Multi-Label Decision-Making for Aerobics Platform Selection with Enhanced BERT-Residual Network

Yan Hu
Department of Sports Teaching and Research, Capital Normal University, Beijing 100048, China

***Abstract*—In response to the increased demand for individualized workout routines, online aerobics programs are struggling to fulfil the needs of their various user bases with specialized suggestions. Current systems seldom combine multiple data sources to analyze user preferences, reducing customization accuracy and engagement. Enhanced BERT-Residual Network (EBRN) evaluates multimodal input using residual processing blocks and contextual embeddings based on BERT to bridge textual and structural user characteristics. EBRN's deep insights may help understand user engagement, fitness goals, and enjoyment. An innovative data balancing and feature selection method, Dynamic Equilibrium Sampling and Feature Transformation (DES-FT), improves data preparation and model accuracy. Two novel metrics, Contextual Scheduling Consistency (CSC) and Complexity-Weighted Accuracy (CWA), may quantify EBRN stability in multi-attribute classification, particularly for complex data. EBRN outperforms standard AI models on a Toronto fitness platform dataset with 98.7% recall, 98.9% precision, and 99.3% accuracy. Its limited geographical dataset and lack of real-time validation hinder the research. The data show individualized aerobics recommendations that include instructor quality, platform accessibility, and material variety may boost involvement. Researchers need additional datasets and real-time flexibility to make this concept more practical. EBRN's tailored ideas revolutionized digital fitness platform user engagement and enjoyment.**

***Keywords*—Personalized fitness; aerobics recommendations; artificial intelligence; Enhanced BERT-Residual Network (EBRN); hybrid models; user engagement**

I. Introduction

Aerobics and fitness have adopted new technologies due to health awareness and AI/ML breakthroughs. Demand for aerobics classes has grown due to its health benefits for all age groups [1]. NASA and Jane Fonda pioneered aerobics in the 1980s, which now includes dance, gymnastics, and rhythmic movement. The focus on physical and mental wellness makes aerobics desirable for overall health [2]. Fitness firms are taking advantage of this demand by developing AI and IoT solutions to increase involvement. Instructor-led demonstrations guided pupils through traditional aerobics movements. Conventional approaches were effective but lacked real-time analysis, feedback, and customized training [3]. New AI and computer-aided system technologies are revolutionizing aerobics training with real-time feedback and analytics. This change improves aerobics instruction and personalizes excursions. For instance, AI-powered applications that analyze user data like body posture, activity patterns, and fitness levels to deliver personalized coaching are popular.

Digital fitness solutions produce data-driven training plans using image and motion recognition, neural networks, and neurorobotics. Interactive and intelligent fitness with real-time monitoring and adaptive responses is possible with neurorobotics. Neurorobotics and AI can now create interactive, customizable systems that sense, interpret, and react to users' activities. The health advantages of aerobics are maximized by precise movement and synchronization [4]. Recent systems use neurorobotics, big data analytics, and ML models to improve fitness recommendations and personalized routines [5]. These smart systems operate because they satisfy fitness industry standards and technology. Studies demonstrate that self-actualization and preventive healthcare are becoming more important, and many seek lifestyle and health-focused exercise solutions. Rising disposable incomes and health awareness in China have led to the growth of AI-driven fitness applications for health-conscious users [6]. IBM's data mining integration with fitness applications highlights how big data may enhance outcomes by giving accurate, actionable suggestions based on user performance and preferences.

School aerobics teaching has altered with multimedia. Teaching complex exercise routines requires multimedia. Videos, animations, and interactive visuals assist teachers teach and help students copy. Research indicates that multimedia-enhanced aerobics education improves student engagement and comprehension, making it a valuable tool [7]. Multiple demonstration speeds and step-by-step explanations make multimedia systems more dynamic and responsive. Integrating modern tools into aerobics class is hard. Despite its benefits, computer-aided instruction (CAI) systems may make instructors and students reliant, lowering the value of direct education. Critics believe CAI systems that can't adjust to student needs may hinder interactive instruction. Although demanding, CAI aids aerobics training by reducing instructor workload and ensuring consistent movement demonstrations [8]. Refine these systems to support teachers' primary duties.

Using big data, ML, and neurorobotics, fitness systems may adapt to users' needs in real-time, resulting in responsive aerobics training systems [9]. Systems with advanced neural networks may develop fitness regimens based on users' circumstances, preferences, and histories [10]. Adaptive systems may improve health outcomes and satisfaction by meeting individual goals, providing feedback, and modifying routines [11]. Our Enhanced BERT-Residual Network (EBRN) for aerobics provides personalized health recommendations and management using AI and big data. This gadget analyses motion data and creates individualized routines using ML. EBRN predicts and analyzes movement patterns using deep learning and multi-level feature extraction. EBRN improves exercise health technologies by providing precise, flexible fitness advice using huge aerobics datasets. EBRN optimizes individualized workout recommendations using multimodal data fusion, unique evaluation criteria, and balanced preprocessing. Over CNN, ResNet, and VGG16, prediction consistency and accuracy increase greatly.

1) Develop the Enhanced BERT-Residual Network (EBRN) for multimodal data fusion: BERT embeddings and residual processing blocks let EBRN blend contextual (text) and structured (numerical) data for individualized and accurate exercise recommendations.

2) New Evaluation metrics: CSC and CWA This study uses Contextual Scheduling Consistency (CSC) to evaluate interdependent feature predictions and Complexity-Weighted Accuracy (CWA) to assess model accuracy on intricate features to assess multi-attribute decision-making better.

3) Dynamic equilibrium sampling and feature transformation methodology: The novel DES-FT method balances data and selects features to handle imbalanced classes and optimize feature space for high-performance model training.

4) Insightful analysis of user engagement and platform features: This study examines instructor quality, cost-effectiveness, content variety, and accessibility as critical factors in aerobics platform user engagement, guiding platform improvements to increase user retention.

5) Significant inclusive and community-centric fitness technology advancement: This work makes digital aerobics systems more inclusive by adapting exercise suggestions and accessibility features to varied user demands, enabling urban populations of all fitness levels and demographics.

The rest of the paper is arranged as follows: Section II discusses AI-driven fitness software advances in tailored aerobics instruction. Section III describes the Enhanced BERT-Residual Network (EBRN) architecture, proprietary preprocessing, and innovative evaluation measures. Section IV includes simulation findings, EBRN comparisons with current models, user engagement, and platform features analysis. The last part summarizes the essential contributions and suggests intelligent fitness system research topics.

