure, which is visible in these images. This structural arrangement is conducive to the use of the composite material in TENGs. The electrostatic potential, essential for effective TENG operation, is illustrated in Figure 2e, revealing a notable surface potential difference of approximately 135 mV. Further structural confirmation is provided by the X-ray diffraction pattern shown in Figure 2f, which verifies that the MXBC composite remains chemically stable without undergoing any undesired reactions. This high potential difference is advantageous for amplifying the electrical output and sensitivity of the TENG, enabling detailed motion feedback during dynamic activities, such as

table tennis. Material durability is critically evaluated through tensile testing. The results are presented in Figure 2g. Although pure MXene films exhibit superior TENG sensing capabilities, their mechanical strength is inadequate, with a fracture stress of 2.9 MPa and strain of only 0.9%, limiting their long-term usability in wear-intensive environments. In contrast, MXBC composites with varying MXene to BC ratios (1:1, 1:2 and 2:1) exhibit significantly enhanced tensile strengths. Among the three blends, the 1:1 MXBC sample exhibits optimal mechanical properties, including a stress of 18.8 MPa at a tensile displacement of 2.6%. This composition also presents an ideal Young's modulus of 1.53 GPa, as shown in Figure 2h, consistent with the desired mechanical characteristics for sports applications. The electrical conductivity of the MXene and BC materials, which is a crucial parameter for TENG performance, is analyzed with reference to Figure 2i. The inclusion of MXene significantly improves the conductivity of BC, achieving an impressive value of 0.333 S/m at a 1:1 mass ratio. The mechanical performance testing summary is shown in Fig. S1 in the ESM. Overall, the prepared MXBC composite material demonstrates robust mechanical properties suitable for high-impact environments and maintains excellent conductivity and sensitivity. These attributes make it highly effective for real-time monitoring of various motion dynamics during sports, providing valuable feedback on player actions.

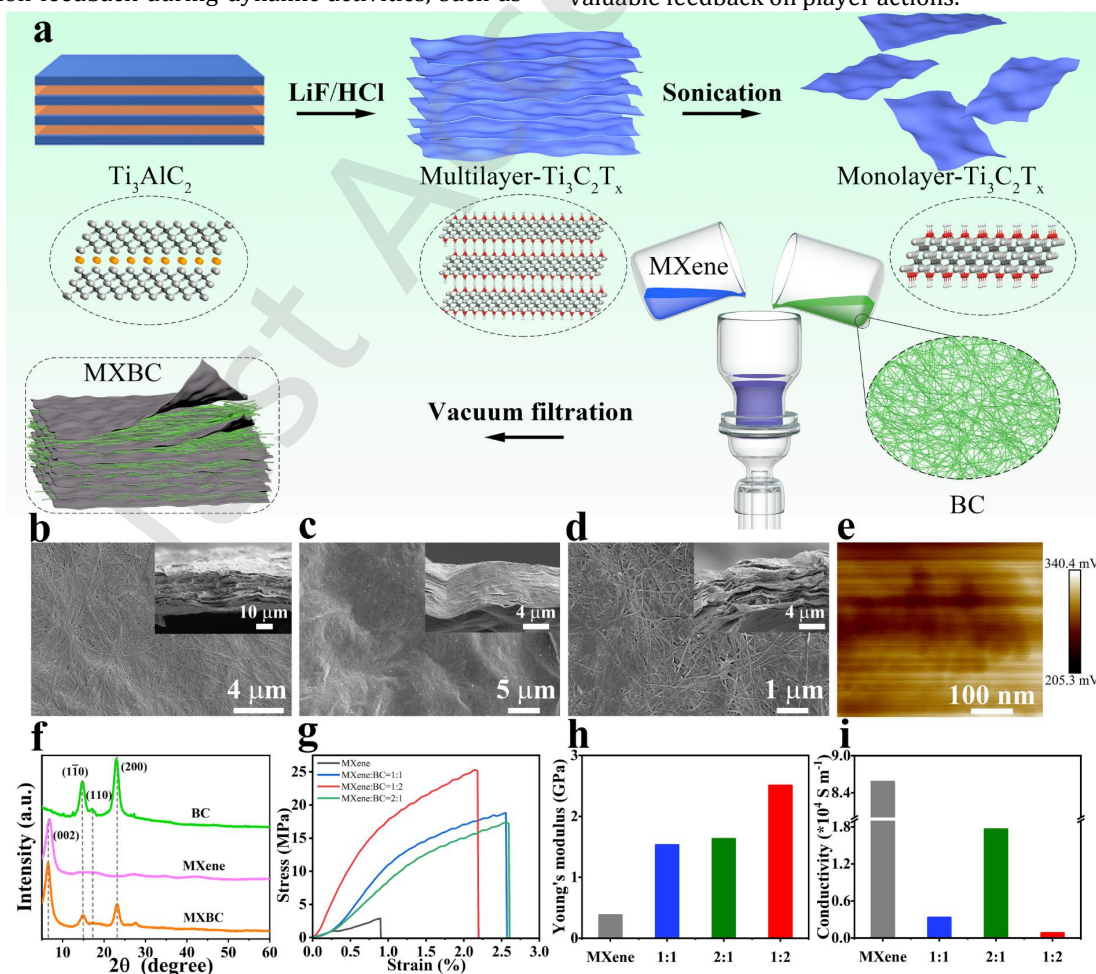
**Figure 2** Fabrication and characterization of MXBC. (a) Preparation process of MXBC composite film, SEM images of (b) MXene, (c) BC, and (d) MXBC, with inset in the top right corner showing their cross-sections and (e) potential distribution map; (f) corresponding XRD patterns; (g) schematic

diagram of tensile strength of MXene and BC mixtures at different ratios; (h) Young's modulus, and (i) conductivity graph.

To further validate the rotation motion sensing capabilities, a series of TENGs based on MXBC films with various MXene to BC ratios were prepared (Figure 3a). These flexible films, each exhibiting a metallic luster and smooth surface, were installed on a table tennis paddle configured to operate in single-electrode mode. The voltage signals generated during collisions with a table tennis ball in topspin low-speed (On-Low) mode are presented in Figure 3b. To optimize the selection of materials for these experiments, preliminary collision tests were conducted, and the serving speed of the machine was adjusted accordingly.

The initial tests using pure MXene demonstrated that its recovery from single collisions within a unit time was suboptimal, resulting in indistinct collision curves. In contrast, the MXene:BC (1:2) film produced regular and distinguishable unit collision curves, even though, the electrical signal decayed over time, and the simplistic voltage curve features complicated the distinguishing of 10 different serving modes. High-resolution XPS characterization of a full series of samples is shown in Fig. S2 in the ESM, including pristine BC, pristine MXene, and MXBC composite films with mass ratios of 1:2, 3:4, 1:1, 3:2, and 2:1. Accordingly, the 1:1 mass ratio delivers the optimal surface potential difference. And the most favorable outcomes were observed using the MXene:BC (1:1) ratio. This composition yielded easily distinguishable unit collision curves and provided rich voltage curve features, enhancing the effectiveness of classification and recognition processes in ML applications.

Overall, the MXene:BC (1:1) composite exhibited the most abundant and promising feature signals for rotation motion-feedback monitoring. The motion sensing mechanism of the

MXBC film with a 1:1 ratio is schematically illustrated in Figure 3c. At the initial state, the intercalated structure of the MXBC film presents a flat surface (i). Upon impact with the table tennis ball, the collision site on the MXBC film deforms (ii). After the release of the compressive force, the deformation recovers, producing distinctive feature details (iii). With its excellent mechanical properties, the MXBC film reliably returns to its original state after repetitive impacts, resulting in stable and reproducible signals.

