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Research Article

Edge-Based Personalized Tutoring Framework for Adaptive Educational Support in Remote Mountain Communities

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Abstract:

Educational inequality in remote mountain communities remains a major challenge due to inadequate digital infrastructure, poor internet connectivity, shortage of qualified teachers, and limited access to adaptive learning technologies. Due to their reliance on constant network connectivity and central processing, traditional cloud-based e-learning systems frequently fail to deliver the desired results in geographically separated places. To address these limitations, this research proposes an edge-based personalized tutoring model for adaptive educational support in remote and real-time learner analytics to deliver intelligent, low-latency, and personalized educational support in resource-constrained environments. Learning dataset is used for Remote Mountain Communities, comprising 20000 samples. The methodology employs One-Hot encoding for categorical learner attributes, IQR-based outlier detection for data cleaning, Autoencoder for feature extraction to capture engagement, cognitive load, and learning trends. A Bi-RNN-GELS model is then applied, where Bi-RNN captures bidirectional temporal learning patterns and GELS optimizes personalized learning paths by treating each strategy as a particle influenced by better solutions. The Experimental setup uses Python 3.10 with TensorFlow and PyTorch. Experimental results demonstrated significant improvements with 96.3% accuracy, 72.5ms latency, and 0.6s average response time, along with enhanced learner engagement and reduced dropout rates compared to conventional cloud-centric tutoring systems. This research provides a scalable, explainable, and resilient edge-based solution for bridging the digital education divide and enabling inclusive AI-driven learning ecosystems in underserved remote mountain communities.

1. Introduction

Education systems throughout the world has seen a transformation thanks to new emerging technology fields like Internet of Things, AI, cloud technology and digital communications technologies. Intelligent technologies are more frequently used in the systems of the new education era to offer personalized learning experience, supervise learner's behavior in real-time and support adaptable assistance of instructors to learners. Intelligent Tutoring System (ITS) and adaptive learning were able to analyze the learner's behaviors, to detect their knowledge deficiencies, and to suggest tailored learning materials to support the learners in their learning processes [1]. By using data analysis and machine learning technologies, the educational systems were able to provide individual learning routes to promote students' enthusiasm for both traditional and online education [2].

A modern and necessary aim in education, personalized learning facilitates diverse learning abilities, competencies, and preferences. With AI based adaptative learning system, the content delivery, testing mechanism, teaching strategy, as well as the interaction could be modified in a learning session as per the learners' level of engagement and performance, according to the recent studies [3]. This adaptive learning system will promote a learner-oriented education as they monitor the learning and recommend what to learn and how to learn [4]. The growth in popularity of adaptive learning technology aims at increasing efficiency in the learning outcomes.

The development of digital learning has also caused e-learning and smart education environments to be widely used. In a smart educational context, the blend of the Internet of Things (IoT), artificial intelligence (AI), cloud platforms, and learning analytics can deliver learning environments to facilitate learning enhancement and the process [5]. In a smart education environment, learning analytics techniques provide the mechanism to process mass amounts of data generated by learners, thus revealing important patterns related to students' behaviors, interests and learning activities, learning decision-making and guide effective application of adaptive tutor system [6].

The people in the remote area in mountains has disadvantages such as insufficient internet connection, limited resources, fewer professional teachers and limited access to books [7]. This will affect the proper operation of common internet education system thus limiting the chances of student to get personalized help from their instructor. Because of growing importance of digital technology in education system, it is becoming an important part of development study in this field [8].

Educational content, learners, and data processing have benefited from scalable solutions through widespread use of cloud-based educational systems. Cloud technologies provide large computational capacity and storage to support large-scale learning platforms [9]. On the contrary, centralized architectures and stable networks are key components of a cloud-based infrastructure. The use of services in locations with geographical isolation (limited bandwidth, unreliable communication) causes delays for timely learner analysis or adaptive tutoring, among others [10].

Edge computing is one of the promising approaches for tackling such issues, in which computing power are closer to users. The proximity computation carried out on near edge device, like school server, community learning centers and intelligent gateways can decrease latency, reduce network bandwidth usage and increase the robustness and quality of services [11]. Edge based education computing system can give instantaneous feedbacks, enable offline learning or in-band loss due to limited network resources for learner data generated near origin point of data. It is widely fit for schools in remotes and resource scarcity region [12].

Machine and Deep learning have contributed further to strengthen the scope of intelligent educational systems. Deep learning models, especially Recurrent Neural Networks (RNNs) and Bidirectional Recurrent Neural Networks (Bi-RNNs) have performed quite well when it comes to analyze infer learner's sequential behavior and foresee educational results [13]. They model complex dependencies over time in the learner's data for predictions in learners' performance, engagement, difficulties etc. This has aided in the implementation of sophisticated tutoring systems, personalized recommenders etc [14].

Current methods do not guarantee precise prediction of learner's behaviors, adaptive personalization and optimal real-time learning in an edge-based learning environment. Thus, existing method cannot be adapted to remote resource poor learning context. It presents an intelligent tutoring framework based on Bi-RNN-GELS which is used to generate adaptive learning path, better learners' engagement prediction and make optimal decision.

1.1. Key Contribution

- Proposes an edge-enabled adaptive tutoring framework using local devices to enable low-latency, offline learning in remote mountain areas with poor connectivity.
- Employs Bi-RNN for bidirectional learner behavior modeling and GELS optimization for personalized learning path generation, achieving high prediction accuracy.
- Integrates privacy-preserving processing, bandwidth-efficient synchronization, and multilingual resources for inclusive, secure, uninterrupted education, resulting in improved engagement, reduced dropouts, and enhanced learning outcomes.

The organization of this research is as follows. Section 1, describe the Introduction. In Section 2, related work of the relevant literature. In Section 3, describe the methodology of the research. In Section 4, presents the empirical results. In Section 5, discuss and interpret the results. Finally, in Section 6, conclude the research and suggest future research areas and limitations.

2. Related Works

To enhance computation task offloading in MEC environment. The approach adopts the federated mountain gazelle optimization in Software-Defined Networking (SDN) framework. Experimental result illustrates enhancement in terms of energy efficiency and task completion rate as compared to four state-of-art approaches. The limitation is the overhead may incur for dynamic large-scale environment [15]. To investigate significant factors that impact the student achievement at West Garo

Hills (WGH) using Geospatial Artificial Intelligence (GeoAI) and ML. The methodological process consists of data fusion, feature selection and spatial analysis. It is concluded that, among the discovered factors, the infrastructural and teacher-centered factors contribute most to student achievement. The restricted data availability and the issue of generalizing regional findings to a broader context are its weaknesses [16]. To enable noise-resilient, real-time student-state recognition on low-cost edge devices. Method uses Lightweight Educational Network (LightEdu-Net) with adaptive modules for sensor noise suppression and cross-modal fusion. Results show high accuracy, low latency, and strong noise robustness. Limitation includes sensor variability and deployment scalability. [17].