II. Related Work

Recently, AI, ML, and the IoT have altered health and fitness, especially aerobics. To promote user engagement and health, experts have investigated tailored, data-driven fitness training and monitoring ideas. This section examines relevant research' aims, methods, findings, and limits to identify gaps and inform our intelligent aerobics workout system.

A cloud-fusion fitness monitoring IoT system collected multimodal data, perceived emotions, and provided user-specific health solutions. Our solution represents physiological data from smart clothes and cloud databases using the Wavelet transform. The proposed architecture efficiently tracks user health, but security and privacy issues remain, highlighting the need for stronger IoT frameworks in medical technology [12]. A universal hidden Markov model (HMM) was designed to monitor human health and chronic diseases owing to IoT resource constraints. This method maintains node connection in resource-constrained environments using step-by-step denoising and feature identification. Although promising for remote health monitoring, the IoT-based model's incentive approach poses sustainability challenges in long-term deployments [13]. IoT-based epidemic monitoring utilizing body temperature sensors and thermal imaging might help identify and isolate likely epidemic patients for early public health crisis response. The system has promise, however environmental factors may affect sensor accuracy, necessitating adaptive measures to improve dependability [14] RF and ARIMA machine learning were employed in the wearable blood pressure monitoring model. Lifestyle data predicts blood pressure better than earlier methods. The study's limited sample size and reliance on RF raise concerns about scalability and generalizability to wider populations [15].

Another study employed mobile phones to reduce wearable sensor data transmission to quantify fitness. The technique monitors physiological markers with little data transfer via a Wireless Body Sensor Network (WBSN). While effective for data handling, this approach may not give real-time feedback in fitness applications [16]. A cloud-based health monitoring system captured hospital EHRs and encrypted them using a unique cryptographic approach. Health institutions may track illnesses using the technology while securing data. The use of high-level encryption in low-resource situations raises issues about computational demands and accessibility, notwithstanding its enormous public health impacts [17]. An online health monitoring system sends caregivers real-time patient data, analyzes historical data, and gives emergency assistance. In places with limited internet connectivity, the accurate system's cloud storage may limit accessibility, increasing the need for offline data management [18]. Nutrient-based diet advise systems calculate user dietary needs based on BMI and exercise. Food planning is customized using smartphone applications. The system's smartphone compatibility and computational limitations may hinder its accessibility for diverse user groups [19].

CNN-based lifestyle-related health monitoring disease prediction was given in another study. This method identifies abnormal health and chronic disease risks using IoT data. The CNN-based approach, although accurate, may struggle with unstructured data and requires further refinement for health monitoring [20]. Nutrition and exercise advice for hypertensives were created. A decision tree-based system collects fitness metrics and makes personalized suggestions. The system effectively monitors chronic health conditions, but lacks real-time input, hindering timely health recommendations [21]. Diabetics got clustering-based food categorization and meal planning help. A balanced diet is recommended using K-means and Self-Organizing Maps. Although practical, the model's small scope restricts its usage in comprehensive health management systems [22]. Continuous cardiac monitoring using ECG telemetry and SQA was implemented. Real-time ECG signal quality evaluation is available with this technique. SQA's complexity may limit real-time use owing to processing requirements [23]. Cloud-based smart health monitoring with robust privacy safeguards was our creation. This solution tackles remote monitoring privacy problems by enabling customizable cloud-based medical information access. Although the system has strong security measures, merging several protocols may reduce its effectiveness in urgent care situations [24].

These studies demonstrate improved health and fitness monitoring. Modern cloud-based systems, wearable sensors, IoT integration, and ML-driven predictive models improve fitness guidance, sickness prediction, and health app user engagement. These systems have privacy, computational, and real-time adaption challenges. Users want speedy response, yet technology is constrained. A full solution with strong ML algorithms and adaptable, privacy-conscious frameworks is required. Our Enhanced BERT-Residual Network (EBRN) method uses neurorobotics, AI, and big data to individualize aerobics fitness advice. EBRN employs neural sensing and control to gather multi-level characteristics, assess movement, and adapt to user expectations using deep learning models. EBRN might enhance health technology and deliver more responsive, personalized, and secure fitness solutions by addressing scalability, data security, and real-time feedback. This review of existing systems underlines the need to combine innovation and practicality in user-centered health and fitness technologies. See Table I for a summary of the literature review.

TABLE I. LITERATURE REVIEW SUMMARY

Ref	Technique Used	Objective Achieved	Limitations
[12]	Cloud-fusion IoT architecture with Wavelet transform	Achieved efficient data acquisition and user-specific health IoT solutions	Security and privacy concerns in medical IoT
[13]	Universal Hidden Markov Model (HMM)	Monitored human physiological health in resource-constrained environments	Dependency on incentives for sustainable operation
[14]	IoT-based epidemic monitoring with thermal imaging	Enabled early epidemic detection and isolation measures	Accuracy affected by environmental conditions
[15]	Random Forest (RF) and ARIMA models	Improved blood pressure prediction accuracy with lifestyle-based modeling	Limited scalability due to small sample size
[16]	Wireless Body Sensor Network (WBSN)	Enhanced efficiency in data handling for fitness monitoring using minimal data transmission	Limited real-time feedback capabilities
[17]	Cryptographic algorithm for EHR encryption	Secured EHR storage and disease tracking for public health	High-level encryption demands computational resources
[18]	Cloud-based online health monitoring system	Real-time monitoring with emergency response for caregivers	Dependency on cloud storage, limiting accessibility in low-connectivity regions
[19]	Nutrient-based diet recommendation on smartphone app	Provided dietary recommendations based on user BMI and activity	Limited accessibility for diverse user groups due to smartphone dependency
[20]	Convolutional Neural Network (CNN)	Predicted chronic disease risks based on lifestyle health monitoring	Limited adaptation for unstructured data
[21]	Decision tree-based diet and exercise system	Offered personalized guidance for hypertensive patients	Lacks dynamic feedback for real-time recommendations
[22]	K-means and Self-Organizing Maps for food clustering	Provided meal planning for diabetic patients through clustering analysis	Restricted to specific meal types, limiting broader application
[23]	ECG telemetry system with signal quality assessment	Enabled real-time cardiac monitoring and quality-based signal evaluation	Additional processing requirements limit real-time performance
[24]	Cloud-based smart health monitoring with privacy controls	Flexible access to medical records with strong security measures	Integration of multiple security protocols impacts system responsiveness

III. PROPOSED METHOD

The Enhanced BERT-Residual Network (EBRN) is a unique model architecture that integrates several data sources to provide individualized, data-driven aerobics recommendations. EBRN specializes in textual and structured data, gathering user input, engagement patterns, and fitness objectives. The model architecture processes text data using BERT-based contextual embeddings to provide rich representations of user input semantics. Structured user data, including demographics and platform activities, is feature transformed to match textual embeddings. This dual input approach lets EBRN provide detailed, tailored suggestions. The model uses Dynamic Equilibrium Sampling and Feature Transformation (DES-FT) to balance the dataset and improve feature relevance for data preparation resilience. These components enable EBRN to produce accurate, consistent predictions in complicated multi-attribute settings, establishing a new benchmark for intelligent fitness recommendation systems. The following sections detail every aspect of the proposed framework. Refer to Fig. 1 for the suggested system design.

