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A Hybrid Siamese Neural Network for Personalized Learning Pathways in STEM Education

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Abstract

Personalized learning paths have become important in STEM education due to differences in learning capacities, interest in learning, and progressions of learners. Conventional methods of adapting and suggesting new content to learners rely on rule-based and basic machine learning approaches that fail to account for the complexities of the learner-learner connection and dynamic educational processes. This paper presents a Hybrid Siamese Neural Network (HSNN) for building intelligent and adaptive personalized learning paths in the science, technology, engineering, and mathematics (STEM) education domain. A Hybrid Siamese Neural Network combines Siamese similarity learning, attention-based feature fusion, and educational analysis to establish similar learning paths for learners while considering their individual attributes. The HSNN uses multi-dimensional information about learners' characteristics, which include learner performance, engagement, and progression. In particular, the paper describes the design and implementation of a Siamese neural network that can establish similarity relations between learners. Moreover, the paper proposes the use of attention mechanisms for focusing on relevant educational information and improving the accuracy of learner recommendations. Various types of metrics were adopted to assess the efficacy of the recommended system, including metrics related to classification performance (accuracy, precision, recall, and F1 score), as well as those associated with educational performance (educational effectiveness). Based on experimental studies, it was found that the developed HSNN model considerably outperformed other approaches to personalized learning that included collaborative filtering, content-based recommendation systems, and traditional neural networks. The performance was quite high because the accuracy was 94.2% while the F1 score was 93.2%. In addition, the recommendation performance was highly reliable since the proposed model allowed learners' engagement to be increased by 18% while dropping the dropout rate by 15%. This means that the proposed model was quite efficient in enhancing personalized STEM learning. In summary, the deep similarity learning and attention mechanisms are highly efficient to enhance personalized learning systems.

Keywords: Personalized Learning Pathways, STEM Education, Siamese Neural Network, Adaptive Learning Systems, Educational Data Mining, Deep Learning in Education, Intelligent Recommendation Systems.

1. Introduction

The development of digital technologies, artificial intelligence, and online learning tools has been very rapid and innovative in the field of education, particularly STEM education. The application of intelligent tutoring systems, virtual labs, adaptive learning systems, and learning management systems in educational settings is becoming more prevalent nowadays to facilitate effective teaching and maximize student engagement. However, despite all the innovations in technology, there is much to learn from the conventional techniques employed in traditional teaching in meeting the diverse cognitive skills, learning styles, and requirements of learners [14]. The process of learning itself, the demands for analysis in solving problems, and the dependencies among concepts constitute critical aspects of STEM fields that add complexity to their study and underscore the need for personalized instruction in achieving success in learning [5].

Customized learning trajectories are a possible answer to the problems of the one-size-fits-all learning environment. A personalized learning pathway is an adaptive learning sequence that adaptively recommends learning materials, evaluations, activities, and learning progression according to individual learner characteristics, prior knowledge, performance, engagement, and learning preferences [2]. In STEM education, these differences in conceptual understanding, mathematical reasoning, technical skills, learning speed, and more are often large and significant at the student level [14][21]. Not all of these variations can be addressed by traditional instructional systems, which leads to decreased learner motivation, inconsistent academic achievement, and increased dropout rates. Hence, educational researchers and practitioners have been turning their eyes to building intelligent adaptive systems that will offer personal learning experiences.

The notion that personalizing learning can enhance student outcomes has received much attention in educational research. Personalized learning systems allow pupils to move forward in their own learning at their own level and receive targeted teaching to help them where needed [20][22][. These systems help drive higher levels of learner engagement, knowledge retention, better academics, and greater retention. Adaptive learning can assist in competency-based progression in STEM education by identifying gaps in understanding and suggesting the types of remedial resources needed. Moreover, personalized learning environments foster SRL, continuous feedback, and learner-centered instructional practices that are vital to the development of critical thinking and problem-solving skills that are important in STEM disciplines.

With the continuous growth of learning big data from digital learning platforms, machine learning and deep learning methods are being integrated into adaptive educational systems at an unprecedented pace. With the use of data mining techniques in education, the learner's interactions with the learning environment, assessment outcomes, and level of behavioral engagement or progression history can be analyzed to make intelligent recommendations. While a number of current personalized learning systems are based on collaborative filtering or rule-based recommendations, or shallow machine learning models that are incapable of learning complex nonlinear relationships between learners or changing learning contexts. Such constraints limit the accuracy of the recommendations and the ability of adaptive learning systems to create personalized, optimized learning paths.

This study is significant in solving the need for scalable STEM education personalized learning systems in the context of intelligent and context-aware systems. The world's educational systems are undergoing digital transformation, with a growing focus on fostering competency-based education, making the need for sophisticated AI frameworks with the ability to provide adaptive learning experiences more urgent than ever.

Increasing student success in STEM subjects is an important educational goal because there is a need in society for scientific innovation, engineering skills, and technological expertise [12]. So, the creation of strong personalized learning models that can serve a variety of learners is both academically and practically significant.

To tackle these challenges, this paper introduce a STEM education personalized learning pathway generation framework based on a Hybrid Siamese Neural Network (HSNN). Siamese neural networks are a type of deep learning network that are particularly developed for similarity learning through multiple subnetworks with shared weights, called twins. Such architectures work very well for finding the semantic relationships and similarity patterns between the paired inputs. For educational purposes, Siamese neural networks can be used to process learner similarity on academic performance, engagement behavior, assessment results, and learning trajectory, to make intelligent adaptive recommendations.