To reveal the inherent physical mechanism that distinguishes the voltage waveforms of topspin, backspin, left-spin, and right-spin table tennis, we decouple the ball-film collision into vertical compression motion and tangential rotational sliding motion[51]. The complete first-principles derivation of the modified Maxwell displacement current containing shear displacement is provided in Note 1 in the ESM. The effective overlapping contact area is defined as a bivariate function related to tangential sliding displacement and vertical compression displacement. A complete causal chain is established as follows: diverse spin directions result in opposite tangential sliding trends during contact-separation processes, which alter the polarity and intensity of shear current components, ultimately producing characteristic differences in voltage baseline offset, pulse width, and trailing secondary peaks. It should be noted that the established tangential friction model provides a qualitative mechanism to interpret the voltage response during table tennis collision, rather than a quantitatively validated physical model. Several simplifications are adopted in the contact-area derivation. Thus, this model is primarily used to analyze signal variation trends under small-deformation conditions.

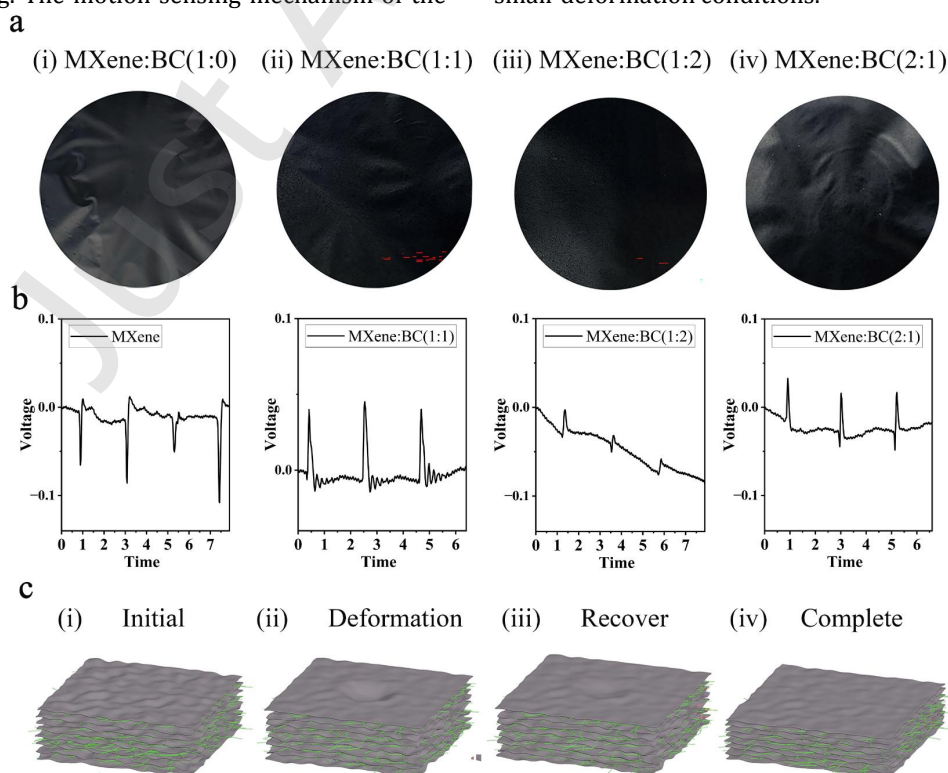


Figure 3 Physical image of MXBC film and voltage and deformation during collision Comparison of table tennis rotation sensitivity of the MXBC with different ratios. (a) Photographs of MXBC films with ratios of 1:1, 1:2 and 2:1 and pure MXene film. (b) Comparison of the acquired voltage signals of TENGs based on different MXBC films. (c) Schematic illustration of rotation motion sensing mechanism of MXBC film with ratio of 1:1.

2.3 Sensing Demo

Consistent with the previously discussed principles of friction-induced output voltage across contact – separation cycles, the MXBC film exhibits superior sensitivity to friction movements compared to alternative materials. The experimental setup involves affixing the material film to a table tennis paddle, as shown in Figure 4a. The serving machine is adjusted to vary the serving mode, enabling systematic testing under controlled conditions. Upon ball impact, the contact material generates a continuous voltage output, which is captured by a voltage data acquisition system (Figure 4b). The experiment incorporates 10 distinct serving modes to simulate various game scenarios: topspin at low (On-Low) and high speeds (On-High), backspin at low (Under-Low) and high speeds (Under-High), left-spin at low (Left-Low) and high speeds (Left-High), right-spin at low (Right-Low) and high speeds (Right-High), and straight serves at low (Straight-Low) and high speeds (Straight-High). Each serving mode produces unique signal patterns, which are visualized in Figure 4c after minimal processing.

Given the diversity of the original signals obtained and their rapid acquisition timing (0.01 s as the unit time), the

resulting data complexity is considerable. To manage this dataset, the sample duration is standardized to 5 s, yielding a robust dataset of 1000 samples per serving mode. In single-electrode mode, the contact duration of the table tennis ball is exceedingly brief and directly influenced by the serving speed. Moreover, the contact area and duration between the ball and paddle vary depending on the serve type, creating distinct instantaneous voltage signals and signal change curves for each method. Although analyzing these signals at 0.01-s intervals yields a substantial data volume, manual processing of such extensive TENG data for identification and classification purposes presents significant challenges.

To efficiently and accurately differentiate between these serving modes, we incorporate advanced computational techniques. Leveraging rapid advancements in artificial intelligence, ML offers a powerful solution to these experimental challenges outlined above. ML algorithms are adept at handling large datasets, extracting meaningful patterns, and automating the classification process, significantly reducing the need for manual data processing and enhancing the overall efficacy of the experimental setup.