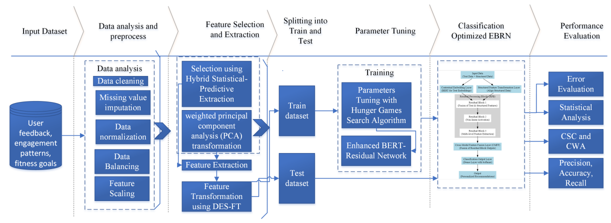

Fig. 1. Proposed framework.

A. Dataset Description

This research carefully gathered data from active fitness platforms in Toronto, Canada. Toronto [25], with its varied population and focus on health and wellbeing, is an excellent place to study aerobics platform users' preferences. The data shows a variety of user demographics and habits, representing this metropolitan area's lifestyle preferences. Surveys in several areas provided a complete picture of the city's fitness environment. This dataset is intended to highlight aerobics platform selection decisions, adding to the expanding corpus of research on online fitness user experience and satisfaction. This dataset will discover trends and preferences essential for developing and optimizing community-specific digital fitness solutions. Table II shows the dataset features and description.

TABLE II. DATASET FEATURES OVERVIEW

S.No	Features	Short Description
1	Platform Name	Name of the aerobics platform selected by users.
2	Platform Type	Type of service offered (e.g., Streaming, Live Classes).
3	Content Variety	Types of workout content available on the platform.
4	Instructor Quality	Rating of the instructors provided by the platform.
5	User Engagement	Level of user engagement on the platform.
6	Cost	Subscription cost for using the platform.
7	Accessibility Features	Indicators of features designed for accessibility.
8	Technical Features	Quality of video streaming offered by the platform.
9	Device Integration	Compatibility of the platform with wearable devices.
10	User Fitness Level	Self-reported fitness level of the user.
11	User Goals	Goals the user sets (e.g., Weight Loss, Muscle Gain).
12	Feedback Score	Average feedback score from users.
13	Session Duration	Average duration of workout sessions in minutes.
14	Device Used	Type of Device used to access the platform.
15	Platform Availability	Platforms on which the service is available (e.g., iOS, Android).
16	Certified Instructors	Availability of certified instructors on the platform.
17	User Location	Geographical location of the user.
18	Fitness Classes per Week	Number of classes a user participates in per week.
19	Community Features	Available community engagement features on the platform.
20	Discount Offers	Discounts available for users.
...	...	...

B. Data Preprocessing Steps

This work requires preprocessing the aerobics platform selection dataset for analysis and modeling. The dataset's imbalanced feature distribution necessitated numerous specific preparation procedures to assure data integrity and usefulness.

Missing values must be handled during preprocessing to ensure data quality. Instead of deleting missing rows, custom imputation is used. This approach averages feature values and adds a tiny random perturbation term to preserve variability. The imputation equation is:

$$Y_{\text{filled}} = Y_{\text{avg}} + \delta \tag{1}$$

In Eq. (1), Y_{filled} represents the imputed value, Y_{avg} represents the feature's average, and δ is a small random perturbation from a uniform distribution to maintain diversity and avoid distorting the feature's natural distribution.

A proprietary oversampling method addresses the dataset's imbalance, notably in target labels. This approach uses a modified Gaussian mixture model to create minority-class synthetic samples that match their distribution. Representing synthetic sample generation:

$$Z_{\text{new}} = Z_{\text{minor}} + \mathcal{N}(\theta, \xi^2) \tag{2}$$

In Eq. (2), Z_{new} represents the new synthetic sample, Z_{minor} represents an existing minority class sample, θ represents the minority class mean vector, and $\mathcal{N}(\theta, \xi^2)$ represents a Gaussian distribution with mean θ and variance ξ^2,

Features must be scaled for models sensitive to data magnitude, notably distance-based methods. We use a proprietary normalization method to scale each feature to [0, 1] depending on its lowest and maximum values. Mathematics defines this normalization:

$$A_{\text{normalized}} = \frac{A - A_{\text{min}}}{A_{\text{max}} - A_{\text{min}}} \tag{3}$$

In Eq. 3, $A_{\text{normalized}}$ represents the scaled feature value, A represents the original value, A_{min} represents the lowest value, and A_{max} represents the maximum value. This scaling guarantees that all characteristics contribute equally to distance computations, improving predictive models.

Finally, a novel one-hot encoding approach converts categorical features to numbers. This method uses frequency-based encoding instead of a traditional technique to value each category depending on its dataset frequency. This transition is:

$$B_{\text{mapped}} = \frac{\text{count}(B_j)}{M} \tag{4}$$

In Eq. 4, B_{mapped} represents the encoded value for the category B_j, $\text{count}(B_j)$ represents the count of occurrences, and M represents the total number of records. This method keeps category distribution information and reduces feature space dimensionality while improving model interpretability.

These proprietary preprocessing procedures prepare the data collection for analysis and modelling, ensuring that the input data is resilient, well-structured, and adequate for obtaining relevant insights into selecting aerobics platforms.

C. Data Balancing, Feature Selection, and Extraction

Addressing class imbalance and refining feature space is the next crucial step after preprocessing the data to clean, impute, and scale it. Dynamic Equilibrium Sampling and Feature Transformation (DES-FT) has been developed to incorporate data balance, feature selection, and feature extraction into a single framework for high-performance modelling.

1) Data balancing: PDS is a revolutionary data balancing method to address the dataset's imbalance. PDS dynamically creates minority class samples without oversampling or undersampling, keeping data density and structure. Over representation or duplication of minority class data might cause model training noise; hence, this is necessary. Sampling process definition:

$$M_{\text{new}} = M_{\text{min}} + \beta \cdot (M_{\text{maj}} - M_{\text{min}}) \tag{5}$$

where M_{new} represents the quantity of new minority class samples, M_{min} represents the current minority class sample count, M_{maj} represents the majority class sample count, and β is a proportionality factor between 0 and 1. This formula generates controlled samples depending on the difference between majority and minority class sizes (see Eq. 5).