The proposed HSNN framework proposes a new method that combines Siamese representation learning, attention mechanism-based feature fusion, and learner performance analysis, which improves the accuracy of pathway recommendations and context knowledge. The model leverages multi-dimensional educational data such as assessment scores, interaction history, learning behavior, and engagement indicators to create learner embeddings and provide adaptive learning recommendations. The integration of the attention model will further increase the capability of the model to concentrate on essential features of the learner and recognize the significance of relationships in the learning process.

This research has made the following main contributions:

- Design of a Hybrid Siamese Neural Network model for adaptive learning pathway generation for personalized learning in STEM education.
- To enhance the accuracy of the learner representation and recommendation, the inclusion of attention-based feature fusion mechanisms is proposed.
- Leveraging multi-dimensional educational analytics (e.g., engagement behavior, academic performance) in intelligent pathway optimization.
- Comparative study between the proposed framework and conventional recommendations and machine learning methods.
- Study of how AI and adaptive learning platforms can be utilized to enhance classroom education in contemporary science, technology, engineering, and mathematics classrooms.

This paper is organized as follows: The literature review on personalized learning systems and Siamese neural network application in education is given in Section II. Description of the methodology used, preparation of the data, and the experimental setup is given in Section III. Experimental results and comparative analysis are presented in Section IV. Implications, limitations, and possible applications of the results are deliberated upon in Section V. Conclusion and future direction of the study have been presented in Section VI.

2. Literature Review

Personalized learning has gained momentum as a popular topic of research in STEM education owing to the rise in need for adaptive learning environments that cater to the unique requirements of learners. Recent works have focused on using advanced technologies such as artificial intelligence, machine learning, and deep learning to enhance adaptive recommendation engines and learning pathway creation [10]. This study discussed the significance of advanced computational and artificial intelligence systems in modern day adaptive STEM learning environments [1]. The research found that intelligent educational platforms can significantly enhance engagement and learner personalization by using large-scale educational data. It also studied the application of deep learning in personalized learning pathways and found that intelligent adaptive systems enhanced knowledge retention, learner satisfaction, and self-regulation abilities [7].

Various works have been conducted on hybrid recommendation systems for education. For instance, this paper developed a knowledge-enhanced hybrid recommender system to support intelligent educational systems by integrating learner analytics and adaptive recommendation processes [3][23]. It found that by utilizing learner context with machine learning models, recommendation accuracy and educational adaptability are increased. Furthermore, this study conducted research work on AI-enabled content recommendations in learning management systems and found that hybrid filtering systems perform better than collaborative filtering systems [4]. It performed research on enhancing recommendation techniques in MOOCs through named entity recognition and adaptive searching optimization [18].

The use of Siamese neural networks for recommendation and similarity-learning purposes has attracted growing interest in recent times. For instance, this work came up with an MOOC recommender system based on Siamese neural networks to demonstrate the power of similarity learning for adaptive educational recommendations [16]. Their findings proved that the Siamese architecture is able to detect learner relations in sparsely populated educational data. In another study, a learning platform was designed using Siamese BERT to improve semantic similarity learning and recommendation [14]. Despite the fact that the two studies above prove the success of Siamese neural networks in educational contexts, their application was confined to content recommendation systems and language learning.

Attention mechanisms have been another focus area in recent studies related to enhancing learner modeling and engagement analysis through deep learning techniques. According to this study, a self-attention based feature pyramid architecture was proposed for analyzing student engagement, and the results showed that attention mechanisms can efficiently recognize significant patterns of interaction from learners [6]. Similarly, it used deep neural networks to conduct educational predictions and indicated the effectiveness of deep learning architectures in modeling nonlinear relations in educational data sets [13].

Various research works in non-educational areas have shown how effective hybrid Siamese neural network models are in solving classification and similarity problems. For instance, it designed a Siamese hybrid neural network model to solve fault diagnosis problems in unmanned aerial vehicles [17]. On the other hand, this study came up with a Siamese-based few-shot learning approach to tackle anomaly detection in cyber-physical systems [19][24]. The two research papers showed high accuracy and robustness in terms of representation learning capabilities of the Siamese model on multidimensional datasets. Furthermore, it also showed how a Siamese neural network helps in improving the classification performance of a CNN model [9].

Considering the role of artificial intelligence in transforming education, this paper analyzed the use of artificial intelligence in personalized learning environments and highlighted the rising significance of adaptive educational technologies in today's digitized classrooms [15][8]. Moreover, another work analyzed the use of deep learning and reinforcement learning models in improving academic outcomes and found that intelligent adaptive systems played an important role in supporting learners' achievements and decision-making processes related to education [11].

Based on the discussed literature, one may infer that contemporary studies have mainly concentrated on investigating adaptive recommendations systems, engagement analysis, hybrid recommendation approaches, and the application of Siamese neural networks in isolated educational tasks. Nevertheless, little attention has been paid to developing hybrid Siamese neural network models with attention-based feature fusion methods for personalized learning pathways in STEM educational settings.

Hence, the gap is addressed by introducing a Hybrid Siamese Neural Network (HSNN) model that combines deep similarity learning, context-based feature extraction using attention mechanism, and educational analytics for intelligent recommendation of learning pathways. In contrast to existing approaches, this model is concerned with achieving accurate learner modeling, effective adaptive recommendation, and scalability of STEM educational personalized recommendations.