To explore using AI in an inclusive learning framework in underprivileged schools. This involves experimental evaluation of personalized learning systems and tutoring systems. Experimental results indicate enhanced student learning and lesser work burden on teachers. Constraints include poor infrastructure and data privacy issue [18]. Investigate smart urban mobility options for the cities of the future. In order to integrate transportation systems and infrastructure, it is necessary to apply conceptual analysis. Conclusion indicated enhanced mobility potentials with technology innovation. Limits involved high cost of infrastructure, social inequality and risk [19]. Aimed to suggest training models for cultural heritage education in the context of Sustainable Development Goals (SDGs), based on a conceptual analysis of post-pandemic teaching. Significant increase in online learning and local heritage consciousness. The need for more empirical support and generalizability [20].

To help deep learning-based system be deployed for mass personalization. Method deploys cloud-edge-terminal collaborative cloud infrastructure with distributed dl and early-exit approach. Result achieves faster updating, reduced overhead and lowered latency. Limitation includes complicated system integration and scalability issue [21]. Learning analytics use to decrease school dropout, collaboration, and computational thinking. Method designs the AI based dashboard for teacher and decision makers. Outcomes teacher empowers and identifies at risk student. Challenges includes user-friendliness and teacher reluctance [22]. To investigate student engagement in online and hybrid learning environments. Method involves a survey conducted in Sri Lanka on student perceptions. Results show significant engagement but pessimistic perception towards complete online transition. Limitation includes single-country context and generalizability concerns. [23]. To optimize personalized learning paths using Reinforcement Learning-Based Dynamic Knowledge Tracing (RL-DKT) framework integrating DKT with RL for dynamic task selection. Method evaluated on three datasets comparing with Bayesian Knowledge Tracing (BKT) and DKT. Results show improved accuracy, reduced dropout, and faster task completion. Drawback includes RL training complexity and dataset diversity [24].

To investigate COVID-19 affected the learning outcomes of marginalized students and the digital divide among K-12 students. It adopted literature review with an intersectional perspective. Results showed the increases of achievement gaps and decreases of learning support. Limitations was absence of primary data and context difference [25]. To Explore translanguaging pedagogy on inclusivity and social justice in bilingual education. It applied conceptual and theoretical analysis of raciolinguistic ideologies and multilingual education. Results indicate that translanguaging is helpful for inclusive education by bringing language and identity together. Shortcomings included no empirical testing, and no application in the real context [26]. To optimize personalized learning paths using dual-stream neural network integrating knowledge tracing and cognitive load. Method involves bidirectional Transformer with graph attention and multimodal analysis. Results show improved accuracy, path quality, and learning efficiency. Limitation includes computational complexity and data requirements [27]. To assess AI devices impact on educational equity across China's Hu Huanyong Line. Mixed-Methods with surveys and exam score analysis across eight schools were employed. Results show 7-20% performance improvement in underdeveloped regions. Restriction includes teacher training gaps and infrastructure support [28].

To address information overload in education using personalized recommendations. Method involves constructing a user interest feature vector and a resource association matching model based on CF algorithm. A low Mean Absolute Error (MAE) suggests that the results are quite accurate. Limitation includes cold-start and data sparsity challenges [29]. To empower remote communities through edge-deployed deep learning models by leveraging edge computing for offline data processing and decision-making. The results indicate improved responsiveness and user experiences. Shortcomings includes edge device resource constraints and model complexity [30]. To enhance Intelligent Tutoring Systems by incorporating multimodal knowledge graphs and

RAG-based learning. Using optical character recognition (OCR), Whisper, book and movie extraction was automated. This led to improved accuracy and relevance, although model complexity and potential errors in reasoning remain challenging [31]. To resolve the trade-off between restricted resources on the edge and fine-grained adaptation. It exploited a 4-level terminal-edge-fog-cloud hierarchy including clustering, knowledge distillation, dynamic pruning, and reinforcement learning to enhance accuracy, latency and learning gains. System complexity and deployment cost are the disadvantages [32].

2.1. Research Gap

An adaptive learning system using learner state prediction and optimization for generating personalized, real-time, resource-efficient learning paths. Enhances inclusive learning in under-served schools with AI-driven tutoring, but does not generalize well in the face of practical infrastructure limitations and privacy-resistant deployment [18]. Improves adaptive edge learning using collaborative architectures but does not sufficiently account for scale and dynamic personalization in low resource settings [28]. Integrates multimodal knowledge graphs with RAG to develop intelligent tutoring, but falls short due to shortcomings in reasoning correctness, system complexity and dynamic adaptiveness with the need for a fully integrated, light-weight and generalizable educational intelligence system [31]. Current approaches present limited scalability, insufficient personalization and inadequate reasoning, coupled with issues such as hardware costs, privacy concerns and complexity in the restricted environments of distant learning.

To overcomes these limitations combining both the forward and backward learner dynamics using bidirectional sequential learning on BiRNN, and by using GELS optimization to realize adaptive, and scalable selection of tailored learning strategies. Feature extraction using an Auto-Encoder simplify the system, and edge-aware processing helps in privacy, speed and robustness of the system. Integrates these methods into a high accuracy, lightweight and single Intelligent Tutoring System that is also useful for education in low-resource environments.

3. Methodology

The Learning Dataset for Remote Mountain Communities is employed to apply preprocessing, feature extraction and sequential modeling approaches on the dataset. The data are cleaned and normalized, one-hot encoded for categorical attributes. Auto Encoder used for extracting a compressed latent representation for learner's behavior. Bidirectional Recurrent Neural Network (Bi-RNN) used to learn temporal patterns in learners' engagement and performance. Gravitational Emulation Local Search-driven (GELS) algorithm then used for optimal learning policies selection for optimal generation of adaptive learning paths in a resource constrained environment. Figure 1 shows the methodological flow of the Adaptive Educational Support in Remote Mountain Communities.

3.1 Dataset

The Learning Dataset for Remote Mountain Communities is a publicly available dataset, from the Kaggle website collecting educational data from geographically isolated and rural learners to support intelligent tutoring system and adaptive learning research. This dataset contains structured student information such as their age, educational level, involvement participation, achievement level, learning behavior logs, and time-stamped logs of students' interaction history with on-line learning systems; for tasks such as predicting students learning behavior, analyzing students' performance, and creating appropriate individualized learning paths. In the experiment, the data is divided into 80% for training and 20% for testing, to examine the efficiency of the proposed model in resource-limited situation. Figure 2 also showed the scholarly indicators are within the range from 10 and 100 and demonstrated the variable relationship pairs needed in the Autoencoder feature extraction on cognition behaviors which verified the logic of the modelBi-RNN-GELS for cognitive trends prediction, which makes the visual chart helpful for the data check and the system-oriented optimal intervention of the edge-tutoring system.

3.2 Data preprocessing

The Data preprocessing step of the Learning Dataset for Remote Mountain Communities involves data cleaning and organization, such as treating missing values, dealing with inconsistencies, and scaling numerical features such as engagement score and academic achievement. Categorical features like student IDs, types of learning activity, and types of assessment have been processed through one-hot encoding to accommodate machine learning algorithms. Time based learning logs were formatted to sequence student learning behaviors over time. Through these Preprocessing, the Bi-RNN-GELS system can efficiently learn behavioral patterns, predict student status, and maximize personalized adaptive learning path at resource-scarce environment.