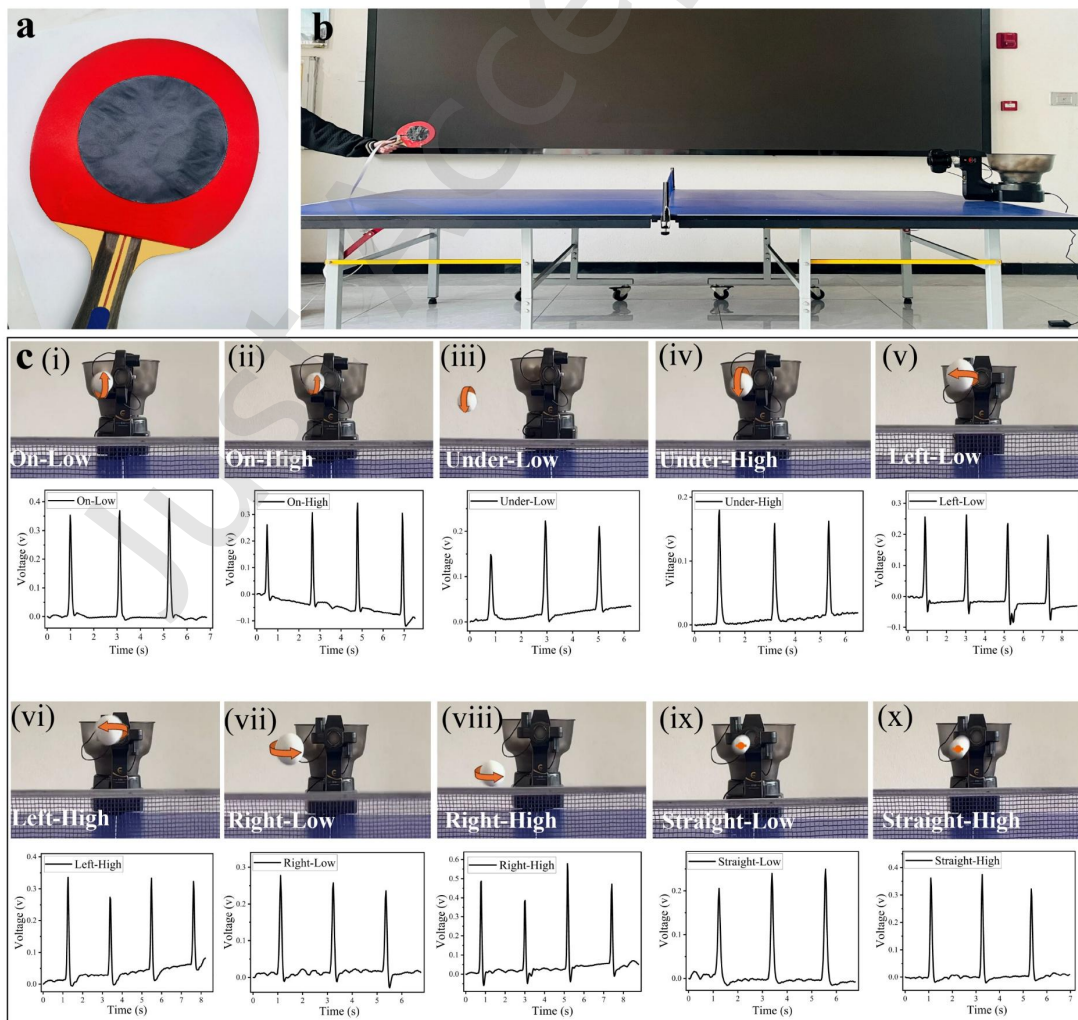


Figure 4 The schematic diagram of the experiment process and the signals collected by different serving methods (a) Physical picture of table tennis. (b) Signal acquisition method and data acquisition system. (c) Physical picture of 10 serving methods and original signal data curves.

2.4 ML training and testing

First, the collected original voltage signal dataset set is preprocessed primarily deleting abnormal signals and supplementing missing signals to ensure high data quality and reliability. Then, a large volume of sample signals undergoes detailed analysis using traditional ML methods. SVM exhibits excellent high-dimensional data processing capability. SVM selects the optimal decision boundary by maximizing the interval, making it robust to noise and outliers. Furthermore, SVM exhibits strong generalizability unseen data, thereby mitigating overfitting. Therefore, we selected SVM as the ML method for processing signal data and combined it with sample electrical signals to classify different serving modes (Figure 5a). The relevant features were extracted from the original voltage signals. Notably, this step is a crucial step for SVM. Adequate feature selection and extraction significantly influence model performance, improving classification accuracy and generalizability. For example, frequency- and time-domain features facilitate SVM training and classification. The data were divided into training sets (80%) and test sets (20%). Figure 5b shows the complete profile of the original voltage signal data collected by the material across 10 different serving modes. The model is trained by optimizing parameters and kernel

functions to improve serving mode recognition accuracy, with the pre-processed sample data into the SVM model as input vectors. A 10-fold cross-validation is performed using linear, polynomial, and radial basis function kernel function to evaluate and improve recognition accuracy across different kernel functions. Predictive performance was evaluated using the same dataset in terms of average accuracy, with the linear, polynomial, and radial basis function kernel functions achieving values of 0.620, 0.415, and 0.485, respectively (Figure 5c). Thus, the linear kernel function was selected as the optimal kernel with the training duration fixed at 200 iterations. As the number of iterations increased, the model accuracy also improved. The mean square error (MSE) and mean absolute error (MAE) were calculated concurrently to quantify the deviation between the model predictions and true values (Figure 5d). The SVM model exhibits accuracy values of 80.1% and 67.2% on the training and test sets, respectively (Figure 5e). The pulse and waveform factor data of the signals reveal a suboptimal clustering effect (Fig. S3 in the ESM). Figure 5f shows a confusion matrix, intuitively displaying prediction results of different serving modes.

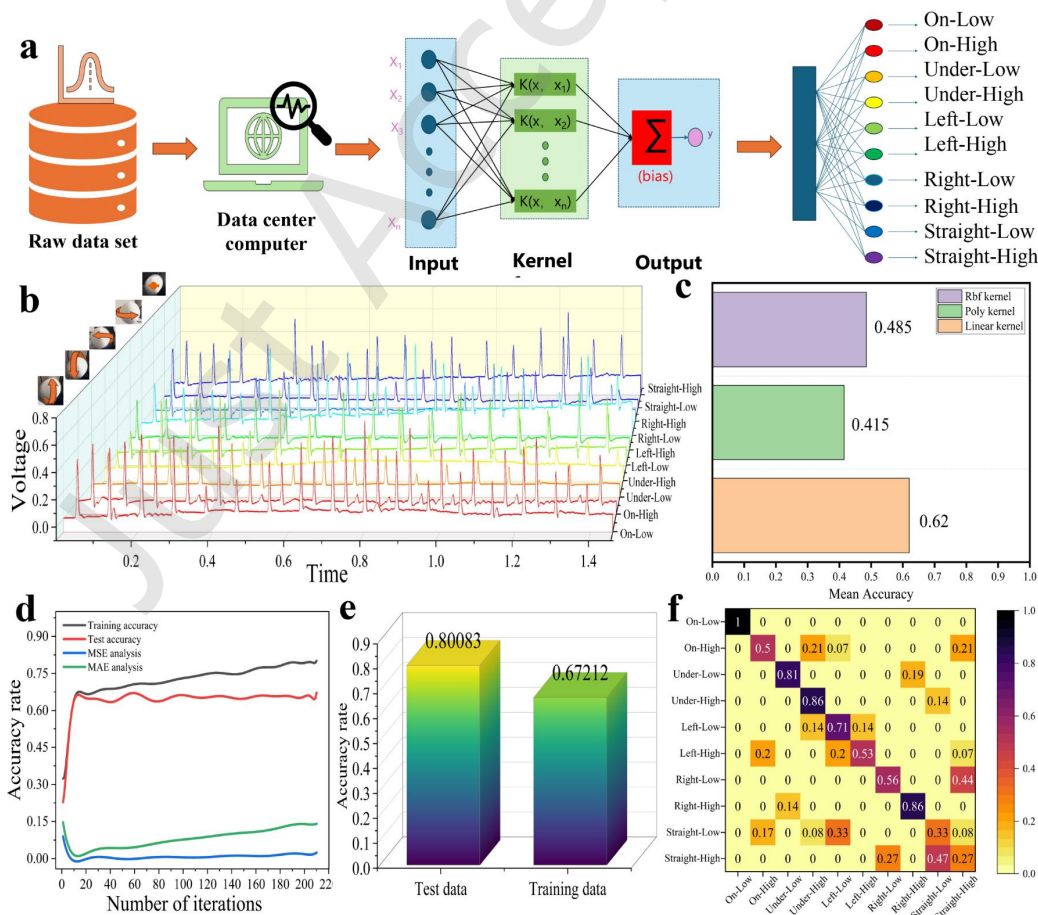


Figure 5 The schematic diagram of the experiment process and the signals collected by different serving methods (a) SVM model flow chart. (b) Overall view of voltage data. (c) Cross-verify kernel accuracy. (d) Accurate curve diagram of model iteration identification and classification. (e) Training set accuracy and test set accuracy result graph. (f) Confusion matrix of ML results.

Although a large dataset was acquired in the experiment (a total of 7580 samples after excluding unqualified data), the previous feature extraction method yielded insufficient feature information. This limitation is due to the unstable signal strength of the obtained data and the single-point limitation of the ping-pong collision mode. Given the low signal-to-noise ratio (SNR) and sparse feature data in the original data, incorporating data enhancement and denoising techniques is necessary to improve recognition accuracy. Common de-noising processing methods include mean, median, filtering, and wavelet filtering. For amplification of fine signal details, mean filtering tends to blur the detailed signal, resulting in the loss of useful signals. Similarly, median filtering exhibits poor performance in addressing white noise. In contrast, multiscale wavelet denoising decomposes signals into subbands of different frequencies, enabling targeted noise removal while preserving important frequency components. Furthermore, wavelet transform leverages fast algorithms for efficient calculation, making it suitable for processing large-scale

sequential data.

