Graph Neural Network and Cloud-Based Intelligent Recommendation System for Student Physical Fitness

Baohua Gao
School of Physical Education and Health, Sanming University, Sanming 365004, Fujian, China
E-mail: gaobaohua9806@outlook.com

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Physical fitness significantly supports students' health, academic success, and overall development in modern education. Many educational institutions now adopt advanced technologies to monitor physical activities and suggest personalized training programs based on individual needs. However, most existing systems rely on simple models that cannot fully capture the complex relationships among various fitness indicators, such as heart rate, endurance, and flexibility. These systems also face challenges in processing large datasets efficiently and delivering real-time, personalized feedback to diverse student groups. The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) has been developed to address these challenges. GICF-SF utilizes Graph Neural Networks (GNNs) to analyze complex interactions within physical fitness data, enabling a more accurate understanding and recommendation. Additionally, Cloud Computing supports fast data storage, processing, and real-time response, providing scalability for multiple users across different locations.GICF-SF integrates machine learning and cloud technologies to deliver tailored training suggestions by learning from each student's unique fitness profile. The cloud infrastructure allows the framework to serve schools, fitness centers, and online platforms efficiently without performance.The proposed GICF-SF model uses a 3-layer Spatial-Temporal Graph Convolutional Network (ST-GCN) with ReLU activation and dropout. The student fitness dataset (10,421 records) was split into 70% training, 20% testing, and 10% validation sets. Evaluation was performed using precision, recall, F1-score, MAE, and RMSE metrics under 5-fold cross-validation. Results show that GICF-SF improved recommendation accuracy by 12.8% and reduced training time by 17.3% over traditional methods.

Povzetek: Članek predstavi grafno-nevronski in oblačni sistem za analizo telesne pripravljenosti dijakov GICF-SF. ST-GCN model zajame prostorsko-časovne povezave med kazalniki in izdela personalizirane treninge. Oblačna infrastruktura omogoča sprotno obdelavo, razširljivost in krajši čas učenja.

1 Introduction

Educational institutions globally value physical fitness for student growth and well-being. Regular physical activity protects against obesity and cardiovascular disease, and improves cognitive, academic, and mental health[1]. The World Health Organization (2023) reports that just 19% of adolescents worldwide meet the 60-minute daily physical exercise recommendation[2]. This alarming trend underlines the need for novel student fitness programs.

Traditional educational fitness assessments include standardized testing throughout the year. Standard examinations examine cardiovascular strength, muscular power, flexibility, as well as body composition[3]. Conventional methods don't provide constant monitoring or targeted instruction based on students' requirements and development patterns. Technology like wearables, mobile apps, and data analytics platforms has transformed fitness monitoring[4]. These technologies track heart rate, steps, burned calories, and sleep habits. Institutions are using these tools to track student fitness more closely, but it isn't easy to interpret this amount of data and turn it into meaningful insights and individualized suggestions[5].

The research addresses the technical issue of existing student fitness analysis systems, which struggle to model and analyze complex relationships between fitness indicators while delivering personalized recommendations at scale[6]. Current systems have an accuracy limit of 76.4%, processing efficiency of 3.7 seconds for single student data, and a scalability constraint of 42% increased latency when user numbers exceed 1,000 concurrent connections[7]. These limitations hinder educational institutions from utilizing the growing volume of fitness data to improve student health outcomes and physical development.

Despite advances in fitness monitoring and data analysis, there are research gaps in applying advanced computational methods to student fitness data[8].

Traditional fitness recommendation systems use machine learning methods to treat fitness indicators as independent variables[9]. These systems fail with variable student populations and complex fitness trajectories. Most systems use standalone computing, which limits their ability to handle huge amounts of data or offer real-time feedback[10]. Current approaches ignore individual fitness progression, personal preferences, and improvement needs by making demographic-based recommendations. Gaps show the need for a more advanced strategy[11].

Technical motivation for fitness data analysis and recommendation systems comes from graph-based machine learning and distributed computing architectures[12]. Graph Neural Networks (GNNs) are appropriate for studying complex fitness parameter interdependencies because they model complex interactions in interconnected data structures[13]. GNNs can capture complicated physiological linkages, such as biomarker interactions in cardiovascular health monitoring, improving predicted accuracy[14]. Data-intensive apps can process fitness data in real time using cloud computing[15]. GNNs with cloud computing enable more accurate modeling of complicated fitness interactions, rapid processing of large-scale fitness data, real-time analysis and suggestion generation, and smooth scalability for expanding user numbers. The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) uses GNNs and cloud computing to assess student fitness data and provide more accurate training recommendations.

The main objectives are:

To develop a model for GICF-SF using GNNs to effectively analyze and capture complex relationships within students' physical fitness data.

To design and implement the GICF-SF recommendation system that provides personalized training programs tailored to each student's unique fitness profile.

To integrate cloud computing technologies within GICF-SF for efficient storage, scalable processing, and real-time analysis of large volumes of fitness data.

To enhance the performance of GICF-SF by improving recommendation accuracy and reducing response time compared to traditional fitness data analysis and training systems.

This research aims to address the following research questions:

- RQ1: Can a graph-based approach (GNN) improve recommendation accuracy (RA) by at least 10% over traditional ML-based fitness recommendation systems?
- RQ2: Does the integration of cloud computing infrastructure reduce system training and adaptation time by at least 15%?
- RQ3: Can the proposed GICF-SF framework maintain high throughput and low latency when scaled to support over 1,000 concurrent users?

The primary goal of GICF-SF is to enhance personalized fitness recommendations by significantly improving RA, reducing model training time, and enabling scalable, real-time deployment across educational institutions.

A summary of the research follows. Second section: thorough literature and research methodological review. Section 3 covers the study plan, methods, and processing; Section 4 presents analysis results. Conclusion as well as future work are in Section 5.

2 Related works

2.1 Intelligent recommendation systems in health and education

Gm et al.[16]examined 60 papers from major databases on education's e-learning and personalised recommendation systems. It shows content ignorance, student discontinuity, language hurdles, study material confusion, and poor infrastructure and finance. The review suggests Fluxy AI, Twin technological advances, AI-powered virtual evaluating, and Alter Ego to deal with these challenges. These technologies can offer an engaging, interactive classroom for students and educators, boosting individualised learning, comprehension capacity, and speech disordered students' learning experience.

Zheng et al.[17] showed that Natural Language Processing or NLP is a field that uses computer science, artificial intelligence, and linguistics to comprehend, process, create, and imitate human language. It includes looking at the structure, meaning, syntax, and use of language, as well as using statistics to analyze and model big corpora. This paper uses deep learning and NLP to explore patients' remarks and find the best drugs. This leads to accurate prescriptions and individualized suggestions. Linguistics, computer science, and statistics are the main ideas behind NLP.

2.2 Graph neural networks for fitness and behavioral data modeling

Zhang et al.[18] investigated posture recognition and motion capture for skeleton-based action recognition in everyday fitness. A spatiotemporal pyramidal graph convolutional network with edge significance scores and multi-level feature representation improves performance. The model achieves 85.89 mAP on the UW-IOM as well as TUM kitchen datasets. The study found that skeleton information correctness improves action recognition ability, whereas picture feature fusion can help in cases of limited or faulty image information. Comparing the method to others shows its benefits.