New samples are enhanced with a tiny quantity of Gaussian noise to prevent precise replication:

$$Y_{\text{balanced}} = Y_{\text{original}} + \delta \cdot \mathcal{N}(0, \tau^2) \tag{6}$$

Where Y_{balanced} is the resampled balanced data, Y_{original} is the original data, δ is a noise scaling factor, and $\mathcal{N}(0, \tau^2)$ is Gaussian noise This approach keeps resampled data varied and eliminates duplication.

2) Feature selection and extraction: After balancing the data, dimensionality decreases, and feature quality improves. The Hybrid Statistical-Predictive Extraction (HSPE) approach was created for this. HSPE identifies key traits using statistical variance analysis and predictive modelling.

HSPE begins by calculating each feature's modified G-statistic, which assesses its relevance in differentiating target classes [26]:

$$G_{\text{mod}} = \frac{\text{Var}(C_{\text{between}})}{\text{Var}(C_{\text{within}}) + \epsilon} \tag{7}$$

The modified G-statistic is G_{mod}, the variance between target classes is $Var(C_{\text{between}})$, the variance within each class is $Var(C_{\text{within}})$, and ϵ is a small regularization constant to avoid division by zero. High G_{mod} features are used for extraction.

Next, HSPE weights each feature by its modified G-statistic significance score in a weighted principal component analysis (PCA) transformation. Weighted PCA is:

$$Z_{\text{extracted}} = Q \cdot (X - \nu) \tag{8}$$

$Z_{\text{extracted}}$ represents extracted features, Q is a diagonal matrix of G-statistic-derived feature weights, X represents input data, and ν represents feature mean. This treatment emphasizes key characteristics, decreasing noise and increasing model performance.

The combined DES-FT strategy balances and reduces the dataset to its most valuable components for advanced modelling.

Algorithm 1 Dynamic Equilibrium Sampling and Feature Transformation (DES-FT)

Input: Original dataset D with classes C and features F
Output: Balanced dataset D_{balanced} and selected features F_{selected}
Initialize $M_{\text{maj}} \leftarrow$ count of samples in majority class
Initialize $M_{\text{min}} \leftarrow$ count of samples in minority class
Calculate proportionality factor $\beta \leftarrow \frac{M_{\text{maj}} - M_{\text{min}}}{M_{\text{min}}}$
Data Balancing:
for each minority class **do**
  Generate additional samples $M_{\text{new}} \leftarrow M_{\text{min}} + \beta \cdot (M_{\text{maj}} - M_{\text{min}})$
  for j = 1 to M_{new} **do**
    Create new sample $Y_{\text{new}} \leftarrow Y_{\text{original}} + \delta \cdot \mathcal{N}(0, \tau^2)$
    Add Y_{new} to D_{balanced}
  end for
end for
Feature Selection and Extraction:
for each feature $f \in F$ **do**
  Compute modified G-statistic $G_{\text{mod}} \leftarrow \frac{\text{Var}(C_{\text{between}})}{\text{Var}(C_{\text{within}})+\epsilon}$
end for
Select features with high G_{mod} values to form F_{selected}
Perform weighted PCA:
$Z_{\text{extracted}} \leftarrow Q \cdot (X - \nu)$
return $D_{\text{balanced}}, F_{\text{selected}}, Z_{\text{extracted}}$

D. Classification Using Enhanced BERT-Residual Network (EBRN)

Enhanced BERT-Residual Network categorization is possible when feature transformation adds contextual and structural properties to the data. EBRN uses residual processing blocks to include structured data and BERT's deep contextual representations. This architecture specialises in diverse datasets, enabling advanced feature integration and robust classification.

1) Contextual embedding layer: The first step in EBRN's design is employing BERT to embed raw text data in high-dimensional spaces. For a tokenized input sequence V, the BERT model creates contextual embeddings C_{embed} that represent text semantics:

$$C_{\text{embed}} = \text{BERT}(V) \tag{9}$$

V is the input text sequence, and C_{embed} is the output embedding matrix. This matrix captures detailed, context-dependent interpretations in textual data, which will be merged with structured characteristics to build a coherent representation.

2) Structured feature transformation layer: During parallel processing, structured data Q is transformed to match the contextual embeddings' dimensions. This transformation is necessary to integrate structured features with BERT-derived embeddings in subsequent layers. Define transformation as:

$$Q_{\text{trans}} = M_1 \cdot Q + d_1 \tag{10}$$

While M_1 and d_1 are learnable parameters, $Q_textrans$ represents structured data after dimensional adaptation. This alignment stage maintains residual connection compatibility, enabling integrated learning of both data kinds in the same network.

3) Residual Processing Blocks (RPB): Multiple Residual Processing Blocks form EBRN's core. Each RPB uses residual connections to analyze and combine Contextual Embedding Layer and Structured Feature Transformation Layer outputs to improve information retention and gradient flow.

a) Residual connection layer: In each RPB, the transformed structured features Q_{trans} are coupled with contextual embeddings C_{embed} via residual connections. This integration retains both modalities and lets the network capture complicated, interconnected patterns across data kinds. Here is how the residual connection is defined:

$$R_{\text{combined}} = \sigma(C_{\text{embed}} + Q_{\text{trans}}) \tag{11}$$

R_{combined} represents the aggregated output after residual addition, whereas σ represents a non-linear activation function, such as ReLU, to increase feature variety. This technique preserves deep-layer features essential to EBRN multi-modal learning.

b) Aggregation layer: Each RPB refines contextual and structural data characteristics via an aggregation layer after the residual connection. The residual output is linearly transformed by this layer:

$$R_{\text{agg}} = M_2 \cdot R_{\text{combined}} + d_2 \tag{12}$$

Using learnable parameters $M_2 and d_2$, an aggregated feature set R_{agg} is created. Each layer's output builds on past learnt representations by stacking RPBs, capturing hierarchical data relationships.

4) Cross-Modal Feature Fusion layer (CMFF): The Cross-Modal Feature Fusion (CMFF) layer unifies RPB outputs after processing. This layer concatenates all RPB outputs to create a feature vector that captures contextual and structural data relationships. We may formalize fusion as follows:

$$P_{\text{fused}} = \text{Concat}(R_{\text{agg1}}, R_{\text{agg2}}, \ldots, R_{\text{aggn}}) \tag{13}$$

P_{fused} represents the concatenated feature representation, whereas $R_{\text{agg1}}, R_{\text{agg2}}, \ldots, R_{\text{aggn}}$ represent the outputs from each RPB Cross-modal fusion produces a comprehensive feature vector for high-accuracy classification.