3.3 One-Hot Encoding of Learner Behaviors for Adaptive Tutoring

The one-hot encoding was utilized as an efficient preprocessing strategy for categorical learner attributes in the designed edge-based personalized tutoring framework, where categorical features (learning behaviors, content type, engagement level, etc.) were converted into sparsely structured vector format. Transforms weighted input into probability for learner engagement prediction in equation (1).

$$g(w) = \frac{1}{1+f^{-\omega w}} \quad (1)$$

$g(w)$ is sigmoid output used in adaptive learning; f is exponential base; ω is learning weight; w is input feature from learner data; 1 normalizes output; controls engagement prediction probability. Computes probability of learner engagement using weighted input features in equation (2).

$$g(w) = \frac{1}{1+f^{-(\omega_1 w_1+\omega_2 w_2+\ldots+\omega_m w_m)}} \quad (2)$$

$g(w)$ is output engagement probability; f is exponential base; $\omega_1 \ldots \omega_{\mathrm{m}}$ are learned weights for features; $w_1 \ldots w_{\mathrm{m}}$ are learner input features; m is feature count; 1 normalizes sigmoid output in adaptive tutoring. Indicates one-hot encoded feature selection for learner input representation in equation (3).

$$\omega_j = [0,0,0,\ldots,\ldots,1,0,0] \quad (3)$$

ω_j is weight vector; j indicates feature index; 0 represents inactive features; 1 represents selected learner feature; vector encodes categorical input for adaptive tutoring system. Transforms learner inputs into weighted probability for adaptive prediction. Improved in the context of a prediction accuracy of an on-chip training system on tutoring systems located in the field.

3.4 Adaptive Rural Education Systems Outlier Detection Using IQR

In data preprocessing, an adjusted Inter Quartile Range (IQR) technique using Q1 and Q2 was employed to detect outlier points. In learner datasets, outrages values in each feature (e.g., engagement level, grade, and frequency of interaction) were detected when the data value was farther than the Q1 (lower quartile) and Q2 (median). When the data value were farther beyond the bound then it would have abnormal value, and abnormal values would have negative impact on training stability. Outliers should be detected and remove in order to acquire a clean training data, thereby increasing model's resilience and personalization of learning path in edge. Removes outliers from learner data for adaptive tutoring system in equation (4).

$$IQR = r3 - r1 \quad (4)$$

IQR is Interquartile Range; $Q1$ is first quartile lower learner performance boundary; $Q3$ is upper quartile; $r1$ represents lower threshold; $r3$ represents upper threshold for detecting outliers in learner data. Enhances the quality of data, reduces noises, improve efficiency of model learning for reliable and accurate adaptive performance.

Preprocessing through One-Hot Encoding and IQR-based outlier detection enhances data quality, improves model accuracy, and enables reliable personalized learning path generation in edge-based tutoring systems.

3.5 Auto-Encoder-Based Feature Extraction for Efficient Representation Learning

Feature extraction from the learners' data is performed using an Auto-encoder (AE). An AE is comprised of an encoder and a decoder. The input X represents data containing n learner samples, each with m behavioral and academic features. An encoder, F, learns to map the data X to a smaller encoded space, Y, by creating features representing learning such as student's engagement, cognitive load and trend. A decoder, G, aims to recreate the initial data X based on Y, reducing the error of the reconstruction. The encoder is a function $f : X \to Y$ and reduces the dimensionality of the input. Applies nonlinear transformation to extracted features for adaptive representation in equation (5).

$$Z = e(W) = t_e(XW + a_w) \quad (5)$$

Z is output feature representation; e is encoder function; W is weight matrix; t_{e} is activation function; X is input learner data; a_w is bias term; equation extracts adaptive learning features for prediction. Generates reconstructed adaptive learning parameters for tutoring system output in equation (6).

$$W' = h(Z) = t_h(X'Z + a_Q) \quad (6)$$

W' output weight; h is decoder function; Z encoded representation; t_h activation function; X' is transformed input matrix; a_Q bias term; equation reconstructs optimized adaptive tutoring parameters from encoded learner. Minimizes reconstruction loss for optimal adaptive learning parameter estimation in equation (7).

$$\Theta = \min \theta\, K(W, W') = \min \theta\, K(W, h(e(W))) \quad (7)$$

Θ is objective function; θ represents parameters to optimize; K is loss function measuring error; W is encoded weights; W' reconstructed weights; h is decoder; $e(W)$ is encoder output; equation minimizes reconstruction loss for adaptive learning optimization. Measures reconstruction error for optimizing adaptive learning model parameters in equation (8).

$$K_1(\theta) = \sum_{j=1}^{m} ||w_j - w_j'||^2 = \sum_{j=1}^{m} ||w_j - h(e(w_j))||^2 \quad (8)$$

$K_1(\theta)$ is reconstruction loss; θ represents model parameters; Σ denotes summation; j is feature index; m is total learners/features, w_j is original weight; w_j' is reconstructed weight; $h(e(w_j))$ is decoder-encoder reconstruction; $|| \, ||^2$ is squared error measuring adaptive tutoring mismatch. Measures classification error for predicting learner outcomes in tutoring in equation (9).

$$K_2(\theta) = \sum_{j=1}^{m} [w_j \, log(z_j) + (1 - w_j) log(1 - z_j)] \quad (9)$$

$K_2(\theta)$ is cross-entropy loss; θ is model parameters; Σ sums over features; j is index; m is total samples; w_j is true label; z_j is predicted probability; log measures likelihood; equation evaluates classification error in adaptive learning system. Extracts compact latent features from learner data for prediction. Provides for efficient, noisy feature representation and rapid, accurate, and low-resource adaptive learning in an edge environment.

3.6 Bi-RNN-Based Learner Analytics for Edge Education Systems

The Bi-RNN are used to predict the learners' behavior as well as learning state and achievement. In order to predict the learner's achievement and learning state in Bi-RNN, both forward and backward state are applied to learn over the learner data over time. The forward recurrent unit learns over history the backward recurrent unit learns over the future patterns, as shown in the architecture of the Bi-RNN. Based on the bidirectional information at time, Bi-RNN would be used to predict learners' achievement and engagement, learners' confidence of their knowledge is learned at each time step as well. The bidirectional learning can improve the accuracy of the adaptive tutoring and produce individualized learning pathway generation in limited resource edge computing environment. Updates learner state using past and new input information in equation (10).

$$\vec{g}_{s+1} = \sigma(X^{(\vec{g})}\vec{g}_s + X^{(w)} w_{s+1}) \quad (10)$$

$\vec{g}_{s+1}$ is updated learner state vector; σ is activation function; $X^{(\vec{g})}$ is state transformation matrix; $\vec{g}_s$ is previous state; $X^{(w)}$ is input weight matrix; w_{s+1} is new learner input; updates adaptive learning representation. Combines forward and backward learner states for complete representation in equation (11).