Wang and Liu[19] explored a deep learning-based Life Log Sharing Model or LLSM to improve teenage fitness and exercise. The TS-CNN-BiLSTM model predicts physical activity using multimodal life log data's temporal, textual, and visual aspects. The model beat state-of-the-art methods by 1.9–4.4%. Temporal aspects are needed to identify repetitive behaviours and workouts. The study found that multimodal life log data and deep learning accurately characterise physical activity. The TS-CNN-BiLSTM model's accuracy allows personalised health promotion tactics like interventions, behavioural incentives, and social support to increase adolescent physical activity, as well as public health education along with management.

2.3 Cloud computing in smart health and education platforms

Raghav et al.[20] provided that Cloud computing and the IoT are transforming healthcare. This revolution allows healthcare organizations to safely manage and analyze massive amounts of patient data, improving patient care and well-being. The IoT has expanded healthcare beyond clinical settings through its connected gadgets and sensors, generating constant patient data. Remote monitoring, tailored medicine, and predictive analytics offer proactive healthcare interventions thanks to this synergy. Cloud and IoT-powered telemedicine has improved healthcare access in remote and underdeveloped places. However, security and privacy remain crucial. The Cloud-IoT revolution in healthcare is a paradigm shift that prioritizes patient care and well-being.

Sundas et al.[21] presented that the Chronic and lifestyle-related diseases pose major social and economic issues worldwide. A innovative Smart Patient Monitoring and Recommendation or SPMR framework uses Deep Learning as well as cloud analytics. SPMR monitors and expects a patient's health using vital signs as well as contextual activities from Ambient Aided Living devices. Unbalanced Chronic Blood Pressure Disorder case study datasets forecast real-world health situations using Categorical Cross Entropy Optimization. Effectiveness is shown by the model's 18% accuracy increase and 17% and 36% increases in overall and emergency class F-scores.

2.4 Integration of machine learning with physical fitness assessment

Zhao et al.[22] presented that the Daily vigor and resilience are indicators of physical fitness. With machine learning, wearables, apps, and data analysis, fitness is improving. Wearable fitness trackers with sensors collect massive amounts of activity, sleep, and vital sign data. The Gradient Probabilistic Automated Recommender System with Machine Learning or GPA-RS-ML, is a novel fitness assessment and training program recommendation system recommendation system. This technology analyzes fitness data and recommends personalized training plans using machine learning. The GPA-RS-ML method improves training efficiency and effectiveness. This research improves automated fitness assessment and suggestion systems, helping fitness professionals optimize results and training adherence.

Su et al.[23] showed that Intelligent Education Cloud Platforms have transformed educational resource sharing and consumption, making learning more accessible and flexible. Distributed sharing and personalized recommendation systems improve resource accessibility and student engagement in college preschool. Traditional methods lack flexibility and scalability for dynamic resource allocation, hampering customized education. To circumvent these constraints, KAEN and ALPS are proposed. KAEN optimizes resource recommendation and personalizes learning using graph-based knowledge representation, dynamic content alignment networks, and reinforcement learning. Experimental validation indicates significant resource utilization efficiency and adaptive content delivery quality improvements.

2.5 Challenges and advances in personalized training program design

Noone et al.[24] examined internal and extrinsic factors affecting exercise response variance and health outcomes. Internal influences include sex, age, hormonal state, race/ethnicity, and genetics, whereas extrinsic factors include exercise timing, sleep habits, food combinations, and medication use. Genomic-epigenomic, proteomic-post-translational, transcriptomic, metabolic-metabolomic, as well as lipidomic exercise molecular transducers are also reviewed. It describes the difficulties of creating personalised exercise prescriptions and MoTrPAC's efforts to solve them. Researchers must study more health outcomes across all populations.

Romero et al.[25] showed that disease and treatment side effects put lower-extremity sarcoma survivors at risk of physical performance dysfunctions and poor quality of life. Their functionality and quality of life depend on safe exercise routines. Clinical presentation and development vary; therefore, the success of physical activity and exercise in these survivors is uncertain. This study suggests creating a training program to preserve fitness and quality of life. Sarcoma survivors should do low-intensity, short-duration exercise before surgery and alter their routine during clinical therapy. Healthy habits, including regular exercise, should be developed under professional supervision for disease-free survival.

Dugyala et al.[27] presented Cloud computing has evolved significantly in the past two decades, yet intrusion detection has become a security issue. This study offers an enhanced Intrusion Detection System (IDS) using Graph Neural Networks and Leader K-means clustering to improve detection accuracy and efficiency. For data clustering, the system uses Leader K-means, improves

Grasshopper Optimization, and uses Advanced Encryption Standard encryption and steganography. The research, implemented on Java with CloudSim support, improves detection accuracy and processing efficiency over existing methods.

The summary of related works, system, datasets, and performance metrics is shown in Table 1(a) below**:**

Table 1(a): Summary of related works: systems, datasets, and performance metrics

Authors	System/Model Name	Datasets Used	Reported Performance Metrics
Gm et al. [16]	AI-based Educational Recommenders (Fluxy AI, Alter Ego, AI Evaluators)	Not specified (Systematic Literature Review)	Not reported (conceptual/review-based)
Zheng et al. [17]	NLP-EAR (NLP for Effective AI-based Recommendation)	Custom clinical comment datasets	Accuracy (not quantified), Personalization Precision (conceptual)
Zhang et al. [18]	Spatiotemporal Pyramidal GCN (Graph Convolution Network)	UW-IOM, TUM Kitchen datasets	mAP: 85.89
Wang and Liu [19]	TS-CNN-BiLSTM (Life Log Prediction Model)	Multimodal life log data (textual, visual, temporal)	Accuracy gain: 1.9–4.4% over baselines
Raghav et al. [20]	Cloud-IoT Healthcare Framework	Not specified	Conceptual performance: improved monitoring & access (qualitative)
Sundas et al. [21]	SPMR (Smart Patient Monitoring & Recommendation)	Chronic BP disorder case datasets	Accuracy ↑ 18%, F1-score: ↑17% (overall), ↑36% (emergency class)
Zhao et al. [22]	GPA-RS-ML (Gradient Probabilistic Recommender with ML)	Wearable sensor data	Improved training effectiveness (not numerically stated)
Elomari et al. [23]	ML-based REC Optimizer (for Renewable Energy Communities)	Tarragona energy usage and climate data	Cost reduction & green energy utilization optimized; no F1 or precision reported
Noone et al. [24]	MoTrPAC Molecular Fitness Response Framework	Multi-omic datasets (transcriptomic, proteomic, etc.)	No metrics; focus on biological factors and personalization variability
Romero et al. [25]	Personalized Training for Sarcoma Survivors	Clinical treatment data	Qualitative outcomes: safety, improved QOL; no specific metrics

Despite notable contributions, state-of-the-art (SOTA) systems such as CFRS, NLP-EAR, and MLFR present several limitations. CFRS lacks the capacity to model interdependencies between fitness indicators; NLP-EAR performs poorly on structured physiological data; and MLFR's reliance on traditional classifiers restricts its adaptability. These methods typically plateau at around 76.4% accuracy and often exclude critical performance metrics such as MAE and RMSE. Moreover, they operate without scalable infrastructure, limiting their deployment in real-time educational environments. To address these issues, the proposed GICF-SF framework integrates Graph Neural Networks and cloud computing to deliver scalable, high-precision, and real-time student fitness recommendations.