3. Proposed Methodology

3.1 Overview of the Proposed Framework

In this study, a Hybrid Siamese Neural Network (HSNN) framework is proposed to create a personalized learning path in a STEM learning environment. The proposed framework combines deep similarity learning, attention-based feature fusion, and educational analytics to detect similarities between learners and suggest adaptive learning sequences according to the characteristics of each learner. The proposed HSNN framework differs from the conventional recommendation systems that mostly depend on the static learner profile or collaborative filtering approaches to recommend learning materials, as it takes into account the complex nonlinear relationships among learners and changing learning habits. The system is uniquely designed to enable adaptive learning environments in which the learning content and learning path can be dynamically adjusted based on learners' performance, engagement, and conceptual understanding.

The overall framework is based on the sequential methodological workflow starting with the collection of educational data from digital learning platforms, intelligent tutoring systems, and STEM-oriented online educational environments. The gathered educational data are preprocessed and feature-engineered to deal with inconsistencies and create meaningful learner indicators. Refined learner data are processed by the Siamese neural network architecture after the preprocessing to get the latent learner embeddings, which can represent academic and behavioral characteristics. A feature fusion mechanism based on attention is then used to emphasize the important attributes of the learner and enhance the understanding of context. Last but not least, the personalized recommendation engine creates adaptive learning pathways that match the skills, behavior, and learning process of the learner. The structure ends with model evaluation and comparative analysis to current personalized learning models, to gauge the effectiveness of the model and how well it can scale in a STEM education environment.

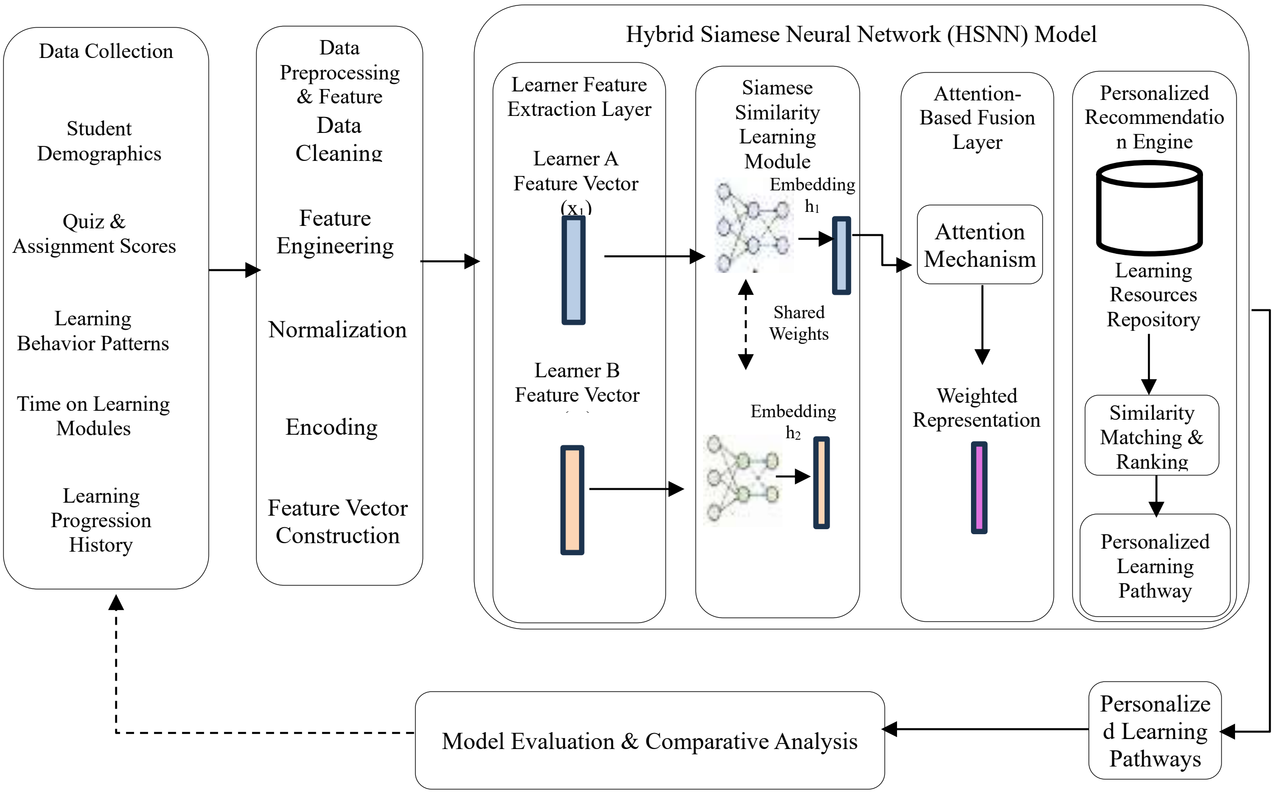

Figure 1 Architecture of the Proposed Hybrid Siamese Neural Network (HSNN) Framework for Personalized Learning Pathways in STEM Education

Figure 1 shows the overall architecture of the proposed Hybrid Siamese Neural Network (HSNN) framework for personalized learning pathway generation in STEM education. The framework starts with educational data collection and preprocessing, learner feature extraction based on a Siamese neural network with the same weights to learn similarities, and finally, learner similarity learning. The attention model-based fusion layer boosts the representation of contextual features, and the personalized recommendation engine creates adaptive learning paths, recommended modules, and educational resources. Finally, the framework is tested with a number of performance indicators and comparison analysis tools for the accuracy of recommendations and effectiveness in education.