In wavelet denoising, the setting of the threshold function plays an important role in the extraction of effective signals and is a key factor affecting the final denoising effect. First, an appropriate wavelet function is selected for the multi-scale wavelet decomposition of the original signal data, yielding approximation coefficients, which represent the overall trend and low-frequency information of the signals, and detail coefficients, which contain the high-frequency information of the signal and feature details. In this study, the commonly used "db8" orthogonal wavelet basis function was selected for its high stability and computational efficiency. Regarding thresholding methods four functions were evaluated: soft, hard, greater, and less thresholds. Wavelet denoising was applied to unit samples using these four functions on the same sample data. The denoising performance was quantified by calculating the reconstruction error (RE), SNR, peak SNR, and normalized cross-correlation (NCC) between the original and denoised data (Table 1).

Table 1. Threshold function test comparison.
Data set 1:

	Soft	Hard	Greater	Less
RE	0.000282	0.0000688	0.00259085	0.00130248
SNR	56.7524	62.8801	47.1244	50.1111
PSNR	57.2076	63.3358	47.5796	50.5663
NCC	0.9894	0.9972	0.8873	0.9450

Data set 2:

	Soft	Hard	Greater	Less
RE	0.000413	0.0000626	0.00118678	0.00180930
SNR	55.2128	63.4061	50.6300	48.7986
PSNR	55.6134	63.8067	51.0306	49.1992
NCC	0.9780	0.9963	0.9280	0.8879

Based on the results, the hard threshold function achieves a minimal RE of 0.000198, and a high SNR of 65.29; furthermore, it exhibits good preservation of high-frequency and detailed feature information, yielding an NCC of 0.998. Comparative analysis across both sample groups indicates that hard function is optimal for the signal data, achieving superior data performance. The hard threshold function can be expressed as follows:

$$S = \begin{cases} X, & X > T \\ 0, & X \leq T \end{cases} \quad (1)$$

Where X represents the original signal data, T represents the set threshold, and S represents the denoised signal data.

Following de-noising, the approximation and detail coefficients are reconstructed by wavelet transform, yielding

the optimized dataset, as shown in Figure 6a. Across the signal data, the generated voltage signals remained stable and regular after hundreds of repeated trails within the same serving mode (Figure 6b). After applying the optimal denoising threshold function, finer details are displayed. To better display the optimization effect, the denoised curves for topspin, backspin, left-spin, right-spin and straight serves are presented in Figure 6c.

Following the optimization of the original data, recognition accuracy is improved. To improve classification performance, a design scheme is proposed to optimize the feature extraction process. Considering that the obtained voltage signal is sequential, an LSTM model is adopted. LSTM is a cyclic neural network that can effectively process sequential

data (Fig. S4 in the ESM). It can effectively capture medium - and long-term dependencies in time-series data, enabling effective feature extraction from the signal. The memory unit of the LSTM network retains and transmits data information, enabling the extraction of more abundant and comprehensive features from both preceding and subsequent time-series data. An in-depth feature analysis and supplemented t-SNE visualization experiments are conducted in Table S1. Through layer-wise feature

visualization and ablation studies, we identified three categories of high-order dynamic features that the LSTM automatically learns from the raw voltage signals. 300-dimensional feature vectors are extracted from the last hidden layer of LSTM and applied t-SNE for 2D visualization. Three clustering evaluation metrics were computed to quantitatively assess the separability of different serving modes in the latent space.

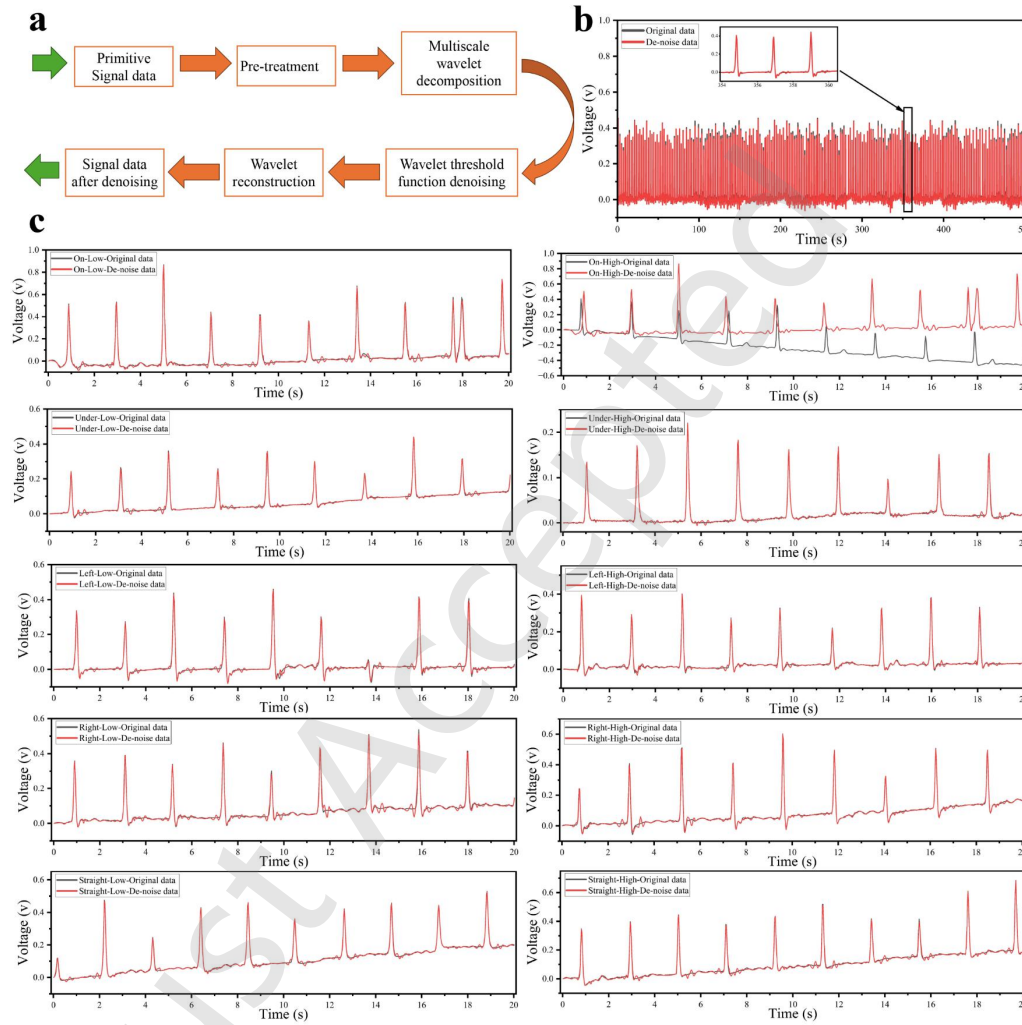


Figure 6 Process and result of noise data denoising (a) Overall flow chart of wavelet denoising. (b) Overall de-noising curve data. (c) Curves of different serving modes in 10, curves of original data, and data after noise removal.

The LSTM-SVM composite model improves recognition and classification accuracy across the 10 distinct serving modes, following the flow-chart shown in Figure 7a. First, the time-series data are segmented chronologically into fixed-length sequences as input data. The time steps of these input data are consistent with the initial setting, and the unit sample time is set at 5 s. Next, an LSTM model is constructed, comprising an LSTM layer containing 300 LSTM units. To avoid gradient disappearance or explosion, the hyperbolic tangent (Tanh) activation function is selected to compress input values between -1 and 1, thereby optimizing data standardization. The Tanh function maps negative input values to a negative output range, making it suitable for processing symmetrical signal data. The LSTM model was trained for 100 epochs, with optimization applied to the

training data to enhance feature learning and model fitting.