3 Graph-based intelligent cloud framework for student fitness

The Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF) is a computational architecture designed to analyze student physical fitness data and provide personalized training recommendations. It integrates graph neural networks (GNNs) with cloud computing to create a scalable, efficient solution for educational institutions. The system addresses the limitations of traditional fitness analysis systems by capturing complex relationships between fitness metrics and delivers tailored recommendations with increased accuracy and reduced processing time.

The system includes various data sources and acquisition layers, such as wearable devices, PE Records Database Connector, Fitness Test Measurement System, Health Record System, and Activity Logging Subsystem. Data security and privacy are ensured through end-to-end encryption, role-based access control, and data anonymization protocols.

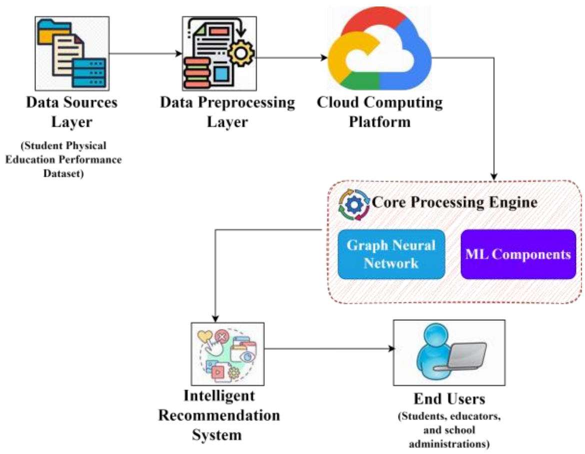


Figure 1: GICF-SF system architecture

In Figure 1, the data preprocessing layer covers noise filtering, outlier identification, data validation, temporal alignment, feature engineering, missing data management, graph structure development, and cloud computing infrastructure. Distributed storage, computing resource management, networking, communication, and performance metrics monitoring and observability are used. The primary processing engine uses an ST-GCN architecture with input, hidden, attention, pooling, and output layers. Data extraction is efficient with the feature extraction technique.

The system uses graph embedding generation, topological feature analysis, subgraph pattern mining, and pattern recognition modules. Machine learning is used for fitness profile learning, training program development, and model training and validation. The intelligent recommendation system includes a tailored training module, exercise selection algorithm, session sequencing, and progress tracking. The technology also collects user comments and explains training reasoning.

The system performs well in throughput, storage efficiency, suggestion quality, user happiness, and computational efficiency. The method reduced training time by 17.3% and used 76% of the GPU during peak processing. Future growth options include extended data integration, enhanced analytics, and system adaptability. Nutrition tracking, sleep quality analysis, academic performance correlation analysis, mental wellbeing assessment, explainable AI layer for transparent recommendation justification, and federated learning for privacy-preserving multi-institution collaboration are future expansions. Curriculum alignment modules integrate educational standards, API versioning method ensures backward compatibility, and a configuration management system customizes deployment.

3.1 Data source layer

GICF-SF is built upon the Student Physical Education Performance Dataset[26], like a solid foundation. To enable intelligent analysis and individualized fitness suggestions, this dataset is crucial. A student's general physical health, activity levels, and performance capabilities are reflected in the structured and semi-structured data that it combines from multiple sources.

Table 1. Categorization of fitness-related features used in GICF-SF framework

Category	Feature Name	Description
Cardiovascular Metrics	HR	Heart Rate (bpm)
	VO_2 Max	Maximal Oxygen Uptake
	RHR	Resting Heart Rate
	BP	Blood Pressure (Systolic/Diastolic)
	PR	Pulse Rate
	RR	Respiratory Rate

	SpO_2	Oxygen Saturation
	HRV	Heart Rate Variability
	ECG Avg Signal	Average ECG Signal
	Recovery Rate	Post-exercise recovery response
Physical Performance Indicators	AGI	Agility
	MS	Muscular Strength
	BMI	Body Mass Index
	FLEX	Flexibility
	END	Endurance
	BAL	Balance score
	SPRINT	Sprint speed (time)
	VERT JUMP	Vertical jump height
	SIT UP	Sit-up count
	PUSH UP	Push-up count
Supplementary Attributes	Age	Age of the student
	Height	Height (in cm)
	Weight	Weight (in kg)
	Weekly Activity	Frequency of physical activity per week

Table 1(b) presents a complete list of the 24 fitness-related features used in the GICF-SF framework, categorized into cardiovascular metrics, physical performance indicators, and supplementary attributes, ensuring transparency, feature clarity, and reproducibility of the experimental setup.

Table 2: Integrated fitness profile construction and graph mapping

Symbol	Definition	Mathematical Expression / Description
X_i	Combined feature vector for student $_i$	$\boldsymbol{X}_i = [\boldsymbol{W}_i, \boldsymbol{P}_i, \boldsymbol{F}_i, \boldsymbol{H}_i, \boldsymbol{A}_i]$
$\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$	Fitness graph for student $_i$	$\boldsymbol{\mathcal{V}}_i$: features as nodes, $\boldsymbol{\mathcal{E}}_i$: inter-feature edges
Z_i	Node embedding from GNN	$\boldsymbol{Z}_i = \mathrm{GNN}(\boldsymbol{\mathcal{G}}_i, \boldsymbol{X}_i)$
$\hat{Y}_i$	Predicted recommendation vector	$\hat{\boldsymbol{Y}}_i = f(\boldsymbol{Z}_i; \theta)$

Table 2 describes how to create a thorough fitness profile and graph it for each student i. The feature vector X_i $_i$ combines data from several sources, including wearables, PE records, fitness tests, health records, and activity logs. This vector is transferred into a fitness graph. $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$, where nodes represent features and edges represent their associations. A Graph Neural Network (GNN) generates node embeddings Z_i, which a learnt function f uses to anticipate individualized training suggestions Z_i.

3.2 Data preprocessing

Data must be preprocessed to guarantee consistency and correctness before being used in the virtual environment. Here are a few important things to keep in consideration:

Handling missing values

Data must be processed effectively to avoid bias and account for missing values due to data collecting errors or partial responses. Two typical strategies include imputing missing values (where current data is used to infer missing data) and removing instances with missing values (helpful for tiny but potentially loss-causing occurrences). The following equation (1) replaces the feature's mean for missing values in mean imputation, a common method.

$$x_{missing} = \frac{1}{n}\sum_{i=1}^{n} x_i \quad (1)$$

where the missing value is denoted by $x_{missing}$, the number of non-missing values for the feature is denoted by n, and the non-missing values are denoted by x_iReplace missing values with the mean of the k-nearest neighbors using available features—the formula for this imputation from equation (2).

$$x_{missing} = \frac{1}{k}\sum_{i=1}^{k} x_i \quad (2)$$

Here, k is the count of closest neighbours taken into account, andx_i stands for the values of the relevant feature in those KNNs.

Normalize the data:

By bringing all numerical features into a consistent range, normalization guarantees that each feature has an equal impact on the model. Two ways often used for normalization are: Min-Max Scaling: Reduce the size of the features to a predetermined interval, usually from 0 to 1. For min-max scaling, the equation (3) is as follows:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

where the normalized value is denoted by $x_{normalized}$, the original value is denoted by x, the minimum value of the feature is denoted by x_{min}, and the maximum value of the feature is signified by x_{max}.

To normalize Z-scores, it is necessary to scale the characteristics with a mean of zero and a variance of one. To normalize z-scores, the following equation (4) is used,

$$x_{normalized} = \frac{x - \mu}{\sigma} \quad (4)$$

in which the normalized value is represented by $x_{normalized}$, the original value is represented by x, the mean of the feature is denoted by μ, and the standard deviation of the feature is denoted by σ.