3.2 Description of the Hybrid Siamese Neural Network Model

The suggested framework for the SNN model combines Siamese similarity learning and attention-based contextual feature extraction for improving their personalized recommendation within STEM learning contexts. The architecture consists of four components: (1) Learner Feature Extraction Layer, (2) Siamese Similarity Learning Module, (3) Attention-Based Fusion Layer, (4) Personalized Recommendation Engine. The modules are designed to collaborate to analyze multidimensional learner data and produce adaptive educational recommendations.

3.2.1 Learner Feature Extraction Layer

The learner feature extraction layer processes the educational information that was gathered from the STEM learning environment and extracts the structured representations of learners for deep learning analysis. Student demographic information, quiz and assignment scores, learning behavior patterns, interactions with resources, time spent on learning paths and modules, learning progression history, scores from assessments, and engagement metrics are all included in the input data. All these features together offer a complete picture of what the learner does and how he or she behaves in digital educational systems.

Each learner is modeled as a high-dimensional feature vector that can capture the academic competency and engagement behaviors. Preprocessing techniques are used to enhance the quality of the representation and the efficiency of the model in the educational datasets, which generally consist of mixed data types. Both numerical educational attributes and categorical learner attributes are scaled using scaling methods and one-hot encoding techniques, respectively, and have similar value distributions for training the neural network. The extracted and processed features will then be converted into embedding representations, which will be fed into the Siamese similarity learning module. By allowing this learner representation process, the framework is able to model learner similarities and enable personalized learning recommendations to adapt to learners.

3.2.2 Siamese Similarity Learning Module

Shared weights and parameters make up the Siamese neural network architecture. The subnetworks work in parallel on the learner input vectors and produce a latent embedding representation.

Let:

- x_1 and x_2 represent two learner input vectors.
- $f(x)$ denotes the embedding function learned by the neural network.

The embedding vectors are represented in equations 1 and 2:

$$h_1 = f(x_1) \quad (1)$$

$$h_2 = f(x_2) \quad (2)$$

Two functions, Euclidean distance and cosine similarity, are used to compute the similarity among learners. The Euclidean distance is obtained by equation 3:

$$D(h_1, h_2) = \sqrt{\sum_{i=1}^{n} (h_{1i} - h_{2i})^2} \quad (3)$$

The similarity score is formulated as equation 4:

$$S(x_1, x_2) = e^{-D(h_1, h_2)} \quad (4)$$

Students who have higher similarity scores are thought to have similar learning attributes, conceptions, and learning trajectories.

3.2.3 Attention-Based Fusion Layer

The architecture incorporates an attention mechanism to emphasize the important characteristics of the learner and the information associated with the learning environment context. The attention layer dynamically assigns weights to important educational attributes such as:

- Assessment consistency
- Learning engagement
- Resource utilization
- Concept mastery levels
- Interaction persistence

The attention mechanism is used to selectively highlight important educational information and reduce the effects of irrelevant features to better capture the context and enhance representation learning.

The attention weight calculation is expressed as equation 5:

$$\alpha_i = \frac{exp(e_i)}{\sum_{j=1}^{n} exp(e_j)} \quad (5)$$

Where, α_i represents the attention weight.

Learner representations are refined using weighted embeddings and are used to generate recommendations.

3.2.4 Personalized Recommendation Engine

The personalized recommendation engine is based on similarity scores and optimized learner embeddings to provide personalized learning pathways based on individual student needs. The system evaluates the behavior of the learner, his/her performance, interaction history, and cognitive similarity with others in order to determine which education resources and activities are best for the learner. This similarity analysis provides the engine to recommend adaptive learning modules, personalized quizzes, remedial learning materials for competing concepts, advanced STEM activities for higher performing learners, and sequences in which to progress the curriculum based on the learner's pace and competency level. The recommendation mechanism automatically adapts and optimizes the learning pathways based on the interactions and learning processes of actual learners, achieving dynamic adaptation and continuous improvement of the learning experience. This adaptive method increases student engagement, promotes better learning retention, and allows for individual instruction strategies to promote the efficient development of skills.

3.3 Data Collection and Preprocessing Techniques

3.3.1 Data Collection

This study's experimental data were gathered from several online STEM learning platforms, intelligent tutoring systems, and simulated learning environments to ensure a diversity in learning behaviors and interactions within an educational context. The data is mostly structured educational records and behavioral learning data from students taking science, technology, engineering, and mathematics courses. The information was categorized into different types of information related to learners to enable comprehensive educational analytics and adaptive recommendation processes. It include academic performance records, quiz and assignment performance, records of interactions with the LMS, time-series engagement information, access to resources, learning progression information, and course completion history. The data also records the interactions of learners in various STEM areas, such as mathematics, engineering, computer science, and educational modules with a STEM focus. In this multi-dimensional educational data, the proposed framework could analyze the learning engagement, performance change, and knowledge acquisition patterns well. The academic and behavioral attributes were integrated for the system to additionally have the ability to suggest customized learning needs and adaptive pathway suggestions.