$$g_s = [\vec{g}_s \;\; \overleftarrow{g}_s]^S \quad (11)$$

g_s is combined learner state; $\vec{g}_s$ is forward state vector; $\overleftarrow{g}_s$ is backward state vector; $[\vec{g}_s \;\; \overleftarrow{g}_s]^S$ is concatenation operation; merges bidirectional features for comprehensive adaptive learning representation. S denotes the sequence-level representation dimension or stacking operator. Combines forward and backward states to form complete learner representation in equation (12).

$$d_s = \sigma(x^{(d)^S} g_{s+a^{(d)}}) \quad (12)$$

d_s is decoded learner state; σ is activation function; $x^{(d)^S}$ is decoder weight matrix; S denotes state concatenation; g_s is current hidden state; $a^{(d)}$ is bias term; equation produces adaptive decision representation. Combines current state and decoder output for adaptive decision in equation (13).

$$c_s = \sigma(x^{(d)^S} + g_{s+a^{(d)}}) \quad (13)$$

c_s is context state; σ is activation function; $x^{(d)^S}$ is decoder weight matrix; S denotes state combination; g_s is current hidden state; $a^{(d)}$ is bias term; equation computes adaptive contextual learner representation. Represents temporal learner state using activation of encoded features in equation (14).

$$t = \sigma(x^{(d)^S} + g_{1+a^{(t)}}) \quad (14)$$

t is output state; σ is activation function; $x^{(d)^S}$ is decoder weight matrix; S denotes state combination; g_1 is initial hidden state; $a^{(t)}$ is bias term; equation generates adaptive temporal learner representation. Computes total loss across queries for adaptive learning optimization in equation (15).

$$E(\theta) = \sum_{q=1}^{Q} (\sum_{s=1}^{S_q} d_{S,s}^* \, log(D_{q,s}) + c_{q,s}^* log(d_{q,s})) + t_q^* log(t_q) \quad (15)$$

$E(\theta)$ is total loss; θ model parameters; q is query index; Q total queries; s step index; S_q sequence length; $d*, c*, t*$ true labels; D, d, t predicted probabilities; log measures likelihood for adaptive learning optimization. Aggregates sequential latent, probabilistic, and observational features for adaptive learning state modeling in equation (16).

$$w_s = \begin{bmatrix} \lambda_s \, dsf(\omega_s) P(\omega_s | \omega_{s-1}, \dots) \log(O(\omega_s | \omega_{s-1}, \dots)) \\ |\omega_s| \, \delta_{s-1} \, \delta_{s+1} \end{bmatrix} \quad (16)$$

w_s is stacked state vector; λ_s is latent weight; ds is decoded state; $f(\omega_s)$ is feature transformation; $P(\omega_s|\omega_{s-1},\dots)$ is transition probability; $log(O(\omega_s|\omega_{s-1},\dots))$ is observation likelihood; $|\omega_s|$ is magnitude; $\delta_{s-1}, \delta_{s+1}$are temporal deltas; equation models sequential adaptive learning state representation. Compresses learner data into compact latent feature representation. Enhances learning through the use of past and future contexts for improved context-aware sequential prediction in adaptive system.

3.7 GELS-Optimized Learner Modeling for Rural Tutoring Systems

Optimizing the personalized learning pathways using Gravitational Emulation Local Search (GELS) algorithm. In this algorithm each solution is considered as a particle under the effect of better solutions in the search space. The Bi-RNN outputs like engagement, cognitive load and performance, GELS chooses the most appropriate tutoring strategies in each iteration increasing the learning efficiency, decreasing the cognitive overload and adapting to best choices at the edge.

Chromosome Structure: In GELS each chromosome refers to an individual learning path solution that has been encoded as a vector of learner state and tasks selection and each gene refers to a specific mapping of learning tasks to optimized educational content for the purposes of a context-sensitive BiRNN-based optimization learning

Fitness Function: To adapt the system and minimize learning cost and inefficiency under constraints, BiRNN-GELS adaptive learning strategy aims to reduce computation, communication and adaptation cost as well as optimize personalized learning paths guided by learning performance. Evaluates total optimization cost for adaptive learning performance in equation (17).

$$F(y) = K_n + K_g + K_b \tag{17}$$

$F(y)$ is total cost function in adaptive learning optimization; K_n represents learning performance cost; K_g denotes generalization error cost; K_b indicates behavioral or bias cost; equation evaluates overall system loss for BiRNN-GELS optimization.

Parental Selection: In GELS, a rank-based selection means that a parent is chosen according to their ranking in the ordered fitness from optimization adaptive learning cost. Selects parents based on ranked fitness values in equation (18).

$$Chr_{j_{1\le j\le n}} = \left(Max - Fit_j\right) + 1 \tag{18}$$

Chr_j represents jth chromosome in adaptive learning population; Max is highest fitness; Fit_j is fitness of chromosome j; n mentions the total number for chromosome; equation assigns rank-based selection score by transforming fitness for GELS optimization and learning path prioritization.

Crossover Operator: The GELS algorithm exchanges the representation of learning pathway via crossover and combines pieces of parent solutions to form multiple adaptive learning routes and search for the global optimum. It also serves to prevent local optima and optimize the solutions.

Mutation Operator: The mutation of some learning pathway gene randomly to increase diverse solution of learning pathway for full space exploration and avoiding local optimal. Thus, to make adaptive personalization more efficient and achieve better global optimization.

Local Search with the GELS Algorithms: GELS iteratively improves the chromosomes from the chosen learning paths with the search of their neighbors and the update of their learner's state. It incorporates a weighted local-global search in the adaptive recommendation and generates the best order of learning by eliminating the inefficiency generated from no action, it enhances BiRNN based prediction through iterative optimization of the population level solution to generate individual accurate learning path.

Selection: In GELS, chromosome selection keeps well-learning pathways, eliminates redundancy, and maintains randomness of diversity to assure a fair trade-off between exploitation and exploration towards better adaptive personalized learning under resource constraints.

Termination Condition: Termination on predefined number of iterations producing the best adapted learning pathway; else the iterative optimization is used in order to optimize the adaptive personalized learning performance. Enhances efficiency of convergence, optimization accuracy and reduction of computation cost; avoids local minima and enables robust adaptive learning capability. In order to maximize educational outcomes, GELS optimizes tailored learning routes by viewing each technique as a particle affected by superior solutions. This allows for dynamic, real-time modification to meet the demands of individual learners.