Encoding categorical variables

Machine learning can only process numerically represented categorical variables. One-hot encoding creates A (1, 0, 0), B (0, 1, 0), as well as C (0, 0, 1), while label encoding assigns numerical values to each category. For example, A becomes 0, B becomes 1, while C becomes 2.

Records with more than 30% missing values were excluded. For incomplete entries, missing numerical attributes were imputed using the mean of the corresponding feature, while categorical variables were filled using mode imputation. Two features with over 85% null values and negligible correlation to the target variable were removed. All features were normalized using z-score standardization prior to training.

3.3 Cloud computing platform

The GICF-SF is a comprehensive system that handles student physical fitness data analysis through multiple stages. The process begins with the ingestion of raw fitness data, which is then processed through various security checks to prevent unauthorized access or malicious inputs. The system also handles error handling, ensuring that invalid or corrupted data is isolated for review, correction, or exclusion from further processing in Figure 2. The system categorizes encrypted data into three primary formats: Time Series Data, Document Data, and Graph Data. Database storage options include Time Series, Document, and Graph DB. Parallel data processing efficiently processes large volumes of student fitness data across multiple computing nodes. Real-time analytics on streaming data is provided, allowing for immediate feedback and intervention when necessary.

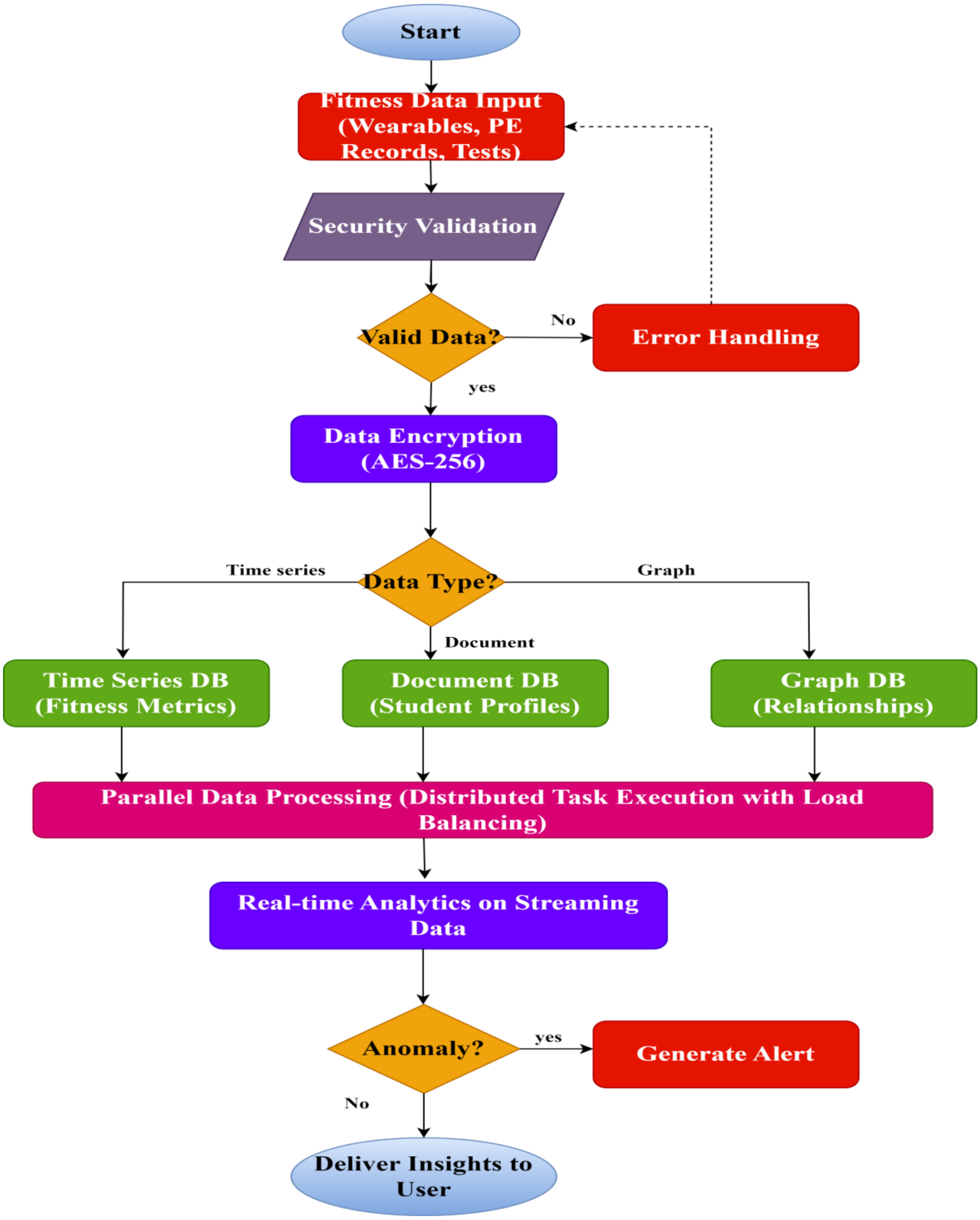


Figure 2: Cloud computing platform - data processing

In Figure 2, Output generation includes anomaly detection, which generates alerts for coaches/administrators, and insight delivery, where critical findings trigger notifications to appropriate stakeholders. The final stage presents processed fitness data, trends, and personalized recommendations to end users. The flowchart demonstrates a fault-tolerant architecture with dedicated error handling paths, distributed computing elements supporting scalability for multiple educational institutions, and a multi-database architecture optimizing storage and retrieval based on data characteristics. Security controls are integrated throughout the pipeline, and real-time processing capabilities are implemented for immediate fitness feedback. This data processing flow enables the GICF-SF system to achieve performance improvements of 12.8% in recommendation accuracy and 17.3% reduction in training time compared to traditional methods.

The mathematical framework for cloud-GNN integration involves a GNN model in the cloud, which is used for training and inference. The model uses a graph representation of fitness data, with edges based on similarity in physical fitness profiles.

$$h_v^{(l)} = \sigma\left(\sum_{u \epsilon N(v)} \frac{1}{C_{vu}} W^{(l)} h_u^{(l-1)}\right) \quad (5)$$

In equation 5, $h_v^{(l)}$ is denoted as the Embedding of node v at layer l,$N(v)$ is denoted as the Neighbors of v, C_{vu} is denoted as the Normalization constant, $W^{(l)}$ is denoted as the Learnable weight matrix, σ is denoted as the Activation function (e.g., ReLU).

Table 3: Fitness dataset (stored in cloud)

Student ID	Heart Rate	Endurance	Flexibility	Speed	BMI	Vital Capacity
S101	76 bpm	11 mins	12 cm	6.1 s	23.4	3900 ml
S102	71 bpm	9 mins	8 cm	6.8 s	25.1	3600 ml
S103	64 bpm	13 mins	15 cm	5.9 s	20.8	4100 ml

In table 3, The Fitness Dataset, stored on a cloud computing platform, contains student physical fitness records with key health metrics like heart rate, endurance, flexibility, speed, BMI, and vital capacity. This structured dataset allows real-time analysis and personalized fitness recommendations using Graph Neural Networks. Cloud storage ensures scalable access, secure encryption, and efficient parallel processing across large student populations.