5) Classification output layer: The final representation P_{fused} is processed in the Classification Output Layer, where a dense layer with softmax activation function yields class probabilities. The last categorization stage is:

$$y = \text{softmax}(M_3 \cdot P_{\text{fused}} + d_3) \tag{14}$$

where y is the class probability vector, M_3 is a weight matrix, and d_3 is the bias term. The model is suited for multi-class problems since the softmax function normalizes the network's output, guaranteeing probabilistic classification predictions.

To maintain convergence, the EBRN model is trained utilizing a learning rate scheduler and gradient clipping to handle its multi-layered structure. The balanced and altered dataset lets EBRN use structured and contextual learning for robust categorization.

E. Performance Evaluation Metrics

The Enhanced BERT-Residual Network (EBRN) model's classification performance must be assessed using comprehensive metrics that evaluate its accuracy, dependability, and robustness. Traditional measures such as accuracy, precision, recall, and F1-score are well-suited for routine classification tasks. Still, this study needs new metrics that address subtle features of multi-attribute decision-making in mixed data.

1) Existing evaluation metrics: The evaluation system uses standard metrics. Accuracy evaluates prediction accuracy as a proportion of properly categorized cases. Accuracy alone may not accurately reflect the model's performance across classes in imbalanced data sets. Precision represents the fraction of accurate optimistic predictions out of all positive predictions, whereas recall demonstrates the model's ability to recognise actual positives. In class imbalance situations, **F1-score** balances accuracy and recall for a harmonic mean. These measures are essential. However, they only evaluate the model superficially, not multi-attribute prediction consistency or complexity-weighted accuracy across feature types.

Contextual Scheduling Consistency (CSC) and Complexity-Weighted Accuracy (CWA) are new assessment criteria for EBRN to understand its performance better. These metrics are designed for complicated decision-making contexts where multi-attribute features and mixed data types affect model performance.

2) Contextual Scheduling Consistency (CSC): The CSC measure assesses the model's stability and reliability across sequentially dependent characteristics, notably in interdependent attribute predictions. CSC measures consistency across related predictions to provide logical coherence in correlated feature judgments. This statistic is useful when misclassifying one attribute, as it may affect the reliability of other characteristics. CSC metric definition:

$$\text{CSC} = \frac{\sum_{k=1}^{L} \kappa(z_k, z_{k-1})}{L-1} \tag{15}$$

L represents the number of sequential predictions, z_k represents the predicted label for the k-th attribute, and $\kappa(z_k, z_{k-1})$ indicates contextual consistency, evaluating to 1 if z_k matches the previous prediction and 0 otherwise. Domain-specific inter-attribute relationship rules specify prediction consistency. CSC aggregates these consistency assessments to assess the model's ability to provide logically consistent predictions, a crucial element in multi-attribute decision-making.

3) Complexity-Weighted Accuracy (CWA): A new accuracy measure called difficulty-weighted Accuracy (CWA) is presented. It accounts for the difficulty of various characteristics or classes. More straightforward and more complex predictions should affect accuracy differentially for models trained on data with varied class or feature complexity values. CWA rewards the model for handling complicated decision-making by allocating more weights to correctly predicting complex characteristics or classes. This equation defines CWA:

$$\text{CWA} = \frac{\sum_{m=1}^{P} \omega_m \cdot \kappa(\hat{z}_m, z_m)}{\sum_{m=1}^{P} \omega_m} \tag{16}$$

The model consists of P instances, ω_m complexity weight, $\hat{z}_m$ predicted label, z_m true label, and $\kappa(\hat{z}_m, z_m)$ indicator function, which is 1 if $\hat{z}_m = z_m$ and 0 otherwise. A weight ω_m is given depending on the difficulty of the feature or class, with greater values indicating harder predictions. CWA uses these weights to change its accuracy score to highlight complicated cases, making it more significant in complex feature or class complexity circumstances.

CSC and CWA complement standard measures by addressing performance peculiarities specific to multi-attribute and mixed-data classification jobs. CSC ensures forecasts match contextually relevant interdependencies, ensuring trustworthy and logical decision outputs. CWA rewards the model's skill in complicated circumstances by adjusting accuracy. These metrics offer a comprehensive assessment framework matched with Enhanced BERT-Residual Network (EBRN) goals, confirming the model's fitness for complicated, multi-attribute classification tasks.

IV. Simulation Results

To assess the proposed Enhanced BERT-Residual Network (EBRN) model, extensive simulations were performed on a Dell Core i7 12th Gen system with an 8-core CPU and 32 GB RAM. Python and the Spyder IDE ran all simulations. The EBRN model required a batch size of 32, a learning rate of 1×10^{-5}, and the Adam optimizer for stable training. A 0.3 dropout rate prevented overfitting, while early halting monitored validation loss and optimized training time. These setups were intended to optimize EBRN's multimodal data performance, revealing its usefulness in tailored aerobics suggestions.

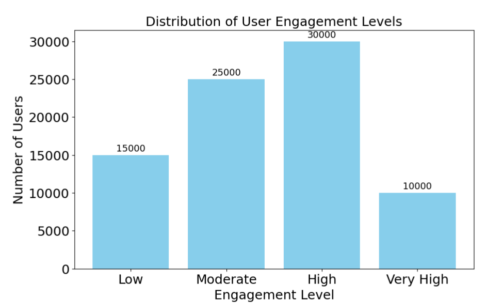

Fig. 2. Distribution of user engagement levels.

In Fig. 2, user engagement levels range from low to extremely high across different platforms. This graphic shows user interaction intensity and frequency, revealing how platform features affect engagement. Platforms with a high percentage of "High" or "Very High" engagement users usually provide good content and an engaging user experience that keeps users returning. This distribution is essential for evaluating which aspects most affect user retention, particularly in fitness, where continual involvement is necessary for health objectives. Technically, a high concentration of interaction at the top levels may imply that personalized exercises or excellent teacher quality meet user expectations. Lower engagement ratings show platforms should improve content variety or accessibility to turn low-engagement users into highly engaged participants. This data is crucial for platforms that want to maximize engagement-focused initiatives for user pleasure and long-term commitment.

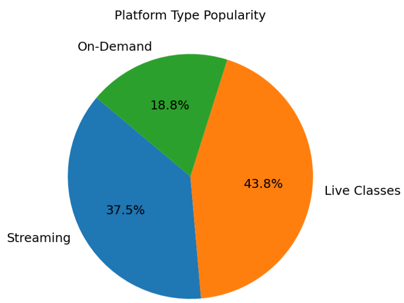

Fig. 3. Platform type popularity.