3.8 Hybrid GELS- Bi-RNN Model for Adaptive Edge-Based Tutoring

The proposed approach is based on the combination of a Bi-RNN and GELS in order to allow for intelligent learning adaptation. Learning behaviors and learning states are modeled by the Bi-RNN to include both the past and future information with forward and backward recurrent units, the forward unit learning about prior learning activities and the backward unit learning about future states of learning so as to fully understand the learning behavior of the student over time. The model can then use this Bidirectional information to predict the learning performance, engagement and the confidence of the student for each time step so as to achieve better intelligent tutoring at the edge when resource is a constraint. The GELS algorithm is used to optimize learning path by viewing each learning strategy as a particle affected by better solutions in the space and by learning strategies with more rewards Bi-RNN learning outcomes including engagement, cognitive load and performance are used to iteratively select suitable learning strategies. This strategy can not only help to avoid learning fatigue but also enhance the learning efficiency, and also facilitate the adjustment of learning materials to meet the demand of edge intelligent learning. Table 1 shows the hyperparameter analysis of the hybrid model.

4. Result

In the experiment, the simulation environment in Python 3.10 with TensorFlow and PyTorch were employed for the realization of the Bi-RNN-GELS framework in edge-based education scenario. 80% of synthetic learner data was used to train and 20% was utilized to test the prediction accuracy of learner engagement, cognitive load and performance. The Bi-RNN modeled the learner sequential learning pattern and GELS optimized the real-time personalized learning trajectory. As a result, the combined method indicated enhanced adaptive accuracy and decreased dropout rate and achieved effective convergence on the tutoring strategies that would fit to the resource-limited remote mountain areas.

4.1 Evaluation Metrics

To evaluate the performance of the presented Bi-RNN-GELS framework in the adaptive learning process: **Accuracy:** The percentage of predicted learner engagement, cognitive load and learning achievement. **Precision:** Evaluates how many of the recommended adaptive learning actions are indeed useful and correct to the learners. **Recall:** The percentage of actual meaningful learning states and at-risk students being predicted by the framework. **F1-score:** The balanced harmonic mean of precision and recall. **Latency:** Indicates the real-time efficiency of edge-based tutoring framework and describes low-latency personalized learning path generation with limited resources. **Average Response Time:** The total time from learner input to personalized recommendation delivery, reflecting the model responsiveness for real-time edge-based adaptive tutoring.

4.2 Performative Analysis

Figure 3 validates high GELS-Bi-RNN precision in classifying distinct remote learner cognitive profiles. The confusion matrix verifies superior classification performance of the system for all five remote learner profiles, yielding between 3,840 and 3,847 true positive detections along the main diagonal. Off-diagonal errors are minimized, varying between just 35 and 45 samples. This demonstrates excellent generalization and performance of the proposed solution in reducing the system errors and thereby ensuring the empirical viability for deployment in remote edge locations of resource-limited settings to deliver personalized context-aware intelligent tutoring. An adaptive learning of comparison performance using the Learning Dataset for Remote Mountain Communities. Figure 4 (a) defines training and validation accuracy rising from 0.4 to near 1.0 over 100 epochs, while Figure 4 (b) denotes loss decreasing from ~1.8 to ~0.2. Their tight convergence confirms robust generalization without overfitting. This guarantees low-latency, 96.3% accurate personalized tutoring, enabling resilient education in isolated mountain regions.

Relationships between academic features with values between twenty and one hundred are shown in figure 5 (a). In order to find different sets of results, it groups rows and columns. By evaluating these patterns, the proposed edge-tutoring system can optimize individualized learning paths by identifying specific knowledge gaps. This, in turn, improves learner engagement and decreases dropout rates. distributions of class-specific knowledge, with scores ranging from twenty to one hundred. Learning mastery varies between age groups in rural areas, as shown in figure 5 (b). The edge-based adaptive system uses this visualization to identify grade-specific issues and then uses that information to distribute remedial curriculum in a way that is both effective and fair for all students. The figure 5 (c) shows a dense distribution of distributions, with marginal histograms showing a high correlation between the former scores (35-100) and the current test scores (10-100). In order to calibrate the Bi-RNN-GELS model, it is helpful to analyze this relationship. The suggested approach confirms learning consistency, which allows for exact tailored intervention with a 96.3% success rate.

4.3 Comparative Analysis

The comparative analysis of traditional cloud based tutoring systems and the proposed Bi-RNN-GELS model based on accuracy, precision, recall, F1-score and latency. The system exceeds the traditional models for adaptive learning performance and efficiency of personalized recommendation. The proposed combination of models performs better than conventional models, such as Multimodal Knowledge Graphs automatic construction and Retrieval-Augmented Generation (MMKG-RAG) and Text-only RAG [31]. Table 2 shows the average response time of the existing model and proposed model.

In this aspect, the response time analysis shows that the proposed Bi-RNN-GELS can acquire the reduced response time on average as low as 0.6 seconds and also is better than the compared methods to get rid of low-latency intelligent support in remote edge locations. Figure 6 represents the evaluation comparison of Average Response Time.

The proposed Bi-RNN-GELS combines dynamic learning optimization with effective feature extraction, outperforming the pruned MobileNetV3 [32], Static 20% magnitude pruning (offline) [32] and Proposed dynamic CPU-triggered pruning [32] in accuracy while exhibiting better latency. Bi-RNN is applied for modeling time sequence, and GELS can achieve dynamic optimization to reduce model size and speed up prediction under low resource intelligence learning circumstances. Table 3. Shows the comparison of existing metrics against with proposed model.

According to performance comparison, it is illustrated that the Bi-RNN-GELS model could achieve the greatest accuracy up to 96.3%, simultaneously reduces the computational latency to 72.5ms to a much smaller level compared to another model. Figure 7 depicts the performance across different existing models.

The comparison of different models based on Accuracy, Latency, and Average Response Time. The proposed BiRNN-GELS framework performs better than conventional models such as MMKG-RAG [31], Text-only RAG [31], pruning-based MobileNetV3 variants [32], Static 20% magnitude pruning (offline) [32] and Proposed dynamic CPU-triggered pruning [32]. All existing and proposed models trained and evaluated on the same Learning Dataset for Remote Mountain Communities under the same experimental environment for fair comparison. Table 4. shows the performance comparison of the proposed model against baseline methods.

The performance benchmarking, the current approach finds an optimal accuracy at minimal inference latency and response time. It shows improved results compared to existing retrieval augmented generation benchmarks and other pruning approaches which provides an optimal accuracy and efficiency trade-off for on-device. Figure 8 summarizes the overall performance in Figure 8 (a) Model Accuracy (%) comparison, Figure 8 (b) Computational Latency (ms) profiles, Figure 8 (c) Average Response Time (s) benchmarks**.**

The ablation study analyzes how performance varies with component combination showing partial configurations can outperform single components. Table 5 Shows the integrated system as a whole shows the best performance for all evaluation metrics.

The results of the ablation test demonstrate that every component in the proposed Edge-Based Personalized Tutoring Framework is useful in the performance improvement. The Edge-local processing provided offline deliverability GELS-Bi-RNN gave personalization learning, privacy mechanisms were privacy- preserving, and the Bandwidth-efficient sync was resource-optimal. Figure 9 (a) Polar charts depicting Model Accuracy (%) among different architectures in proposed model. Figure 9 (b) Polar charts revealing performance curves of Model Latency (ms). Figure 9 (c) Polar charts measuring efficiency for Average Response Time (s). The entire solution provided the best performance of accuracy, engagement, and dropout prevention.