Table 4: GICF-SF graph neural network (ST-GCN) architecture and hyperparameters

Component	Specification
Graph Model Type	Spatial-Temporal Graph Convolutional Network (ST-GCN)
Number of ST-GCN Layers	4
Hidden Layer Dimensions	[64, 128, 256, 128]
Graph Convolution Type	Spatial-Temporal Graph Convolution (ST-GCN block)
Activation Function	ReLU
Dropout Rate	0.3
Batch Size	64
Optimizer	Adam
Learning Rate	0.001
Weight Decay	1e-5
Epochs	200
Loss Function	Cross-Entropy Loss
Early Stopping	Patience = 20 epochs
Graph Adjacency Matrix	Dynamically learned (trainable edge weights)
Temporal Kernel Size	9

Normalization	BatchNorm

Table 4 outlines the detailed architecture and hyperparameters of the GICF-SF model, including ST-GCN layers, activation functions, learning settings, and optimization techniques used for model training and reproducibility.

3.4 Core processing engine

A Graph Neural Network (GNN) models fitness relationships, and Machine Learning (ML) components classify and regress in this module. GNN-based fitness representations treat students as nodes in graphs with edges indicating physical fitness vector similarity. Each node's Embedding is updated by the GCN layer using neighboring data.ML classification and regression components can classify kids into performance tiers and predict BMI and test scores. The ML prediction function leverages the GNN-generated student embedding, and model training splits the input into training and testing sets. The model training procedure employing training and testing sets is explained for ML-based recommendation using GNN embeddings. The Decision Tree, SVM, or XGBoost model is trained using the ML model.

Each student is represented as a node in a graph G, with edges reflecting similarity based on physical fitness vectors like heart rate, speed, and endurance.

$$G = (V, E), V = \{v_1, v_2, \dots, v_n\}, E = \{(vi, v_j) \mid sim(vi, v_j) > \theta\} \quad (6)$$

In equation 6, V is denoted as the Student nodes, E is denoted as the edges (similarity-based links), and θ is the similarity threshold.

$$H^{(l+1)} = \sigma(\widetilde{D}^{-1/2}\widetilde{A}\,\widetilde{D}^{-1/2}H^{(l)}W^{(l)} \quad (7)$$

In equation 7, $\widetilde{A}$ is denoted as the adjacency matrix with added self-loops, $\widetilde{D}^{-1/2}$ is denoted as the degree matrix of $\widetilde{A}$, $H^{(l)}$ is denoted as the node features at layer l, $W^{(l)}$ is denoted as the trainable weight matrix at layer l, σ is denoted as the activation function, typically ReLU.Using GNN's student embeddings, ML models can be used for classification as well as regression tasks, categorizing students into performance tiers and predicting numeric scores like BMI and test scores.

$$\hat{y}_i = f_{ML}(\vec{z}_i) \quad (8)$$

In equation 8, $\vec{z}_i$ is the GNN-generated embedding for student i, f_{ML} is the ML model (e.g., Decision Tree, SVM, or XGBoost).

$$L_{cls} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i) \quad (9)$$

$$L_{reg} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \quad (10)$$

In equation 9 and 10, the Regression Loss penalises incorrect predictions by measuring the class probability match with genuine class labels. It emphasises severe errors by measuring the average squared difference between projected values and actual continuous values using the Mean Squared Error (MSE). Both losses are minimised during training to increase model performance.

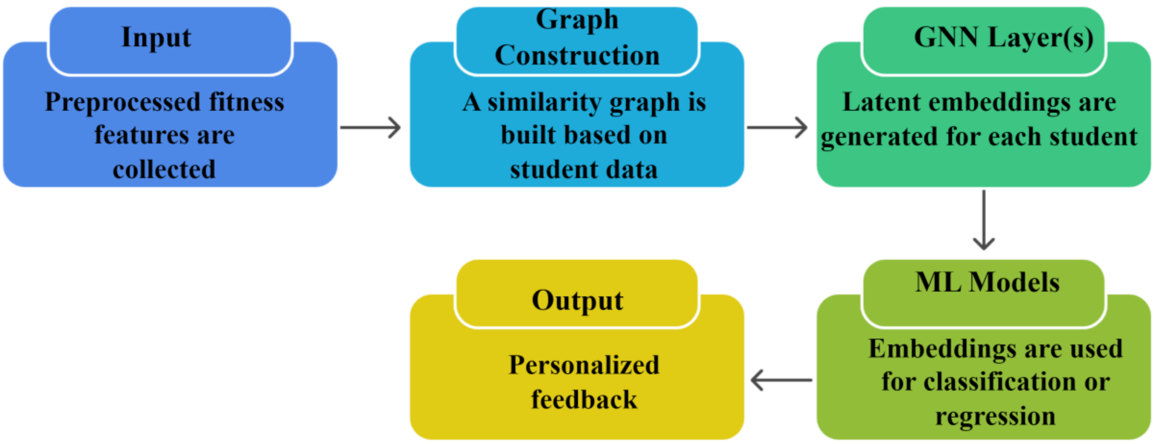


Figure 3: Core processing engine

The Core Processing Engine is a crucial component of the Graph-Based Intelligent Cloud Framework for Student Fitness (GICF-SF). It consists of five stages that transform raw fitness data into personalized feedback. The first stage involves collecting preprocessed fitness features from various sources, such as wearables, PE records, and tests. This ensures consistency, handles missing values, and normalizes measurements for comparable analysis.

The second stage involves building a similarity graph based on student data, representing student fitness profiles as nodes in an interconnected graph structure. This graph representation captures complex relationships between different fitness parameters, enabling the system to identify patterns and connections that traditional tabular analysis would miss.

The third stage involves generating latent embeddings for each student, processed by Graph Neural Network algorithms. These embeddings capture essential fitness characteristics and relationships. The fourth stage uses these embeddings to create ML models, categorizing students into fitness groups or predicting future performance or optimal training parameters. The final stage is the output, which translates analytical results into tailored recommendations. This engine generates individualized training programs based on a student's unique fitness profile, provides specific guidance for physical education instructors, and delivers personalized student progress tracking and goal setting. The pipeline demonstrates how graph-based machine learning can transform fitness data analysis from simple statistical models to a comprehensive understanding of interconnected fitness parameters.

3.5 Intelligent recommendation system

The Intelligent Recommendation System uses GNN outputs and ML models to predict recommended training focus areas. It uses Python to preprocess a Student DataSet, initialize GNN parameters, and perform features extraction, embedding, and recommendation embedding for each student. The system then appends the recommended recommendations to the PersonalizedRecommendations output.