The architecture of a typical traditional LSTM model comprises an input gate, a forget gate, an output gate, and an update cell status. The core components include (1) input gate, (i_t); (2) forget gate, (f_t); (3) output gate, (o_t); (4) input modulation gate, (g_t); (5) internal state, (c_t); and (6) hidden state, (h_t). Each gate processes sequential data derived from the previous state based on the following calculations,

$$\begin{cases} i_t = \sigma(b_i + U_i x_t + W_i h_{t-1}) \\ f_t = \sigma(b_f + U_f x_t + W_f h_{t-1}) \\ o_t = \sigma(b_o + U_o x_t + W_o h_{t-1}) \\ g_t = \sigma(b_g + U_g x_t + W_g h_{t-1}) \\ c_t = f_t c_{t-1} + g_t i_t \\ h_t = \tanh(c_t) o_t \end{cases}$$

(2)

To extract temporal features during forward propagation, the hidden state (h_t) and element state (c_t) of the last LSTM element layer are captured at the time step (t). This intermediate output from the trained LSTM network serves as a feature representation, for subsequent analysis.

The feature formula for the extracted hidden state (h_t) is expressed as follows:

$$Features_t = h_t \quad (3)$$

The feature formula for the extract element state (c_t) is expressed as follows:

$$Features_t = c_t \quad (4)$$

In the experiment, the paddle was connected to an electrode, allowing the instantaneous voltage generated during impact to be displayed on a computer interface (Figure 7b). The MXBC thin film captured voltage data across the 10 different serving modes, which were then preprocessed and fed into the constructed LSTM-SVM composite model. By optimizing the feature extraction layer and employing this high-accuracy recognition and classification model, highly efficient classification results. To empirically validate the generalization capability, we conducted supplementary experiments under three different base plate materials and two extreme humidity conditions. The results are summarized in Table S2.

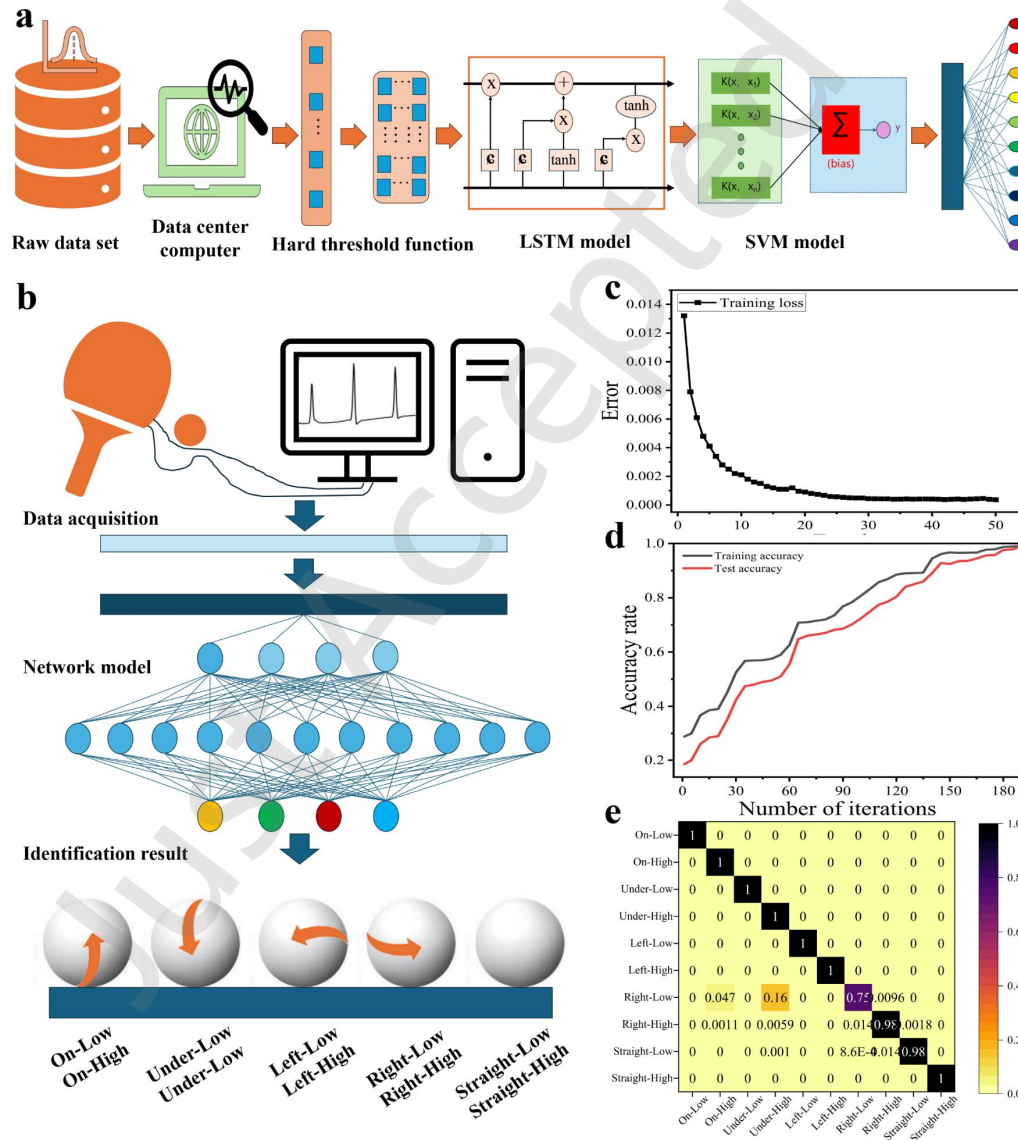


Figure 7 Training process and results of LSTM-SVM composite machine learning model (a) LSTM-SVM composite function flow chart. (b) Get signal data by connecting paddle, analyze and identify 10 serving modes. (c) Loss error curves in the LSTM model for feature extraction. (d) LSTM-SVM composite model recognition accuracy curve. (e) Confusion matrix of machine learning results.

During model training, backpropagation was executed based on the error gradients calculated by the loss function, with the model parameters updated to minimize loss and improve predictive performance. Figure 7c exhibits the loss

function curve. The trained LSTM model was used to extract the temporal features. During forward propagation, the outputs of the middle layer of the LSTM model were obtained as feature representations for the training and test

set. At the end of the iteration, these extracted feature data were fed into the SVM model for final prediction. Following the selection of a linear kernel function and 200 iterations, the accuracy of the model improved. The MSE and MAE were calculated concurrently; these metrics represent the degree of error between model predictions and true values (Figure 7d). Based on the final results, the model achieved accuracy values of the 98.2% and 99.8% on the training and test sets, respectively (Fig. S5 in the ESM). To verify the unique advantages of this hybrid model in few-shot temporal classification tasks, the advantages and disadvantages of different algorithms are quantitatively listed in Table S3 in the ESM.

Subsequently, a confusion matrix was generated to compare the classification results with the actual measured values, providing a detailed visualization of the model performance across different serving modes (Figure 7e). The model exhibits high classification and recognition accuracy across the 10 different serving modes. Compared with the initial SVM model, the optimized LSTM-SVM composite model significantly improved the classification and recognition accuracy. Table S4 in the ESM compares representative triboelectric intelligent sensing systems for various ball sports. Most previously reported TENG sensors only extract electrical signals produced by simple vertical impact or human limb movement, ignoring the tangential shear friction induced by ball spin. The proposed triboelectric sensor overcomes this limitation by capturing coupled vertical and tangential motion signals, thereby achieving multi-type spin classification accuracy of 99.8%. This highlights the innovative value of this study in the field of intelligent table tennis sensing.