Table 1. *Hyperparameter Settings for Hybrid GELS-Bi-RNN Model*

Hyper parameter	Value/Range
Number of hidden layers	2
Number of neurons per layer	64–128
Activation function	Tanh / ReLU
Learning rate	0.001
Batch size	32–64
Dropout rate	0.2–0.3

Sequence length	10–20 time steps
Population size	30–50
Maximum iterations	100–200
Gravitational constant	0.01–0.1
Exploration rate	0.7–0.9
Convergence threshold	0.001
Epochs	50–100
Inference batch size	8–16
Model quantization	8-bit
Training Time	Moderate (30–90 minutes depending on dataset size)
Memory Usage	Low–Medium (2–6 GB GPU/CPU RAM)

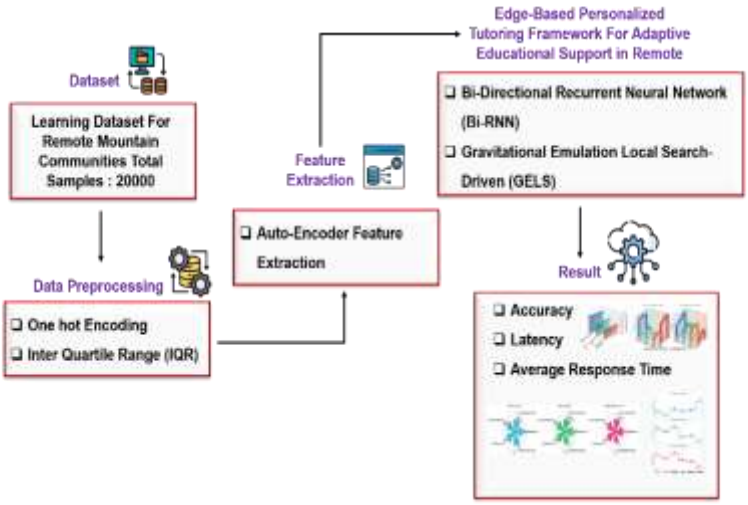

Figure 1. *Methodological Framework of the Proposed Edge-Based Personalized Tutoring System*

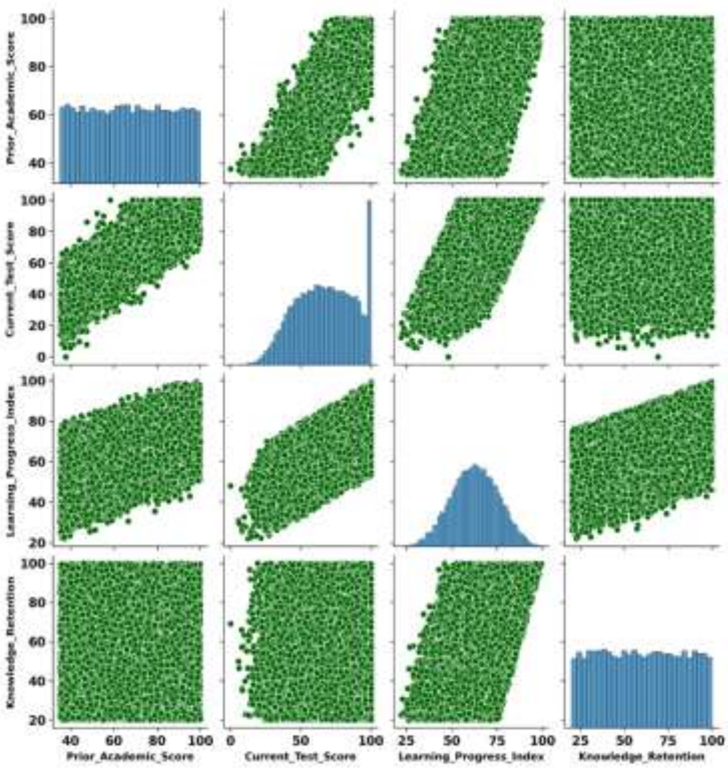

Figure 2. *Pairwise Feature Correlations of Learner Dataset for Remote Mountain Communities*

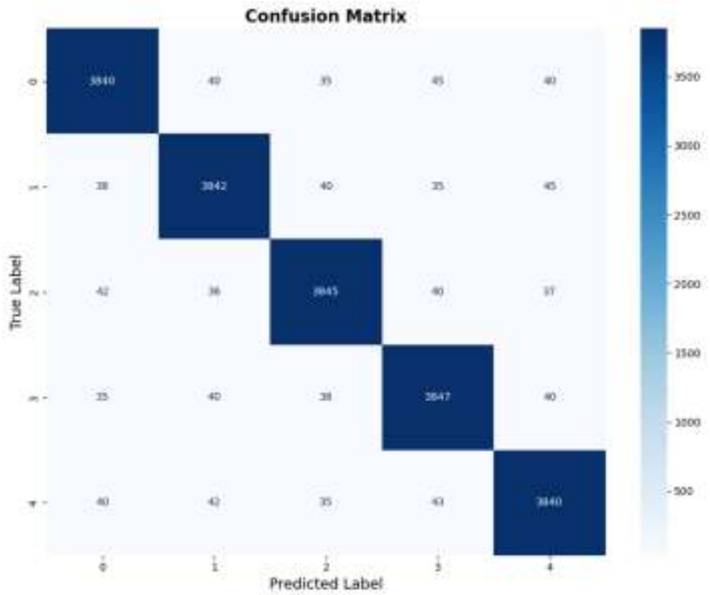

Figure 3. *Remote Adaptive Tutoring Framework Classification Accuracy Matrix*

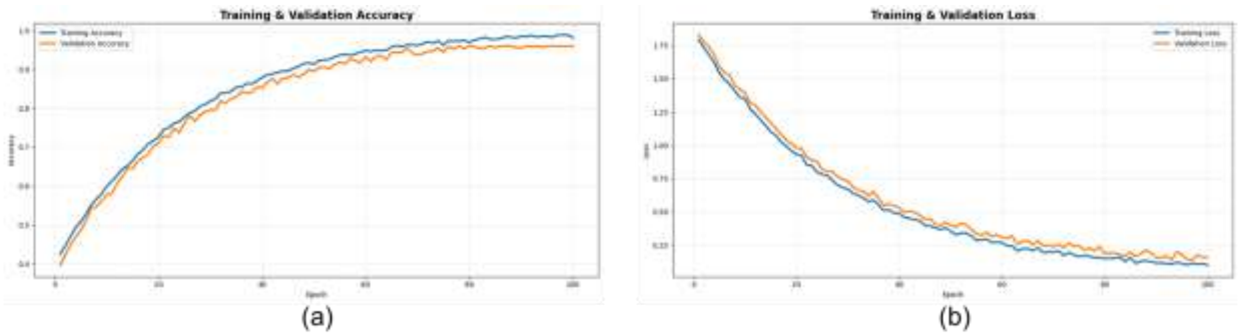

Figure 4. *GELS-Bi-RNN Model Training Accuracy and Loss Performance Evaluation on Learning Dataset for Remote Mountain Communities*