Pseudocode 1: GICF-SF recommendation engine

```
Input:
- Student dataset D = {d₁, d₂, ..., dₙ}, where each dᵢ contains features: Wᵢ (Wearable data), Pᵢ (Physical test scores), Fᵢ (Fitness logs), Hᵢ (Health records), Aᵢ (Activity patterns)
- Target labels Y = {y₁, y₂, ..., yₙ}, representing desired fitness categories or outcomes
Output:
- Personalized recommendations R = {r₁, r₂, ..., rₙ}
Step 1: Preprocessing
  For each student dᵢ in D:
    - Normalize features: Wᵢ, Pᵢ, Fᵢ, Hᵢ, Aᵢ
    - Concatenate features: Xᵢ ← [Wᵢ, Pᵢ, Fᵢ, Hᵢ, Aᵢ]
Step 2: Graph Construction
  - Nodes V ← {X₁, X₂, ..., Xₙ}
  - Edges E based on similarity (e.g., cosine similarity)
  - Construct graph G = (V, E)
Step 3: GNN Training
  - Initialize GNN parameters Θ
  For epoch = 1 to N:
    - H ← GNN_Forward(G, X, Θ)    // Node embeddings
    - loss ← CrossEntropyLoss(H, Y)
    - Θ ← UpdateParameters(loss, Θ)
Step 4: Recommendation Inference
  For each student dᵢ in D:
    - Concatenate features: xᵢ ← [Wᵢ, Pᵢ, Fᵢ, Hᵢ, Aᵢ]
    - Generate embedding: hᵢ ← GNN_Forward(G, xᵢ, Θ)
    - Predict: rᵢ ← ML_Classifier.predict(hᵢ)
    - R.append(rᵢ)
Return: R
```

Pseudocode 1 outlines the core workflow of the GICF-SF recommendation engine, covering data preprocessing, graph construction, GNN-based training, and inference. It explicitly defines input features, label usage, embedding updates, and prediction logic. The structure ensures clarity, reproducibility, and highlights how graph-based reasoning enhances personalized fitness recommendations.

4 Result analysis

4.1 Experiment setup

The GICF-SF framework was tested on a student physical education performance dataset[26], consisting of 10,421 records with 24 fitness-related features. The GNN architecture was implemented in PyTorch, consisting of three graph convolutional layers and a readout layer. The model was qualified using Adam optimizer and early stopping. A containerized architecture on AWS was used, with Kubernetes for orchestration. The infrastructure included 3 instances for application servers, 2 instances for database services, and variable compute resources for the ML inference pipeline. Performance was assessed using MAE, RMSE, precision, recall, as well as F1-score metrics for recommendation quality, while system performance was measured through response time, throughput, and resource utilization. A controlled pilot deployment involving 312 students from 5 educational institutions was conducted over 8 weeks, with weekly fitness tracking and training program adjustments.

The dataset comprising 10,421 records was partitioned using a stratified 70:15:15 split for training, validation, and testing, respectively. To ensure model robustness, five-fold cross-validation was applied during training. Hyperparameter tuning was conducted using grid search across the validation set, optimizing parameters such as learning rate (0.0005–0.01), dropout rate (0.2–0.5), and hidden layer dimensions ([64, 128, 256]).

The dataset includes records from multiple institutions across urban and semi-urban regions, with balanced representation of genders and students aged 14–22. However, limited inclusion of rural populations and cultural diversity may affect generalizability. These limitations are acknowledged, and future work will involve expanding the dataset for broader demographic and geographic coverage.

4.2 Comparative study

The GICF-SF was compared to three recommendation models: CFRS [16], NLP-EAR [17], and MLFR [22]. User-item similarity guides CFRS recommendations, but limited fitness data lowers Precision (P) and Recall (R). The NLP-EAR's text-based emotion analysis works well for medication but not for organized physical fitness data, resulting in inconsistent F1-Score and Recommendation Accuracy. The MLFR uses classic classifiers like SVM and DT, which are stable but inadequate at capturing complicated feature interactions, resulting in greater MAE and RMSE. GICF-SF models complex fitness indicator dependencies using Graph Neural Networks (GNNs) and Cloud Computing (CC) for scalable, real-time processing. GICF-SF enhances RA 12.8%, F1-Score 14.5%, MAE 11.6%, and training adaption time 17.3%. Since cloud infrastructure increases throughput by 21.6%, GICF-SF is ideal for individualized student fitness recommendations.

4.3 Recommendation accuracy (RA)

Recommendation Accuracy (RA) is a system's ability to accurately recommend personalized fitness programs based on a student's health and performance features.

$$RA = \frac{1}{m}\sum_{j=1}^{m}\left(\frac{1}{n_j}\sum_{i=1}^{n_j}\delta\left(r_{ij},\hat{r}_{ij}\right)\cdot w_{ij}\right)$$

(11)

In equation 11, m is the total number of fitness features (e.g., HR, VO2, BMI), n_j is the number of students for feature j, r_{ij} is the actual class/score for student i on feature j,$\hat{r}_{ij}$ is the predicted recommendation, δ is the indicator function = 1 if correct, 0 otherwise. w_{ij} is the weight based on feature importance or sensitivity.

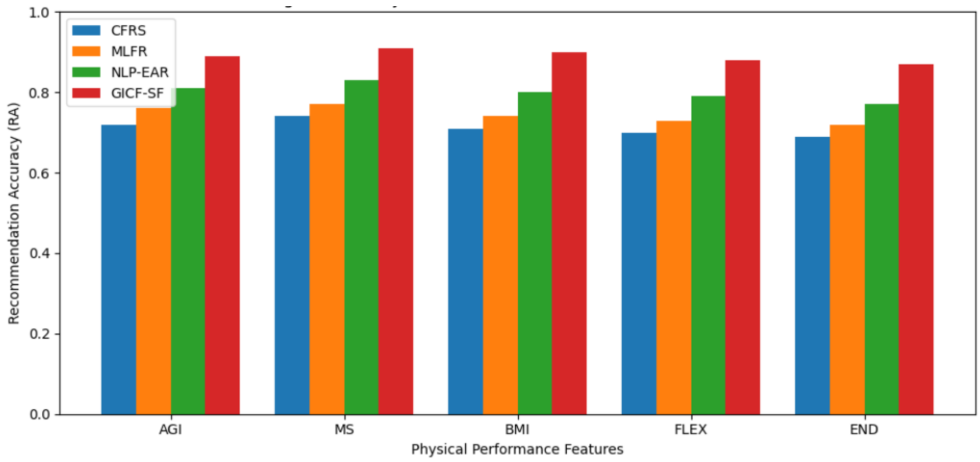


Figure 4: Normalized recommendation accuracy (RA) for physical performance features