3. Conclusion

In summary, an ML-assisted self-powered intelligent motion-feedback sensor based on a thin and durable MXBC film is proposed. MXene nanosheets are uniformly dispersed in the three-dimensional BC network to form a well-intercalated structure, thereby endowing the resulting MXBC film with excellent mechanical properties and good conductivity. Furthermore, the flexible MXBC film possesses other merits, such as wear resistance, processability, light weight, and thin thickness. Benefiting from the unique MXBC nanostructure, an MXBC-based TENG installed onto a paddle surface functions as a self-powered intelligent feedback sensor. This self-powered intelligent feedback sensor can perform velocity and rotation direction sensing, which is crucial for table tennis. To improve sensing sensitivity and accuracy, an LSTM-SVM composite model was established, incorporating effective de-noising techniques. Ultimately, the proposed self-powered intelligent feedback sensor effectively identifies the rotation direction and velocity of a table tennis ball with an accuracy of 99.8%, representing a 48.5% improvement over the conventional SVM method. The findings of this study demonstrate the potential of the proposed sensor for intelligent sports monitoring and big data analytics.

4. Materials and Methods

4.1 Synthesis of $\text{Ti}_3\text{C}_2\text{T}_x$ MXene nanosheets

$\text{Ti}_3\text{C}_2\text{T}_x$ MXene was fabricated from $\text{Ti}_3\text{C}_2\text{T}_x$ MAX (Jilin 11 Technology Co., Ltd) via wet chemical etching. First, 0.5 g of MAX was dissolved in 9-M concentrated hydrochloric acid (HCl, 16 mL) and a lithium fluoride solution (1 g). Under ice bath conditions, the solution mixture was thoroughly stirred for 10 min to slow down the reaction rate. Afterward, the mixed solution was sealed and transferred to a water bath maintained at 40 °C. The mixture was agitated at a speed of 800 rpm for 48 h. The prolonged agitation allowed for the formation of the desired multilayered structure. After the reaction was completed, the resulting solution was washed three times with a 6-M HCl solution to remove any excess lithium ions and fluoride functional groups on the MXene layer surface while preventing oxidation. Subsequently, the solute was washed with deionized water to adjust its pH close to 7. To prevent the solidification of the layered structure, the multilayered MXene mud was placed in a refrigerated environment at temperatures ranging from 0°C to 4°C for 4 h to disrupt the hydrogen bonds between the layers, thereby preventing them from rearranging and solidifying. Finally, the mud was dispersed in deionized water to obtain a solution of specific concentration; after ultrasonication for 30 min, a single-layer MXene sample was obtained.

4.2 Preparation of MXene/BC film

Cellulose nanofibers were purchased from the ScienceK company. To prepare the MXene/BC membrane, a layer-by-layer filtration method was employed to sequentially deposit the two materials. The MXene-to-BC mass ratio was set at 1:1, with 1:2 and 2:1 used as control samples. The total material mass was 60 mg (0.785 m²). Each filtration process was performed in a vacuum three times, with equal material amounts added each iteration. Finally, the resulting composite film was dried on a heating plate at 45 °C for 5 h.

4.3 Characterization

Surface morphologies and microstructures of each film were characterized by scanning electron microscopy (SEM) (Hitachi, SU800, JPN) and an X-ray diffractometer (XRD) (Bruker, D8, GER). The surface potential was measured by Kelvin probe force microscopy (KPFM) (Bruker, Dimension Icon, GER). The motorized force tester (Mark-10, F305, USA) was applied to characterize the mechanical properties. The electrical properties were measured by the four-probe tester (ROOKO, FT-345, CHI) and an electrometer (Tektronix, Keithley 6517B, USA).

Electronic Supplementary Material: Supplementary material (please provide the brief detail of the ESM) is available in the online version of this article at <https://doi.org/10.26599/NR.2026.94909149>.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgements

This work is granted by the National Natural Science Foundation of China (No. 52201043), the Natural Science

Foundation of Fujian (No. 2024J011178, 2025J01999, 2023J01105, 2024J01918), the Resource Chemistry Industry Research Institute Project of Nanping (No. N2024Z003), Fujian Provincial Special Fund Project for Promoting High-Quality Development of Marine and Fishery Industries (No. FJHYF-L-2025-21).

Declaration of competing interest

All the contributing authors report no conflict of interests in this work.

Author contribution statement

Ruilai Liu: Investigation and Funding acquisition. Ruzhi Shang: Conceptualization, Investigation. Xu Cai: Investigation, Formal analysis. Yuhuan Su: Investigation. Longfeng Lv: Visualization.

Hanxiao Shao: Investigation. Haitao Ye: Methodology. Shuang Li: Formal analysis. Haihang Feng: Validation.

Cheng Zhang: Writing-original draft, formal analysis. Jiahao Zhou: Data curation. Mingcen Weng: Formal analysis, Conceptualization. Qiaoqiang Gan: Writing-review & editing, Supervision. Huamin Chen: Writing-review & editing, Supervision, Funding acquisition.

Informed consent

Not applicable.

Ethics statement

Not applicable.

Use of AI statement

None.

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Smart triboelectric motion-feedback sensor for table tennis monitoring

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Supporting information to <https://doi.org/10.26599/NR.2026.94909149>

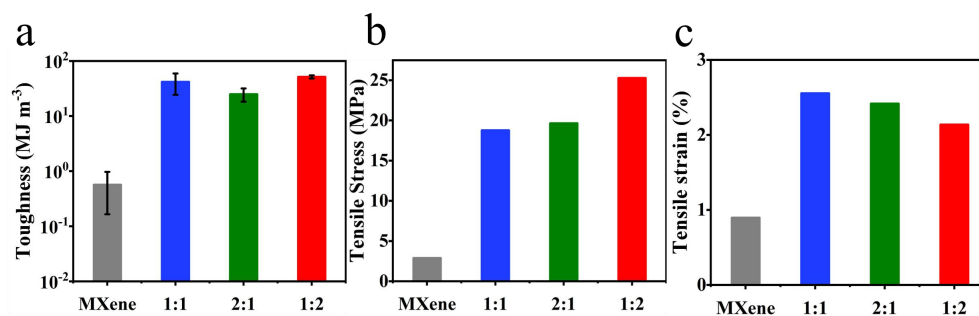


Figure S1 Mechanical performance testing summary. (a) Impact toughness chart, (b) maximum tensile stress chart, and (c) Maximum strain chart for pure MXene, MXene with BC ratio of 1:1, ratio of 2:1, and ratio of 1:2.