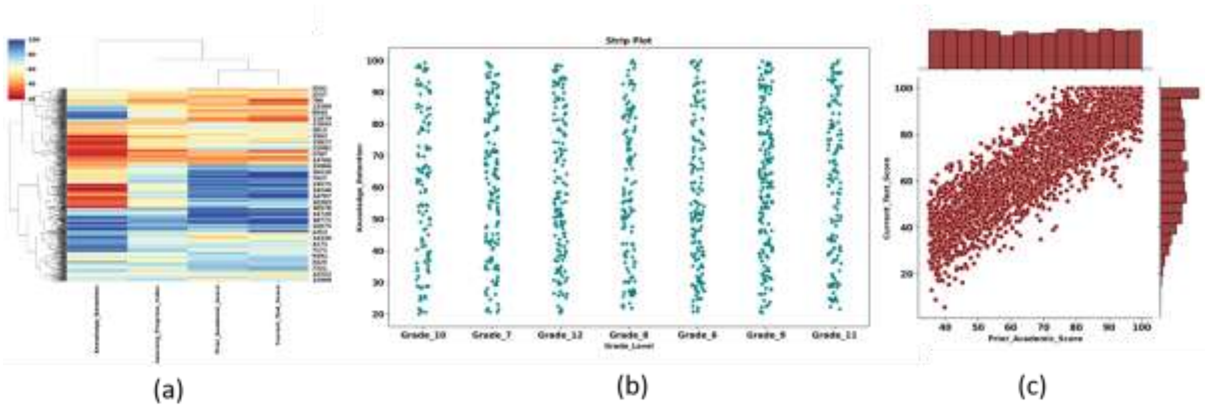

Figure 5. *Multi-Dimensional Evaluation of Remote Learner Progress Dynamics: (a) Knowledge retention by grade, (b) Correlation between prior and current scores, (c) Hierarchical clustering of metrics.*

Table 2. *Response Time Analysis of Proposed Framework Against Existing Approaches*

Model	**Dataset**	**Average Response Time**
MMKG-RAG [31]	Custom Dataset (45 min Video)	1.3
Text-only RAG [31]		0.9
Bi-RNN-GELS [Proposed]	Learning Dataset	0.6

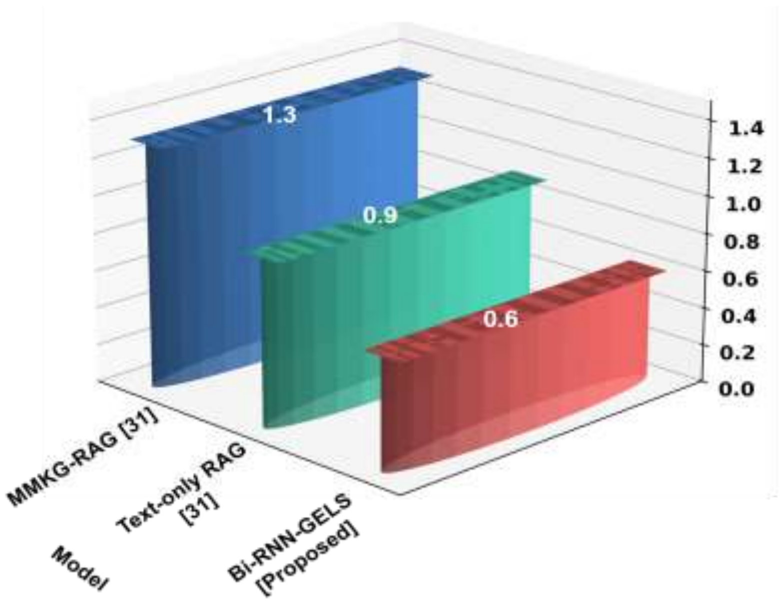

Figure 6. *Evaluation Comparison of Average Response Time Across Different existing Model*

Table 3. *Performance Comparison of Models in Terms of Accuracy and Latency*

Model	Dataset	Accuracy (%)	Latency (ms)
Full MobileNetV3-small (no pruning) [32]	Ed-Net Dataset	95	142.6
Static 20% magnitude pruning (offline) [32]		89.2	94.1
Proposed dynamic CPU-triggered pruning [32]		89.7	99
Bi-RNN-GELS [Proposed]	Learning Dataset	96.3	72.5

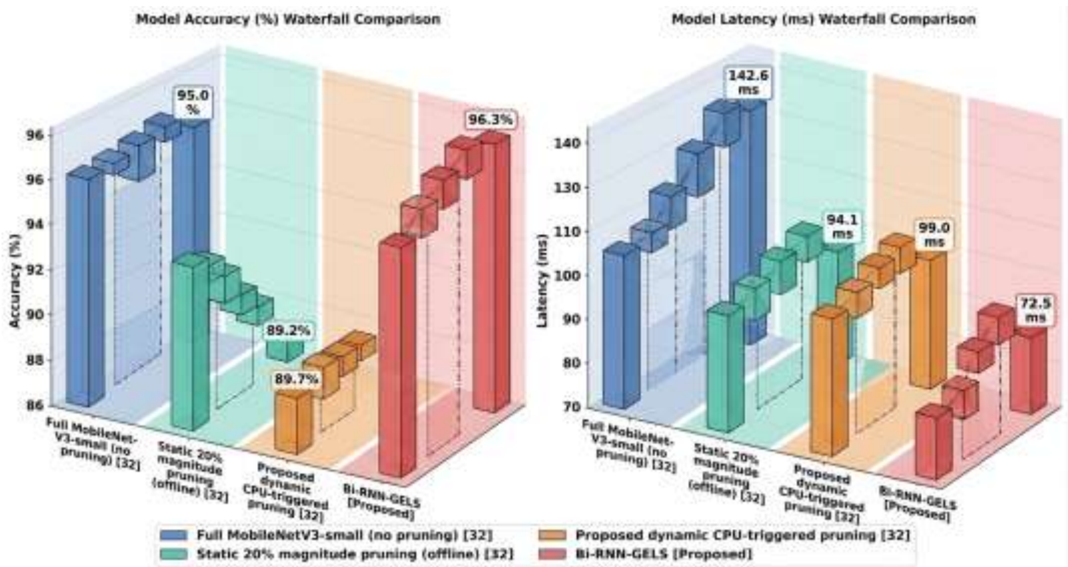

Figure 7. *Comparative Evaluation of Model Accuracy and Latency Performance Across Different Existing Models*

Table 4. *Performance Comparison of the Proposed Model Against Baseline Methods in the Same Dataset*

Model	Accuracy (%)	Latency (ms)	Average Response Time
MMKG-RAG	88.4	135	1.3
Text-only RAG	86.2	120	1.1
Full MobileNetV3-small (no pruning)	90.5	142.6	1.4
Static 20% magnitude pruning (offline)	89.2	94.1	1.0
Proposed dynamic CPU-triggered pruning	89.7	99	0.9
Bi-RNN-GELS [Proposed]	96.3	72.5	0.6