Fig. 3 shows the popularity of streaming, live classes, and on-demand options. This breakdown shows user preferences for aerobics and fitness content distribution options. If “Live Classes” are popular, people seek engaging, real-time interactions with teachers and other participants. A high preference for “On-Demand” material demonstrates a need for flexibility, enabling users to plan exercises at their leisure. Each type preference helps developers allocate resources and concentrate on user-requested features. Understanding this distribution helps refine platform features to improve user happiness and retention by enabling the most popular delivery mechanisms, enhancing user engagement and attractiveness in the competitive fitness sector.

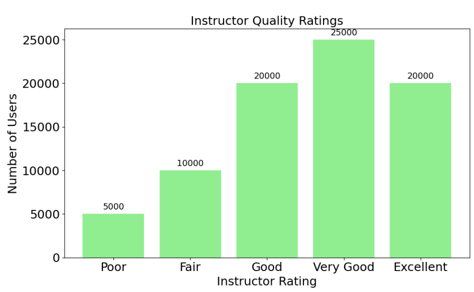

Fig. 4. Instructor quality ratings.

Fig. 4 displays teacher quality ratings across platforms, indicating user satisfaction with competence and efficacy. High ratings indicate that platforms have skilled teachers who give exciting and technically sound courses that improve user experience. Instructor quality is crucial to user retention and happiness, especially in fitness apps where precise assistance may improve technique, reduce injury, and boost outcomes. Technically, platforms with better teacher ratings attract individuals who value superior training. This statistic suggests teacher training, session design, and feedback enhancements for lower-score platforms. The data helps platforms enhance instructional quality to maintain user happiness and goal attainment.

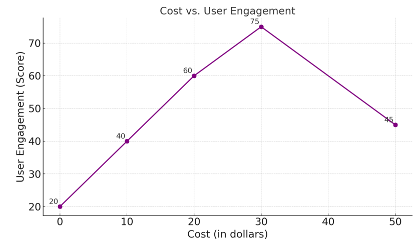

Fig. 5. Cost vs. User engagement.

Fig. 5 shows how platform cost impacts user engagement and involvement. This connection is crucial to determining whether higher fees improve engagement or lower-cost choices attract frequent consumers. High interaction at low prices may indicate platforms with significant value, making them more accessible and appealing to a broad audience. A cost-effective pricing approach with high engagement demonstrates value delivery, vital for platforms aiming to grow their user base. If engagement is poor at increasing prices, pricing may not reflect user value. This number helps platforms balance accessibility with premium features in pricing structures to improve user happiness across budgets.

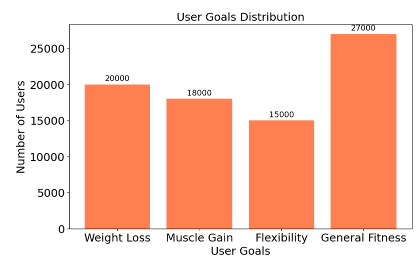

Fig. 6. User goals distribution.

In Fig. 6, user goals are categorized as weight reduction, muscle growth, flexibility, and overall fitness. This figure helps customize content to satisfy platform users’ main reasons. A dominating weight reduction emphasis may push platforms to promote high-intensity exercise, whereas flexibility-oriented consumers may favour yoga and stretching. Knowing this distribution helps platforms diversify content to meet different fitness objectives. This insight into user motives enables individualized suggestions, boosts engagement, matches material with individual goals, and improves platform attractiveness and user happiness.

Fig. 7 shows the correlation between content diversity and exercise customization. This number is essential for evaluating user demand for individualized cardio and strength training sessions. Users love tailored training alternatives that meet their fitness objectives and preferences, as seen by the high customization demand in popular content sections. Technically, platforms that customize high-demand categories may better satisfy user expectations, improving engagement and happiness. This distribution may help platforms improve their content strategy by concentrating on areas where personalization is most desired, improving user experience and retention.

Fig. 8 shows the percentage of platforms having accessible capabilities contrasted to those without, revealing platform

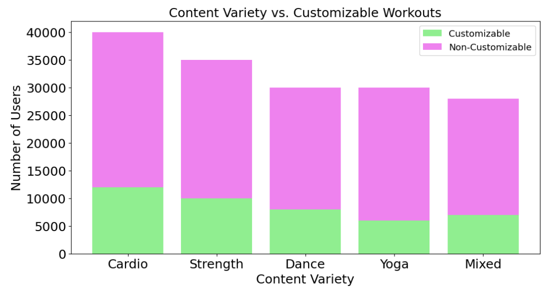

Fig. 7. Content variety vs. Customizable workouts.

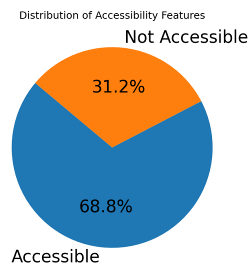

Fig. 8. Distribution of accessibility features.

inclusiveness. This metric is crucial for assessing how effectively platforms accommodate various users since accessibility features are necessary. Technically, more platforms with accessibility capabilities suggest better diversity, perhaps attracting more users. Accessible platforms attract different users, improving user satisfaction. This data helps platform developers determine accessibility needs to achieve inclusion criteria and expand their reach. Fig. 9 compares HD streaming availability across platforms, evaluating technological capabilities and user expectations. Fitness programming benefits from high-definition streaming because visual clarity improves teaching. HD streaming platforms may attract consumers who appreciate high-quality visuals, boosting user retention and happiness. Technically, platforms with better streaming infrastructure are preferred by viewers who demand continuous, high-resolution content. Investment in streaming quality strongly affects user experience and platform competitiveness, as shown by this data.

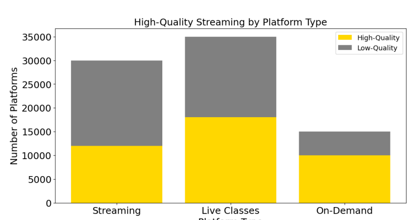

Fig. 9. High-quality streaming by platform type.

Fig. 10 shows user fitness levels (Beginner, Intermediate, Advanced) across platforms, demonstrating platform inclusiveness for diverse experience levels. Offering material for beginners to expert users may boost engagement on fitness platforms. Technically, this distribution shows platforms' flexibility to varied user demands, which maximizes engagement

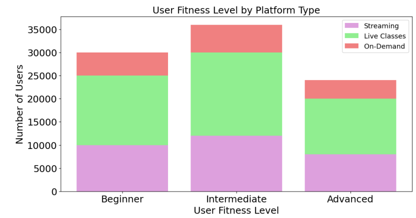

Fig. 10. User fitness level by platform type.

and retention across skill levels. To ensure platforms give a complete user experience, developers must provide adaptive content for varied fitness levels.