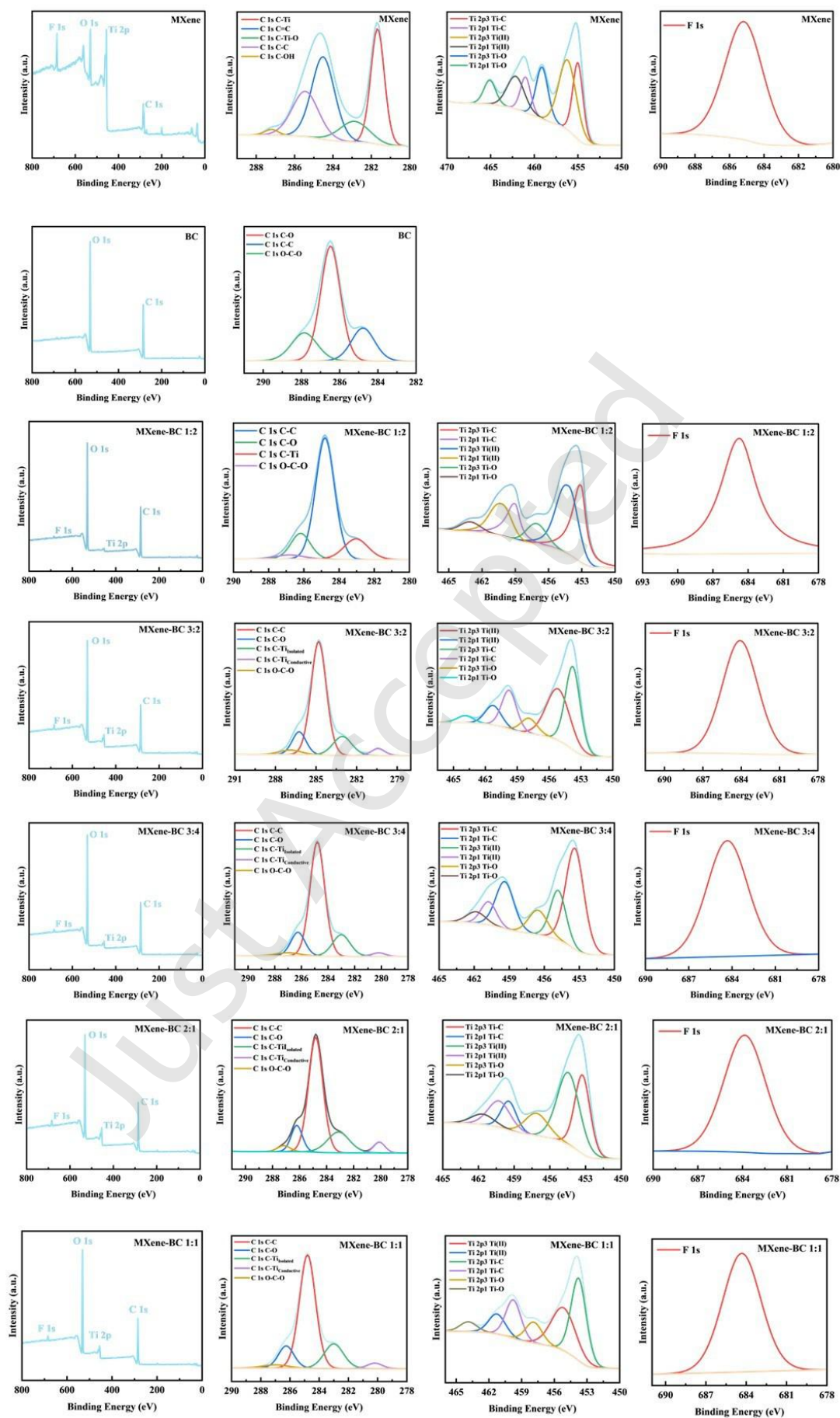


Figure S2 High-resolution XPS characterization of a full series of samples, including pristine BC, pristine MXene, and MXBC composite films with mass ratios of 1:2, 3:4, 1:1, 3:2, and 2:1.

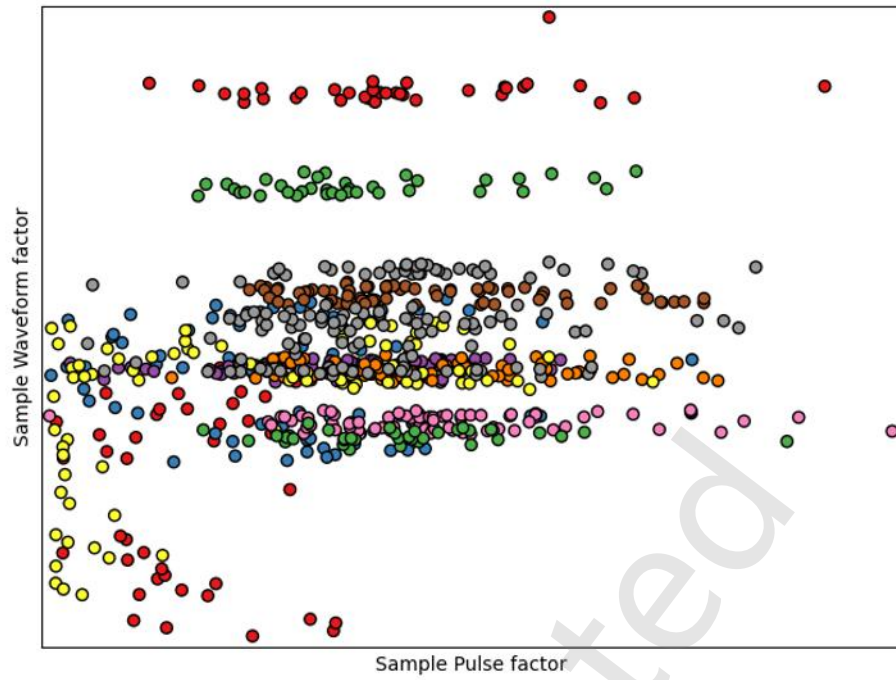


Figure S3 Cluster diagram of pulse factor and waveform factor.

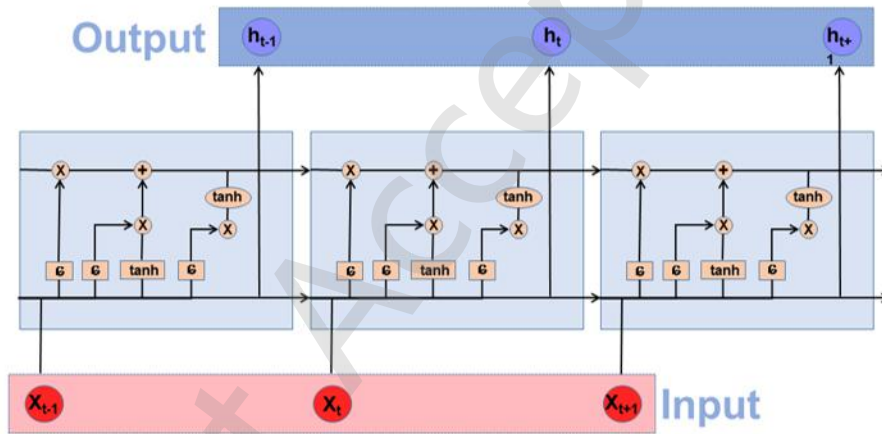


Figure S4 Traditional LSTM model flow chart.

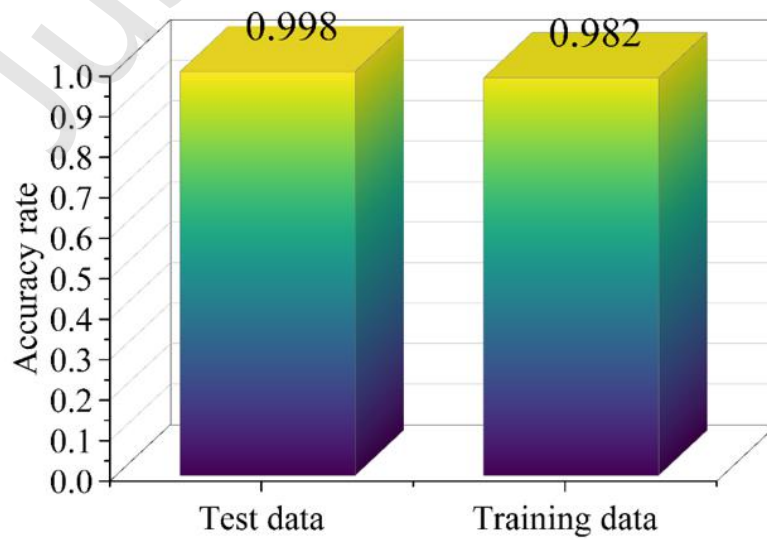


Figure S5 Result accuracy of LSTM-SVM composite model.

Table S1. Clustering evaluation metrics of LSTM-extracted features

Note: Higher Silhouette Coefficient and CH Index indicate better clustering; lower Davies-Bouldin Index indicates better clustering.

Feature Type	Silhouette Coefficient	CH Index (Calinski-Harabasz)	Davies-Bouldin Index
Raw physical features	0.082	126.3	2.847
LSTM features (no denoising)	0.315	892.7	1.234
LSTM features (w/denoising)	0.678	3,256.1	0.412
Improvement (after denoising)	+115.2%	+264.8%	-66.6%

Table S2. Robustness test results under different conditions.