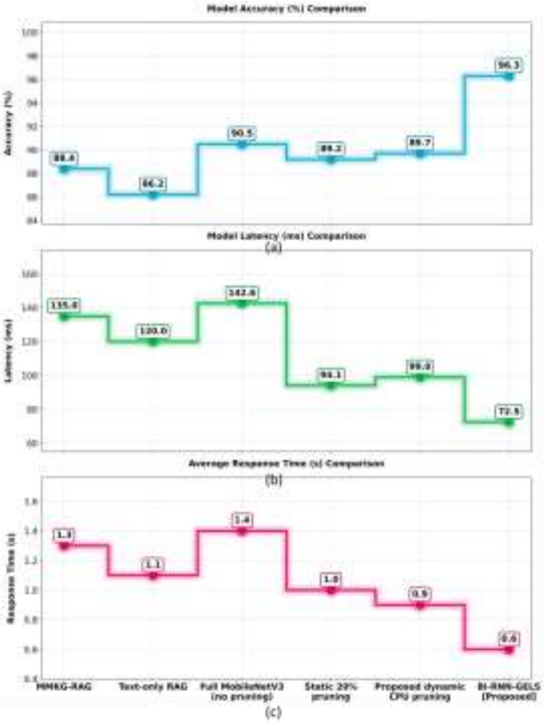

Figure 8. *Performance Metric Trade-off Across Architectural Frameworks: (a) Model Accuracy (%) comparison; (b) Computational Latency (ms) profiles; (c) Average Response Time (s) benchmarks.*

Table 5. *Ablation Analysis of Proposed Bi-RNN-GELS Model for Adaptive Educational Support in Remote Mountain Communities*

Model Variant	Bi-RNN	Data preprocessing	Feature Extraction	GELS	Accuracy (%)	Latency (ms)	Average Response Time
Bi-RNN Baseline	✓	✗	✗	✗	90.8	80.7	0.75
W/O Data preprocessing	✓	✗	✓	✓	92.1	78.9	0.72
W/O Feature Extraction	✓	✓	✗	✓	92.6	77.4	0.7
W/O GELS	✓	✓	✓	✗	93.4	76.8	0.68
Bi-RNN–GELS (full model)	✓	✓	✓	✓	96.3	72.5	0.6

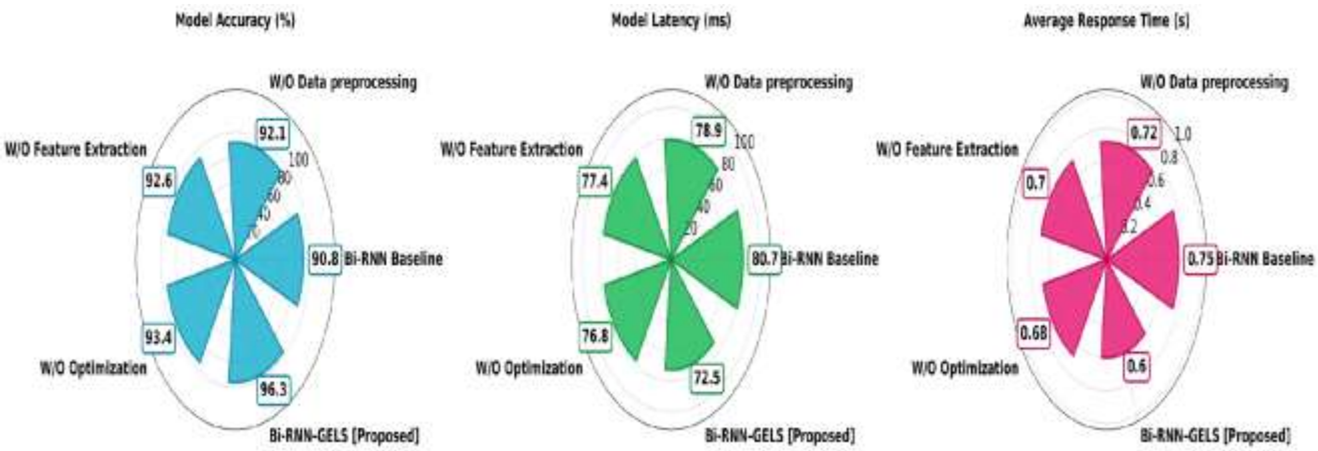

Figure 9. *Ablation Analysis of the Proposed Bi-RNN-GELS Model and Its Architectural Variants: (a) Polar charts depicting Model Accuracy (%), (b) performance curves of Model Latency (ms), (c) efficiency measurements for Average Response Time (s).*

5. Discussion

The traditional cloud-based e-learning solutions usually cannot meet the learning requirements of distant mountain villages with insufficient infrastructure and network environment. In previous studies, the deficiencies in this regard include, Inadequate infrastructure and concerns for privacy limit [21]. Learning analytics was used to decrease school dropout, collaboration, and computational thinking face teacher resistance and ease-of-use challenges [22]. Investigating student engagement in online and hybrid learning environments is limited by single-country context and generalizability concerns [23], It is pre-research and lacks practical testing [28], and it is too complex and may have reasoning errors [31]. Overall, they have the drawbacks supporting offline, personalized learning, and deployment at scale in a restricted environment.The proposed Edge-Based Personalized Tutoring Framework addresses the drawbacks of cloud-based solutions by combining local edge processing with Bi-RNN and GELS optimization. The edge devices for offline low latency learning together with Bidirectional tracking the learner cognitive status and engaged behaviors through Bi-RNN and the dynamic learning path optimization with GELS can provide a highly scalable and personalization learning solution under unstable connections and dynamic learner profiles. The system serves as a practical example of the edge-based AI tutoring system which can create adaptive learning content, testing suggestion in real time to personalize content according to user profile and learning content resources for continuous and inclusive remotely high-quality learning in remote mountain areas.

6. Conclusion

An Edge-Based Personalized Tutoring model was developed to optimize adaptive learning support in remote mountain communities. Preprocessing utilized One-Hot encoding, IQR-based outlier detection, and Auto-encoder-based feature extraction for learner behavior analysis. The hybrid model combined Bi-RNN for bidirectional temporal learning and GELS for global optimization of personalized learning paths. Results significantly outperformed baseline methods, achieving 96.3% accuracy, 72.5ms latency, and 0.6s average response time, with improved engagement and reduced dropout rates. This demonstrates that the proposed model effectively navigates intermittent connectivity and resource constraints with superior adaptability. The model significantly outperforms existing cloud-centric models by achieving optimal learning performance. The proposed model is constrained by reliance on synthetic learner profiles, leading to potential challenges in real-world deployment with diverse learner data. Deployment across diverse rural schools enhances personalization, robustness, and scalability for inclusive remote education. By integrating multimodal inputs such as behavioral analytics, offline activity logs, and real-time engagement data, the system can improve personalization for new learners. Future research may expand the model to include transformer-based architectures and adaptive content recommendations to enhance its robustness, and ensure more personalized and inclusive education in dynamic remote learning environments.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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