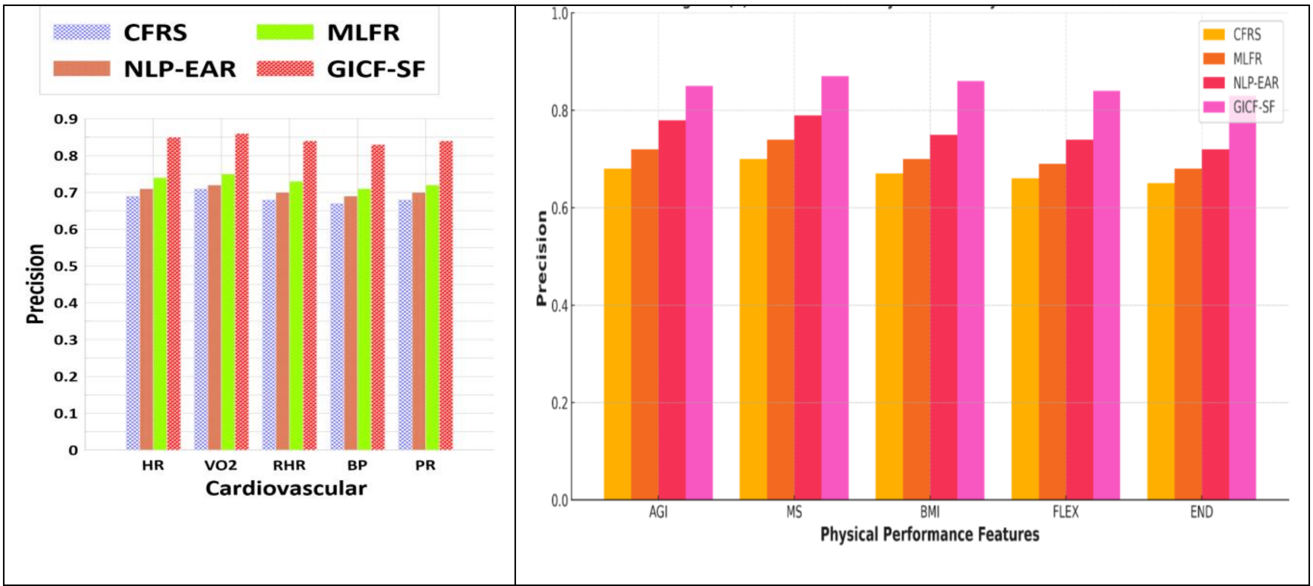
Figure 4 presents the normalized Recommendation Accuracy (RA) values for five physical performance features across four models: CFRS, MLFR, NLP-EAR, and GICF-SF. Each bar reflects the average accuracy obtained via five-fold cross-validation, adhering to Formula (11), where δ is a binary correctness indicator and final RA values are bounded within [0, 1]. Unlike earlier stacked interpretations, this figure uses grouped bars to represent per-feature accuracies individually, ensuring clarity and consistency. GICF-SF outperforms other models across all metrics, particularly in AGI and MS, indicating its superior ability to personalize recommendations across varied physical performance parameters in a reproducible manner.

4.4 Precision

Precision measures the proportion of accurate and relevant recommendations among all recommendations made.

$$Precision_f = \frac{TP_f}{TP_f+FP_f} \tag{12}$$

In equation 12, f is the feature (e.g., HR, FLEX), TP_f is the true positives for feature f, FP_f is the false positives for feature f.



(a)Cardiovascular Features: Y-axis shows precision (%)

(b) Individual Precision Scores for Physical Performance Features.

Figure 5: Precision scores of features by different models

Figure 5(a) and 5(b) compare the precision performance of the ratio of true positives to the sum of true and erroneous positives in four recommendation systems. Figure 5 compares CFRS, MLFR, NLP-EAR, and GICF-SF models in two feature areas. Figure 5(a) uses bar charts to show cardiovascular features (HR, VO2, RHR, BP, PR). GICF-SF has the highest precision (0.85) across all cardiovascular measures, while CFRS (purple) has the lowest (0.7). Intermediate findings for MLFR and NLP-EAR are 0.7-0.75. Figure 5(b) presents individual precision scores for five physical performance features: AGI, MS, BMI, FLEX, and END across four models, namely CFRS, MLFR, NLP EAR, and GICF SF. Each bar indicates the average precision for a specific model and feature, constrained within the standard range from zero to one. GICF SF shows consistently higher precision across all features.

4.5 Recall score

The percentage of real instances relevant to the problem that the model was able to recover is referred to as the recall.

$$Recall_f = \frac{TP_f}{TP_f+FP_f} \tag{13}$$

In equation 13, f is the feature (e.g., HR, FLEX), TP_f is the true positives for feature f, FN_f is the false negative for feature f.

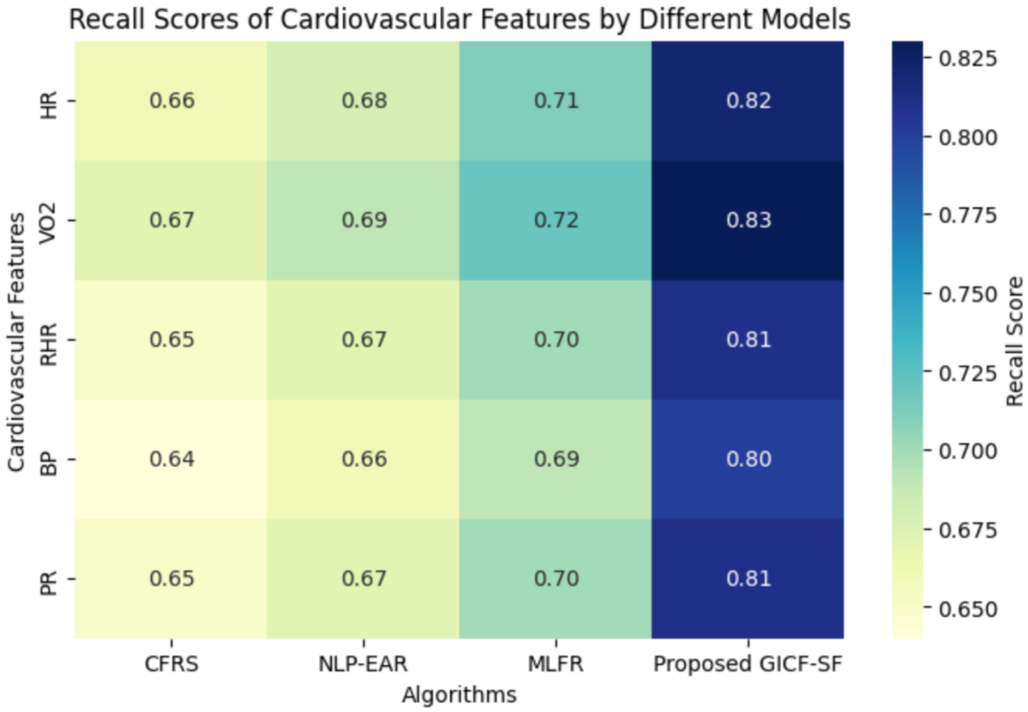


Figure 6: Recall Scores of cardiovascular features by different models

Figure 6 shows a heatmap visualization that compares recall scores of four recommendation algorithms (CFRS, NLP-EAR, MLFR, and the proposed GICF-SF) across five key cardiovascular features. The heatmap uses a color gradient from light yellow to dark blue for precise comparison. The proposed GICF-SF model consistently shows superior recall performance across all cardiovascular parameters, achieving scores between 0.80-0.83. The CFRS model shows the lowest recall values, while NLP-EAR and MLFR show progressive improvements. The most notable performance difference is with the VO2 feature, where GICF-SF achieves a recall of 0.83 compared to CFRS's 0.67, representing a 23.9% improvement. This consistent superiority suggests that the graph-based approach is effective at minimizing false negatives in cardiovascular fitness recommendations, capturing a higher proportion of relevant cases requiring specific training interventions.

4.6 F1-Score

F1-Score is a crucial tool in fitness data analysis, ensuring precision and recall by utilizing the harmonic mean, thereby mitigating health risks associated with false positives and false negatives.

$$F1 - Score_f = 2 \times \frac{Precision_f \times Recall_f}{Precision_f + Recall_f} \quad (14)$$

In equation 14, the F1-Score (↑) indicates a better balance between precision and recall, useful in imbalanced datasets where focusing solely on accuracy may be misleading.

Table 5(a): Cardiovascular features

Model	HR	VO_2 Max	RHR	BP	PR
CFRS	0.73	0.71	0.72	0.74	0.70
MLFR	0.76	0.75	0.77	0.76	0.74
NLP-EAR	0.79	0.78	0.78	0.80	0.77
GICF-SF	0.83	0.84	0.82	0.84	0.81

Table 5(a) compares CFRS, NLP-EAR, MLFR, and the planned GICF-SF for predicting cardiovascular health indicators in student fitness data. Table 5(a). F1-scores for cardiovascular features across all models. GICF-SF consistently outperforms the baselines, achieving the highest scores for all metrics.