Condition	Test Accuracy (%)	Accuracy Drop (pp)	Relative Degradation (%)
Baseline (standard condition)			
		99.8	
		—	
		—	
Different base plate materials			
Pure wood base	98.7	-1.1	-1.10
Carbon fiber base	97.9	-1.9	-1.90
		Aryl-carbon fiber base	
		98.3	
		-1.5	
		-1.50	
Different base plate materials			
30% RH (dry)	99.5	-0.3	-0.30
70% RH (humid)	97.2	-2.6	-2.60

Table S3. Performance comparison of different classification models

***Improvement is calculated compared with the pure LSTM model.**

Model	Training Accuracy (%)	Test Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Parameters (M)
SVM (baseline)	80.1	67.2	68.5	67.2	66.8	—
1D-CNN	93.7	89.7	90.2	89.7	89.5	0.85
Pure LSTM	96.8	92.3	92.8	92.3	92.1	0.42
LSTM-SVM (Ours)	98.2	99.8	99.8	99.8	99.8	0.38
Improvement*	+1.4	+7.5	+7.0	+7.5	+7.7	—

Table S4. Comparative Table of TENG Sensing Systems for Various Ball Sports

Ref.	Sport Type	Installation Position	Detectable Physical Quantities	Recognition Algorithm	Accuracy	Capable of Ball Spin Identification
[1]	Table tennis	Full table surface array	Impact force, ball velocity, landing position, edge-ball judgment	Amplitude threshold segmentation, linear calibration	Landing recognition: 97.5%; edge-ball discrimination: 99.1%	No
[2]	Golf	Inside golf club head	Swing angle, hitting force, club rotation speed	Linear fitting of voltage characteristic curves	Measurement error of angle & speed < 3.2%	No
[3]	Baseball	Palm of smart sensing glove	Swing strength, ball release velocity, pitching gestures	SVM	Gesture recognition: 96.7%; pitching mode identification: 97.2%	No
[4]	general ball hitting	Rope body, training target panel	Hitting frequency, impact intensity	Voltage peak counting method	Hit counting accuracy: 98.0%	No
[5]	Basketball	Front & rear of sports insole	Gait feature, dribbling impact force	Peak value interval classification	Gait discrimination: 95.3%	No
[6]	Basketball	Elbow/knee strap	Dribble impact, bending angle, running gait	Peak interval classification	Gait discrimination: 95.2%	No
[7]	Multiple ball sports	Sports glove	Grip force, arm swing amplitude	KNN	Hand motion classification: 96.0%	No
[8]	Table tennis	Table edge	Edge ball judgment, impact intensity	Voltage threshold	Edge ball detection: 98.5%	No
[9]	Tennis, badminton	Racket grip sleeve	Swing speed, hitting force	Linear fitting	Stroke intensity identification error <4%	No
[10]	Racket sports (tennis/badminton)	Racket surface	Forehand/backhand stroke, swing track	SVM	Stroke classification: 96.5%	No
[11]	Golf	Golf club head	Swing acceleration, hitting distance	Linear regression	Distance prediction error <3.3%	No
This work	Table tennis	Surface of table tennis racket	Vertical impact force, ball speed, topspin / backspin / left-	Feature extraction based on modified Maxwell displacement current + machine learning	Spin classification accuracy: 99.8%	Yes

Supplementary Note 1: Derivation of modified Maxwell displacement current coupled with tangential shear displacement
Based on the expanded Maxwell's equations for triboelectric nanogenerators proposed by Wang et al. (2020), the electric displacement vector is revised by introducing mechanically triggered surface polarization term P_s independent of external electric field:

$$D = \varepsilon_0 E + P + P_s$$

The displacement current density is defined as $J_D = \partial D / \partial t$. For low-frequency collision between table tennis and single-electrode TENG, the electromagnetic wave term $\varepsilon_0 \partial D / \partial t$ can be neglected, and the output signal is dominated by the time variation of triboelectric surface polarization $\partial P_s / \partial t$. Thus:

$$J_D \approx \partial P_s / \partial t$$

The total macroscopic short-circuit current is the surface integral of displacement current density over the friction contact area:

$$I_D = \iint_S J_D \cdot dS = \frac{d}{dt} \iint_S P_s \cdot dS$$

The integral of polarization flux equals the product of saturated triboelectric charge density σ_s and effective overlapping contact area A . Different from the oversimplified model with constant A in original manuscript, the real collision contains vertical compression displacement $z(t)$ and tangential rotational sliding displacement $x(t)$ simultaneously, so the contact area is a bivariate function $A = A(x(t), z(t))$. The total induced charge on electrode is:

$$Q(t) = \sigma_s \cdot A(x(t), z(t))$$

Taking total time derivative via multivariate chain rule yields the modified displacement current containing tangential shear component:

$$I_D = \frac{dQ}{dt} = \sigma_s \left(\frac{\partial A}{\partial x} \frac{dx}{dt} + \frac{\partial A}{\partial z} \frac{dz}{dt} \right)$$

The first term $\sigma_s (\frac{\partial A}{\partial x} \frac{dx}{dt})$ originates from tangential rotational friction, which modulates current peak magnitude, pulse width and waveform symmetry. The second term only considers vertical compression motion as used in the original simplified model. The full expanded Maxwell equations incorporating shear displacement derivatives are written as:

$$\begin{cases} \nabla \cdot (\varepsilon_0 E + P + P_s) = \rho \\ \nabla \cdot B = 0 \\ \nabla \times E = -\frac{\partial B}{\partial t} \\ \nabla \times H = J + \varepsilon_0 \frac{\partial E}{\partial t} + \frac{\partial P_s}{\partial x} \frac{dx}{dt} + \frac{\partial P_s}{\partial z} \frac{dz}{dt} \end{cases}$$

The theoretical results demonstrate that tangential shear friction increases output peak, broadens pulse width and breaks the symmetry of current waveform.

For planar film-ball contact, linear approximation of contact area is adopted:

$$A(x, z) = A_0 - k_1 |x(t)| - k_2 |z(t)|$$

Substitute partial derivatives $\partial A / \partial x = -k_1$, $\partial A / \partial z = -k_2$ into current formula, the explicit output expression is obtained:

$$I_D = -\sigma_s \left(k_1 \frac{dx}{dt} + k_2 \frac{dz}{dt} \right)$$

The term $k_1 \frac{dx}{dt}$ directly reflects the direction and magnitude of tangential friction caused by ball rotation, which dominates waveform discrepancies of different spin modes.

When topspin ball hits the racket film, the ball surface slides forward relative to the triboelectric layer throughout the whole contact-compression cycle. The tangential displacement $x(t)$ maintains a positive value continuously, leading to persistent positive tangential current superimposed on the vertical impact signal. The front overlapping region of contact area shrinks gradually during collision.

Backspin generates completely opposite tangential sliding direction compared with topspin. The ball surface slides backward against the film during compression, producing sustained negative shear current component. The whole voltage waveform baseline drifts downward.

The above theoretical derivation is established based on the short-circuit displacement current I_D . To unify the theoretical model with the voltage-based experimental classification, the inherent device capacitance C and ultra-high input impedance ($Z > 10^{12}\Omega$) of the test system are further incorporated. Under stable sliding conditions with negligible capacitance variation ($dC/dt \approx 0$), the current–voltage correlation is unified as:

$$I_D = C \frac{dV}{dt}$$

This relationship indicates that the voltage signal can fully reflect the dynamic shear and compression-induced charge transfer behavior. Compared with the noise-sensitive transient current signal, the capacitance-stabilized open-circuit voltage exhibits superior anti-interference capability and signal repeatability. Therefore, voltage waveform features are more reliable for practical sliding velocity and spin state recognition, which well explains the rationality of our experimental feature selection and eliminates the inconsistency between theoretical derivation and experimental characterization.

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