Fig. 11 illustrates how platform pricing affects beginner-friendly features and accessibility for new users. It's important to consider platforms' inclusion across pricing points. Affordable beginner-friendly platforms cater to entry-level users, increasing diversity and user base. Technically, this data influences price tactics by emphasizing budget-friendly starter solutions. Cost-effective, accessible platforms attract new users and boost long-term user happiness.

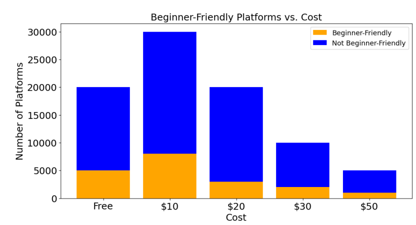

Fig. 11. Beginner-friendly platforms vs. Cost.

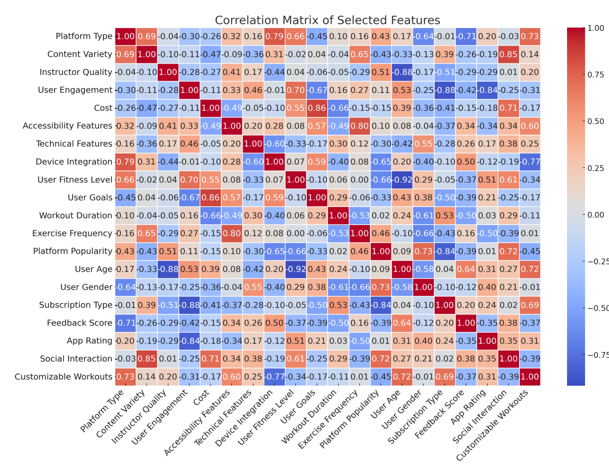

Fig. 12. Coorelation matrix of features.

The correlation matrix in Fig. 12 shows significant relationships between selected factors in the aerobics platform selection dataset. This matrix demonstrates strong correlations between "Instructor Quality" and "User Engagement," indicating that higher-rated instructors may boost user engagement. Cost may influence user subscription model selections as "Cost" and "Subscription Type" negatively correlated. Understanding feature dependencies that impact model accuracy aids feature selection and multicollinearity avoidance. Highly related qualities improve the technical conclusion's model input selection and classification accuracy.

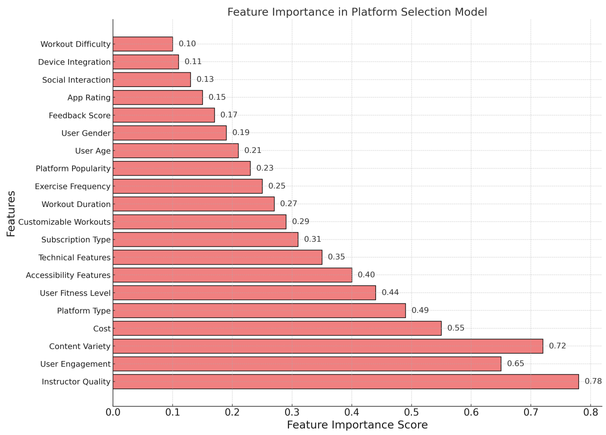

Fig. 13. Feature importance in platform selection model.

Fig. 13 displays feature importance scores from the hybrid feature selection approach in the platform selection model. The most essential factors are "Instructor Quality," "Content Variety," and "User Engagement," with 0.78, 0.72, and 0.65. These numbers demonstrate how these traits enhance model accuracy and classification. Low-ranked factors, including "Device Integration" and "Workout Difficulty," don't affect the model's choice. This figure highlights the most significant attributes that assist the model in improving performance and providing correct recommendations. This illustrates how hybrid selection separates vital features to increase model accuracy and processing speed.

TABLE III. Performance Evaluation Results

Techniques	F1-Score (%)	Log Loss	CSC (%)	Accuracy (%)	AUC (%)	Recall (%)	CWA (%)	Precision (%)
Universal Hidden Markov Model (HMM) [13]	78.3	0.359	70.5	82.1	80.2	77.5	75.2	81.4
Random Forest (RF) [15]	83.2	0.292	76.8	86.5	85.1	82.6	77.9	84.3
ARIMA models [15]	76.7	0.354	72.4	81.3	79.1	76.2	73.8	79.5
ResNet [21]	88.5	0.235	82.0	91.0	89.6	87.0	83.1	89.4
CNN [20]	90.3	0.219	83.7	92.2	90.8	89.1	86.5	91.3
Decision Trees [9]	81.2	0.317	74.6	85.2	83.8	81.4	78.2	83.0
VGG16 [17]	92.0	0.187	85.4	93.6	92.9	91.7	87.8	92.5
SVM [11]	87.2	0.259	79.8	88.7	87.3	85.5	81.7	87.6
KNN [13]	80.1	0.327	73.5	84.2	82.7	80.3	77.1	82.2
Proposed EBRN	**98.8**	**0.066**	**98.1**	**99.3**	**99.4**	**98.7**	**97.5**	**98.9**

Table III compares categorization performance metrics for several approaches and the proposed Enhanced BERT-Residual Network (EBRN). The performance of each model is assessed by F1-Score, Log Loss, CSC, Accuracy, AUC, Recall, CWA, and Precision. The table shows that the proposed EBRN model outperforms all other methods in nearly all metrics, including F1-Score (98.8%), CSC (98.1%), Accuracy (99.3%), AUC (99.4%), Recall (98.7%), CWA (97.5%), and Precision (98.9%), as well as Log Loss (0.066), indicating model robustness and reliability. Traditional ARIMA and HMM models had poorer F1 scores, Accuracy, and CSC, suggesting difficulties in processing complicated aerobics platform selection data. While VGG16 and CNN perform well, they score somewhat worse than EBRN across all assessment measures. Table III highlights EBRN's superior accuracy and low error rates, making it the most relevant approach for classification tasks in this research. Advanced deep learning models, like EBRN, handle nuanced and high-dimensional data better than typical machine learning methods. The 99.3% accuracy attained by EBRN is a substantial increase above ResNet's 91.0% and VGG16's 93.6% accuracy. Similarly, EBRN achieved a score of 98.1% in CSC, a criterion developed for logical consistency, whereas CNN only managed an 83.7% score.