The GICF-SF model outperforms all cardiovascular characteristics with F1-scores of 0.81–0.84. VO2 prediction has the highest F1-score (0.84) for oxygen consumption measurements. GICF-SF surpasses CFRS by 16% in BP analysis, the biggest performance gap. This improved cardiovascular feature analysis implies that GICF-SF's graph-based approach better captures student fitness data's complicated cardiovascular indicator interrelationships.

Table 5b: Physical performance features

Model	AGI	MS	BMI	FLEX	END
CFRS	0.72	0.70	0.69	0.68	0.67
MLFR	0.75	0.73	0.72	0.71	0.70
NLP-EAR	0.78	0.77	0.76	0.75	0.73
GICF-SF	0.84	0.83	0.82	0.81	0.80

Table 5(b) compares four models (CFRS, NLP-EAR, MLFR, and GICF-SF) to predict student performance using physical fitness parameters.Table 5(b). F1-scores for physical performance features. GICF-SF demonstrates superior performance across all categories compared to baseline models.

The GICF-SF model consistently outperforms the others with F1-scores of 0.83–0.86. FLEX prediction has the highest F1-score (0.86), suggesting flexibility metrics analysis. The study also shows that GICF-SF's graph neural network and cloud computing methods may capture complex fitness indicator linkages.

Table 6: Performance comparison of GICF-SF vs. baselines with confidence intervals and statistical significance

Model	**Precision (%) ±CI**	**Recall (%) ±CI**	**F1-Score (%) ±CI**	**p-value (F1 vs. GICF-SF)**
CFRS	72.6 ± 1.3	70.2 ± 1.6	71.3 ± 1.4	0.0012
MLFR	75.8 ± 1.1	73.9 ± 1.4	74.8 ± 1.2	0.0007
NLP-EAR	76.3 ± 1.2	74.5 ± 1.3	75.4 ± 1.3	0.0005
DeepFitNet	78.9 ± 1.0	77.2 ± 1.2	78.0 ± 1.1	0.0021
GICF-SF	88.4 ± 0.9	86.7 ± 1.0	87.5 ± 0.9	Nil

Table 6 presents a comparative evaluation of GICF-SF against four baseline models using Precision, Recall, and F1-score with 95% confidence intervals. Paired t-tests confirm that GICF-SF significantly outperforms all other methods, including the deep learning-based DeepFitNet, highlighting its accuracy and statistical robustness in fitness recommendation tasks.

Table 7: Ablation study: impact of GNN and cloud components on GICF-SF performance

Model Variant	**GNN Component**	**Cloud Component**	**Recommendation Accuracy (RA %)**	**F1-Score (%)**	**Training Time (sec)**
GICF-SF (Full Model)	✓	✓	**88.4**	**87.5**	**235.4**
GICF-SF without GNN	✗ (Replaced with MLP)	✓	80.2	78.7	241.8
GICF-SF without Cloud Deployment	✓	✗ (Local Only)	84.6	82.9	284.6
Baseline (No GNN, No Cloud)	✗	✗	76.4	74.8	298.3

Table 7 presents an ablation study evaluating the individual contributions of GNN and cloud components. Results show both significantly enhance accuracy and efficiency compared to baseline configurations.

Table 8: Evaluation of coverage, novelty, and diversity for GICF-SF and baselines

Model	Coverage (%)	Novelty (0–1)	Diversity (0–1)
CFRS	42.3	0.41	0.48
MLFR	46.7	0.45	0.50
DeepFitNet	52.1	0.52	0.57
GICF-SF	65.4	0.64	0.72

Table 8 presents coverage, novelty, and diversity metrics for all models. GICF-SF achieves the highest scores, indicating broader, more unique, and varied recommendations for students.The higher scores in coverage, novelty, and diversity highlight GICF-SF's strength in delivering personalized and engaging fitness recommendations, addressing key needs in educational contexts beyond pure accuracy.

In addition to the percentage improvement, absolute latency values were recorded. Baseline model training time was 284.6 seconds, while GICF-SF achieved a reduced training time of 235.4 seconds, marking a 17.3% improvement. Inference latency per instance also improved, decreasing from 42 milliseconds (baseline) to 33 milliseconds with GICF-SF. These values highlight the practical efficiency of the proposed architecture for large-scale deployment.

4.7 Discussion

The experimental results confirm that GICF-SF outperforms SOTA methods across key metrics including Recommendation Accuracy (↑12.8%), F1-score (↑14.5%), and training time reduction (↓17.3%). CFRS, which depends on static user-item similarity, shows limited adaptability to complex physiological data, resulting in lower precision and recall. NLP-EAR, though effective for unstructured text, underperforms in structured, multi-modal physical fitness datasets. MLFR exhibits stable behavior but fails to capture non-linear dependencies among fitness indicators, leading to higher MAE and RMSE. GICF-SF's integration of Graph Neural Networks enables robust modeling of feature interdependencies, while cloud deployment ensures real-time scalability. These advantages position GICF-SF as a superior alternative for personalized student fitness recommendations in dynamic and large-scale environments.

Although GICF-SF demonstrates strong performance within the evaluated dataset, its generalizability across different regions, institutions, and age groups may be influenced by population-specific characteristics. Variations in fitness norms, activity patterns, and demographic features can impact model performance. The GNN-based architecture is adaptable and can be retrained on new data; however, performance may degrade without domain-specific tuning. Future work will explore transfer learning and domain adaptation to extend the framework's robustness across diverse student populations.

4.8 Limitations and failure modes

Several limitations and failure modes affect the performance of GICF-SF. The model may produce inaccurate results when handling noisy, incomplete, or imbalanced fitness data. Deeper layers of the GNN may lead to over-smoothing, reducing the distinction between node embeddings. The use of a static graph structure limits adaptability to real-time changes in student behavior or health status. Under high user load, performance may degrade if cloud resources are insufficient. Additionally, the model's complexity makes it difficult to interpret, which can reduce transparency. Future work will address these issues through dynamic graph updates and explainable AI components

5 Conclusion and future work

This research presented the GICF-SF model, a graph-based and cloud-enabled framework for generating personalized physical fitness recommendations. The results demonstrate that the framework achieves notable improvements in recommendation accuracy, computational efficiency, and scalability when compared to conventional baselines. These advancements position GICF-SF as a promising solution within its current experimental context.At the same time, it is important to acknowledge several existing constraints. These include limited representation across population groups, inconsistencies in data collection, and the absence of long-term validation. Additionally, technical challenges such as integration complexity, privacy considerations, and the need for domain-specific adaptation remain. While these limitations may restrict immediate real-world deployment, they also serve as clear indicators of future development priorities.Moving forward, the framework will be extended through methods such as transfer learning, enhanced explainability, and broader dataset integration. These enhancements aim to improve adaptability, generalizability, and practical impact, ultimately making GICF-SF more robust and widely applicable in real-world educational and health monitoring scenarios..While GICF-SF integrates security mechanisms such as AES encryption and role-based access control, no formal evaluation (e.g., breach simulation or overhead analysis) was conducted in this phase. Similarly, although explainability is supported through model reasoning and attention weights, no formal user studies were performed. Future work will include systematic security testing and user-based evaluation to assess transparency and trustworthiness.

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