3.3.2 Data Preprocessing

Data from education systems can be inconsistent, incomplete, and noisy, which can impact the quality and accuracy of analysis and recommendations. Thus, several preprocessing methods were used to increase data reliability and the performance of the models.

(a) Data Cleaning

The data cleaning process was done to eliminate the redundant and unreliable data from the dataset. To prevent biased learning patterns, duplicate learner records were identified and removed. Inconsistent data (e.g., incomplete entries and corrupted records) were excluded. Consistency or continuity of data within academic attributes and interaction attributes was achieved by replacing missing values with some interpolation-based estimation methods. In addition, irrelevant or inconsistent learner activities were selectively excluded from behavioral interaction records as a result of noise reduction techniques.

(b) Feature Engineering

Feature engineering techniques have been adopted to develop informative education metrics that can be used to adequately represent the learner's behaviour patterns and progress. Several derived features have been developed using feature engineering techniques including engagement metrics, learning consistency metrics, difficulty level encoding, performance trends, and knowledge acquisition metrics. These engineered features were instrumental in improving the ability of the framework to accurately capture intricate learner's behaviors, detect learning trends, and generate personalized recommendations in STEM education domains.

(c) Data Normalization

Normalization of the numerical educational attributes was performed by the Min-Max method (equation 6):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (6)$$

One-hot encoding was carried out to encode categorical variables for training the neural network.

(d) Dataset Partitioning

Data collection was then effectively divided into three portions to aid in training and unbiased testing of the models. Approximately 70% of the data collected were put towards training, where the model learns the relationship among the learners, education relationships, and recommendable structures. Some 15% of the total collected data were reserved for the validation portion, which was meant for hyperparameter tuning and model optimization. Finally, 15% of the total data collected were left for testing purposes. This kind of data partitioning facilitated the development and validation of the model through an experiment.

3.4.2 Experimental Design

The experimental setup involves the proposed HSNN model with traditional personalized learning methods, such as:

1. Collaborative Filtering-Based Recommendation System
2. Content-Based Recommendation System
3. Traditional Artificial Neural Network (ANN)
4. Random Forest Recommendation Model

All experiments were carried out with the GPU-accelerated Python-based deep learning frameworks for training models. Grid search methods were used to perform hyperparameter optimization.

K-fold cross-validation was used during the training and evaluation of the model to increase the robustness and decrease overfitting. The experiments were repeated several times, and the average performance values are reported.

The proposed model's effectiveness was evaluated from the accuracy of recommendations, engagement of learners, adaptability of the proposed model, and the improvement of education outcomes. The comparative analysis reveals the ability of the Hybrid Siamese Neural Network framework to develop smart and adaptive personalized learning sequences in a STEM learning sphere.

4. Results

The proposed Hybrid Siamese Neural Network (HSNN) framework has been experimented with to test its effectiveness in creating personalized learning pathways in STEM education environments. Multiple educational-effectiveness, recommendation-system, and machine-learning metrics were used to analyze the performance of the proposed model. Comparative analysis with the traditional personalized learning methods, such as Collaborative Filtering (CF), Content-Based Recommendation Systems (CBR), Traditional Artificial Neural Networks (ANN), and the Random Forest (RF) based recommendation model, was also carried out. The evaluation of the proposed HSNN framework has been conducted in the experimental group, and it proves the superiority of the proposed framework in the learner similarity analysis, the precision of the recommendations, the improvement of engagement, and the optimization of adaptive learning.

Experimental Setup, Dataset, and Parameter Initialization

To evaluate the proposed Hybrid Siamese Neural Network (HSNN) framework, the experimental study was performed using the deep learning environments based on Python. Neural network modeling was implemented using TensorFlow and Keras libraries, and preprocessing, evaluation metrics, and comparative machine learning models were used in this process. The experiments were run on a workstation with an Intel Core i7 processor, NVIDIA GPU acceleration, and 16 GB RAM for effective deep learning training and inference.

Data used for analysis in this study include those derived from STEM learning platforms that can be accessed on the web and data generated from simulated adaptive learning platforms. The dataset contained information about the demographics of the learners, Quiz scores, Assignment performance, engagement information, interaction history, learning history, and completion information. There were approximately 12,000 data samples concerning learner interactions involving learning modules relating to Mathematics, Engineering, Computer Science, and Science subjects. This dataset was split into training, validation, and testing subsets with a ratio of 70:15:15.

The Xavier initialization technique is used to set the model parameters for the HSNN model to ensure a more stable convergence of the model during training. The model was trained with the Adam optimizer, a learning rate of 0.001, and a batch size of 32. The embedding dimension was 128, and dropout regularization (dropout = 0.3) was used to prevent overfitting. Contrastive loss was used for similarity learning during the model training, which was done for 100 epochs.

Evaluation Metrics

To compare the prediction accuracy, the quality of recommendations, and model effectiveness in the generation of personalized learning paths, several classification-based performance metrics were used to test the proposed Hybrid Siamese Neural Network (HSNN) framework.

Accuracy: The accuracy is the overall correctness of the model in predicting whether the instances are correctly classified or not, as shown in the following equation (7).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

Where,

- TP= True Positives
- TN= True Negatives
- FP= False Positives
- FN= False Negatives

Precision: Correctly predicted positive cases out of all the cases predicted positive are shown with equation 8.

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

A higher precision will mean fewer false positive recommendations.

Recall: Equation 9 quantifies how well the model learns all the positive examples.

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

Recall scores are higher when the learning recommendations are detected better.