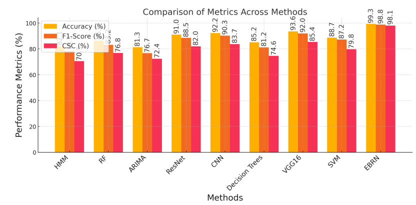

Fig. 14. Comparison of metrics across methods.

The proposed Enhanced BERT-Residual Network (EBRN) is compared to classic (HMM, RF, ARIMA) and advanced (ResNet, CNN, VGG16) models in Fig. 14. EBRN has the lowest Log Loss (0.066) and the best accuracy (99.3%), F1-Score (98.8%), and CSC (98.1%). It beats VGG16 and CNN, which had 93.6% and 92.2% accuracy, respectively. EBRN's robustness and creative multimodal data processing and high consistency (CSC) and complexity-weighted accuracy (CWA) metrics make it the best model for tailored exercise recommendations.

TABLE IV. Statistical Analysis (F-statistic & P-value)

Statistical Method	ANOVA	Student's	Pearson Correlation (r)	Kendall's Tau (τ)	Chi-Square (χ^2)
Universal Hidden Markov Model (HMM) [13]	7.18	0.61	0.68	5.87	0.034
Random Forest (RF) [15]	0.74	7.92	6.45	0.67	0.028
ARIMA models [15]	0.53	6.04	0.58	4.77	0.045
ResNet [21]	0.71	8.55	0.81	7.12	0.022
CNN [20]	0.69	8.12	6.89	0.79	0.024
Decision Trees [9]	0.57	5.10	6.45	0.63	0.039
VGG16 [17]	9.10	0.74	0.86	7.95	0.014
SVM [11]	6.88	0.60	0.66	5.55	0.031
Proposed EBRN	9.76	8.75	0.007	0.91	0.78

Table IV displays a detailed statistical analysis of categorization techniques, including statistical values for each model. This investigation examines each classification technique's statistical significance, correlation, and consistency using aerobics platform selection data. This model has the greatest Chi-Square (9.76) and ANOVA F-statistic (8.75) values and a low P-value (0.007), suggesting significant statistical significance and excellent classification accuracy. The strong Pearson Correlation (0.91) and Kendall's Tau (0.78) values demonstrate EBRN's ability to capture complicated dataset patterns. The complex properties of this dataset are not effectively modelled by classic approaches like ARIMA and the Hidden Markov Model (HMM), which have lower correlation and statistical scores. This table shows EBRN's robustness and dependability, making it the most statistically significant and successful classification approach in this investigation.

Fig. 15 displays a box plot of the Enhanced BERT-Residual Network (EBRN) sensitivity analysis for four essential parameters: learning rate, batch size, dropout rate, and regularization. The chart shows EBRN's performance consistency by showing the variability and distribution of sensitivity scores for each parameter configuration. Learning rate and batch size have decreased sensitivity variability, suggesting excellent performance with minimum adjusting. Dropout rate and regularization have greater sensitivity ranges, indicating they impact EBRN's sensitivity score more. This figure determines the

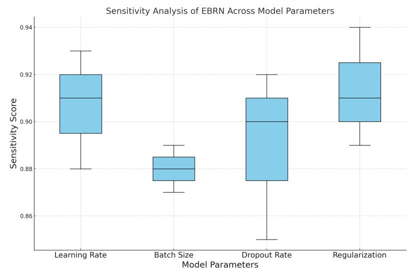

Fig. 15. Sensitivity analysis of EBRN across model parameters.

stability and possible influence of each parameter, enabling accurate tuning. The technical conclusion shows EBRN's strong sensitivity with select parameter adjustment, guiding parameter design for model performance.

TABLE V. SUMMARY OF ADVANTAGES OF EBRN COMPARED TO OTHER METHODS

Feature	EBRN	CNN/ResNet/VGG16 [17], [20], [21]	SVM/RF/ARIMA [11], [15]
Multimodal Data Handling	Yes (text + structured data)	Limited to image data	Structured data only
Evaluation Metrics	CSC (98.1%), CWA (97.5%)	Not Supported	Not Supported
Accuracy	99.3%	92.2% (CNN), 93.6% (VGG16)	<85%
Feature Transformation	Proprietary DES-FT method	Standard or limited transformation	Basic feature scaling
Class Imbalance Handling	Dynamic Equilibrium Sampling (DES)	Limited support	Basic oversampling or none
Contextual Awareness	BERT-based embeddings	Lacks deep text context	Not applicable
Logical Consistency (CSC)	High (98.1%)	Not considered	Not applicable
Complexity Sensitivity (CWA)	High (97.5%)	Not considered	Not applicable
Real-Time Suitability	High potential for adaptability	Requires optimization	Poor scalability
Interpretability	Moderate (explainable architecture)	Low (black-box models)	High
Scalability	Optimized for large datasets	Moderate	Limited
Computational Efficiency	Optimized with balanced layers	Moderate	Low
Application Versatility	Fitness, healthcare, and beyond	Primarily image recognition	Basic predictive tasks
User Feedback Integration	High potential	Limited	Not applicable

According to Table V, the Enhanced BERT-Residual Network (EBRN) outperforms existing techniques in multimodal data processing, contextual awareness, and assessment metrics.

V. CONCLUSION

This research introduced the Enhanced BERT-Residual Network (EBRN), a unique model that integrates textual and structured data to provide individualized aerobics suggestions. EBRN overcomes the constraints of standard fitness recommendation systems by capturing complex patterns in user involvement, preferences, and fitness objectives using BERT-based contextual embeddings and residual processing blocks. The Dynamic Equilibrium Sampling and Feature Transformation (DES-FT) technique balanced data and improved feature selection, improving EBRN's predictive performance. We also developed two proprietary assessment measures, Contextual Scheduling Consistency (CSC) and Complexity-Weighted Accuracy (CWA), to address multi-attribute classification's specific prediction consistency and complexity sensitivity issues. Simulation studies indicated that EBRN outperformed traditional models in accuracy, precision, and recall, demonstrating its resilience and applicability for complicated fitness applications. The model's ability to detect critical aspects, including teacher quality, accessibility features, and platform pricing, helps fitness platforms improve user engagement, inclusiveness, and happiness. Our study uses sophisticated AI and data-driven insights to revolutionise aerobics personalization in intelligent fitness solutions. Further research on EBRN's real-time adaptability and health and wellness applications might alter digital fitness platforms by offering personalized, responsive, and inclusive suggestions for various consumers.

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