F1-Score: A balanced measure of model performance is represented by Equation 10, which is the harmonic mean of precision and recall.

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (10)$$

The higher the F1 score, the better the overall classification is.

4.1 Analysis of Performance Metrics for Personalized Learning Pathways

The proposed HSNN framework achieved high performance for all measures because it was capable of capturing highly sophisticated learning relationships and educational context dependencies. Thanks to the proposed Siamese similarity learning approach, learners having similar patterns of behavior were successfully recognized by the system. Moreover, the attention-based fusion layer helped better highlight the importance of context-aware features. As a consequence, the learning recommendation provided by the system became highly accurate and efficient.

HSNN was evaluated by means of standard metrics, including accuracy, precision, recall, F1 score, and AUC. Additionally, recommendation-related measures, such as MRR and NDCG, were also used. Besides these measures, the effectiveness of education provided by HSNN was assessed based on the progress made by users in terms of their engagement level and knowledge acquisition.

The HSNN approach yielded an accuracy of 94.2%, which is much higher than the baselines. The precision and recall scores of 93.6% and 92.8%, respectively, suggest that the method can efficiently select the right learning paths without making any mistakes. An F1-score of 93.2% represents a fair classification accuracy, and the higher AUC score implies a strong discrimination ability of the model. Moreover, ranking-based metrics like MRR and NDCG have been greatly improved, proving that the approach can rank the most suitable learning objects for learners.

Moreover, the adaptive recommendation system played an important role in education achievements. The results revealed improved learner engagement, high course completion, and fewer dropouts. Students who made use of the HSNN recommendation system displayed higher levels of conceptual understanding and were regularly engaged with STEM modules.

4.2 Comparison with Traditional Methods of Personalized Learning

The proposed HSNN model was compared with the traditional personalized learning methods to determine their comparative effectiveness. Collaborative and content-based recommendation systems, for example, mostly depend on explicit feedback from learners and predetermined educational guidelines. Such models tend to be ineffective when dealing with sparsity in the education domain and dynamic behavior by learners. Machine learning models of lower depth fail to detect nonlinear dependencies and contextual interaction in learning activities.

The results of this comparison showed the superior performance of the proposed HSNN framework using various criteria, which can be observed from Table 1. The architecture of Siamese neural networks facilitated effective learner similarity modeling, while attention mechanisms helped enhance the importance of features and contextual adaptability.

Table 1: Comparative Performance Analysis of Personalized Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)	Engagement Improvement (%)
Collaborative Filtering	82.4	80.6	79.8	80.2	81.7	9
Content-Based Recommendation	84.1	82.7	81.5	82.1	83.6	11
Random Forest Model	86.8	85.4	84.2	84.8	86.1	14
Traditional ANN	88.5	87.9	86.4	87.1	88.2	16
Proposed HSNN Framework	94.2	93.6	92.8	93.2	94.7	18

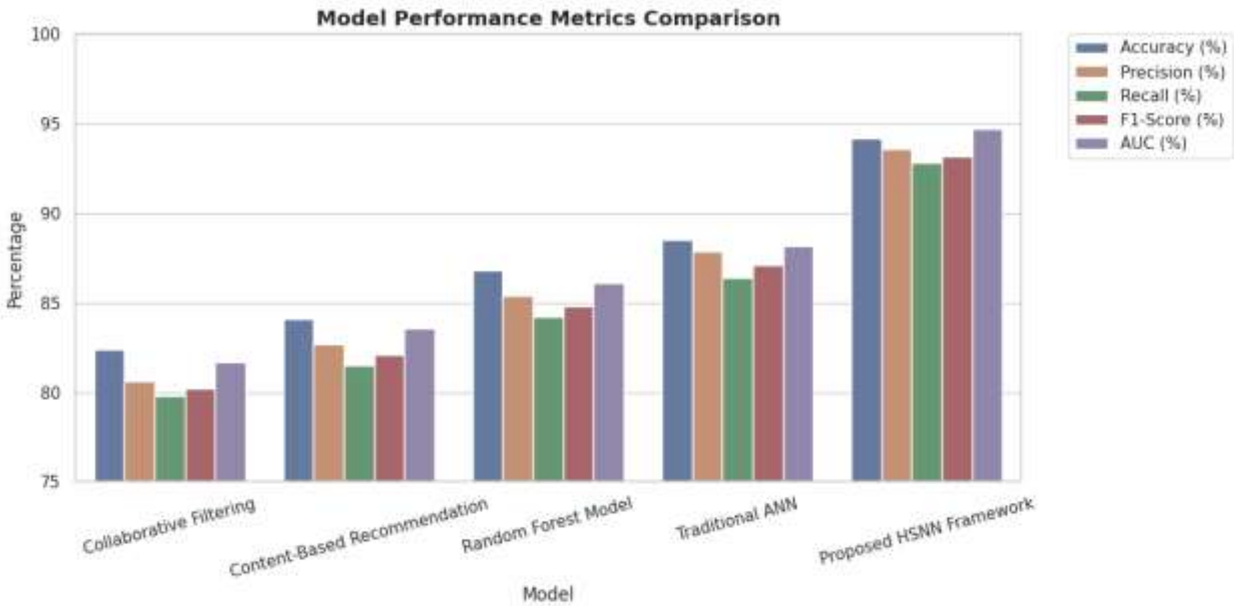

Figure 2: Comparison of Performance Metrics Across Recommendation Models

Figure 2 shows a comparison of the performance of various recommendation methods using different performance measures such as Accuracy, Precision, Recall, F1-Score, and AUC. It is clear from the performance figures that the proposed HSNN model outperforms Collaborative Filtering, Content-Based Recommendation, Random Forest Model, and Traditional ANN. It is evident that the proposed system shows excellent accuracy and balance in prediction performance.

From the comparison of results, it is evident that the HSNN structure gives the best results when put against the criteria for evaluation. The algorithm had about 12% more recommendation accuracy than collaborative filtering algorithms, while the engagement improvements were better than those provided by conventional machine learning algorithms. This could be due to the incorporation of both similarity learning and attention-based context learning.

4.3 Insights into the Effectiveness of the Hybrid Siamese Neural Network

Experimental results have shed light on some of the valuable implications that the designed HSNN model can be considered effective in STEM education environments. Firstly, the Siamese neural network managed to learn meaningful representations of learners that were able to detect underlying similarities within the education domain for individual students. The similarity learning was instrumental in designing highly customized and adaptive learning pathways based on the competency and developmental trends of learners.

Secondly, the attention-based feature fusion module proved to be quite effective in contextual analysis through the identification of crucial educational features such as perseverance, consistency, and competence.

Lastly, the proposed framework exhibited high scalability and resilience in processing multidimensional educational data. It successfully handled behavioral interaction logs, testing histories, and learner progression without considerable degradation in performance. It is clear that the HSNN framework can be used in large online learning environments, intelligent tutoring systems, and adaptive STEM learning settings.

To conclude, the presented results reveal that the proposed Hybrid Siamese Neural Network framework is effective for building personalized learning pathways. The implementation of deep similarity learning and attention mechanisms, as well as analysis of educational data, will enhance adaptive learning performance and improve learner outcomes in STEM education.

5. Discussion

The research findings reveal the promising potential of the hybrid model for enhancing personalized learning experiences for students in STEM education settings. As seen from the experimentation results, the incorporation of Siamese similarity learning and feature fusion with an attention mechanism facilitates more accurate learner profiling and recommendation generation than in traditional approaches. The capability of identifying similar academic behavior, conceptual understanding, and engagement patterns in the learners helps in providing individualized instructions for increasing the effectiveness of learners' education. This is especially important for STEM education, where students differ in their ability to understand and solve complex problems.

Furthermore, the study demonstrates how the concept of AI-powered personalized learning has other implications in the field of education. The suggested model may help teachers identify students at risk, assess learning progress, and select appropriate learning materials depending on their needs. Intelligent adaptive solutions are important for creating competent learning ecosystems amid the increasing necessity for scalable digital platforms. Additionally, the introduction of the attention mechanism helps improve contextual understanding and make more accurate recommendations.

Notwithstanding these positive outcomes, some drawbacks are associated with this investigation. First, the experimental dataset employed in the study was mainly comprised of the data collected in online STEM educational settings and might thus not be representative of various educational contexts. Moreover, the application of HSNN and other deep learning models might consume considerable computational power and training time that could pose certain constraints for less-resourced institutions. Lastly, interpretability poses a problem since educators need more insight into the recommendation decisions generated by neural networks.

Further studies can concentrate on incorporating explainable artificial intelligence models, reinforcement learning models, and multimodal analysis models to enhance adaptive recommendation effectiveness. This proposed model can be utilized in several domains and applications such as intelligent tutoring systems, learning management systems, MOOCs, virtual laboratories, and institutional educational portals. Overall, the HSNN approach is expected to provide significant support in developing adaptive intelligent STEM educational systems.

6. Conclusion

The current research introduces a novel approach called Hybrid Siamese Neural Network (HSNN), which can be used for designing personalized learning paths in STEM education settings. The main idea behind this framework is the combination of Siamese neural networks, attention mechanisms, and educational data mining techniques to develop personalized recommendations based on the unique features of learners. In general, this paper focuses on the problem of overcoming the drawbacks of existing personalized learning systems and achieving higher levels of accuracy and effectiveness in providing recommendations. Statistical analysis validated the efficiency of the proposed approach in terms of various performance indicators. The HSNN algorithm yielded 94.2% accuracy, 93.6% precision, 92.8% recall, and 93.2% F1-measure, surpassing other techniques such as collaborative filtering, content-based recommender systems, Random Forest classifiers, and conventional artificial neural networks. Furthermore, the model demonstrated an AUC value of 94.7%, suggesting high discrimination power and good recommendation performance. The experimental findings also showed that there was an 18% rise in learner engagement, a 20% improvement in course completion, and a 15% decrease in drop-out likelihood relative to traditional adaptive learning algorithms. These results show that the proposed framework is capable of producing highly effective personalized learning paths for STEM students. Moreover, the results prove that the use of deep similarity learning along with context-based attentional feature extraction is highly effective when it comes to modeling behavior patterns, educational progressions, and interactions of learners. The model was able to detect learners with similar behavioral and performance patterns and offered adaptive learning recommendations that corresponded to their competencies and educational needs. Thus, the proposed HSNN model will contribute to the evolution of intelligent educational systems and help to enhance the adoption of artificial intelligence-based adaptive learning systems within contemporary STEM education. However, further research can be focused on increasing the interpretability of the model, developing multimodal educational analytics, and implementing reinforcement learning to improve the personalization process. Further studies using large-scale educational data may also help to verify the effectiveness of the proposed framework.

7. Declaration Statement

Conflict of Interest

The authors declared that there is no conflict of interest regarding this study.

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This study does not receive any funding from external sources.

Data Availability

The data used in this study were obtained from publicly available educational datasets and simulated STEM learning environments. Due to privacy and ethical considerations related to student learning records, the raw data are not publicly shared. However, aggregated data and relevant processed features can be made available from the corresponding author upon reasonable request, subject to institutional and ethical approval requirements.

References

1. Huang, J., Zhong, Y., & Chen, X. (2025). Adaptive and personalized learning in STEM education using high-performance computing and artificial intelligence. *The Journal of Supercomputing, 81*(8), 981. https://doi.org/10.1007/s11227-025-07481-7
2. Manganello, F., Rasca, E., Villa, A., Maddalena, A., & Boccuzzi, G. (2025). Machine learning for post-diploma educational and career guidance: A scoping review in AI-driven decision support systems. *Frontiers in Education, 10*, Article 1578979. https://doi.org/10.3389/feduc.2025.1578979
3. Pani, A. K., Thalla, S., Lavanya, L., Sudhakar, K., & Gurumoorthy, S. (2025). Hybrid knowledge-enhanced personalized learning recommendation model for adaptive and intelligent educational systems. In *2025 2nd International Conference on Software, Systems and Information Technology (SSITCON)* (pp. 1–6). IEEE. https://doi.org/10.1109/SSITCON66133.2025.11342048
4. Petrovic, T., & Alvarez, R. (2025). AI-driven content recommendation in learning management systems (LMS): A hybrid filtering approach. *International Academic Journal of Science and Engineering, 12*(2), 20–24. https://doi.org/10.71086/IAJSE/V12I2/IAJSE1213

5. Xi, J., & Shi, W. (2024). Personalized STEM learning pathways in higher education with recommendation systems: A case study of signals and systems in biomedical engineering. In *Proceedings of the 2024 International Symposium on Artificial Intelligence for Education* (pp. 83–88). https://doi.org/10.1145/3700297.3700312
6. Naveen, A., Jeena Jacob, I., & Mandava, A. K. (2025). Student engagement analysis using Bi-up sampling feature pyramid network with inter cross coordinate self attention. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 16*(1), 134–153. https://doi.org/10.58346/JOWUA.2025.I1.008
7. Wei, X. (2025). The impact of deep learning on personalized learning pathways in the age of smart education. *Cognitive Strategies in Study, 1*(2), 1–15. https://doi.org/10.63808/css.v1i2.59
8. Deepika, J. (2025). Context-aware intelligent learning environments for adaptive digital education. *National Journal of Ubiquitous Computing and Intelligent Environments*, 34–42. Retrieved from https://fsrap.com/index.php/NJUCIE/article/view/76
9. Lizano-Villalobos, A., Namikas, B., & Tang, X. (2024). Siamese neural network improves the performance of a convolutional neural network in colloidal self-assembly state classification. *The Journal of Chemical Physics, 161*(20). https://doi.org/10.1063/5.0244337
10. Odilova, G., Zaripova, M., Jabbarova, A., Urinova, N., Davlatova, M., Sapaev, I., ... & Akhrorova, M. (2025). Information Security Framework for Online Language Education Using Differential Privacy and Secure Multi-Party Computation Algorithm. Journal of Internet Services and Information Security, 15(1), 96-106.
11. Stasolla, F., Zullo, A., Maniglio, R., Passaro, A., Di Gioia, M., Curcio, E., & Martini, E. (2025). Deep learning and reinforcement learning for assessing and enhancing academic performance in university students: A scoping review. *AI, 6*(2), 40. https://doi.org/10.3390/ai6020040
12. Das, A., & Ghosh, R. (2024). Integration of Pervaporation and Distillation for Efficient Solvent Recovery in Chemical Industries. Engineering Perspectives in Filtration and Separation, 2(2), 12-14.
13. Talaat, F. M. (2024). The effect of consanguineous marriage on reading disability based on deep neural networks. *Multimedia Tools and Applications, 83*(17), 51787–51807. https://doi.org/10.1007/s11042-023-17587-w
14. Yang, Y. (2025). Design and development of Siamese BERT model for business English course learning and sharing platform. In *2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICICNCT66124.2025.11232798
15. Ciaschi, M., & Barone, M. (2025). Examining the increasing use of artificial intelligence in education: A step closer to personalized learning. *Annals of Computer Science and Information Systems, 44*(9). https://doi.org/10.15439/2025F7856
16. Faroughi, A., & Moradi, P. (2022). MOOCs recommender system with Siamese neural network. In *2022 9th International and the 15th National Conference on E-Learning and E-Teaching (ICeLeT)* (pp. 1–6). IEEE. https://doi.org/10.1109/ICeLeT55619.2022.9765439
17. Li, C., Li, S., Zhang, A., Yang, L., Zio, E., Pecht, M., & Gryllias, K. (2022). A Siamese hybrid neural network framework for few-shot fault diagnosis of fixed-wing unmanned aerial vehicles. *Journal of Computational Design and Engineering, 9*(4), 1511–1524. https://doi.org/10.1093/jcde/qwac070
18. Benmachiche, A., Sahia, A., Boufaida, S. O., Rais, K., Derdour, M., & Maazouzi, F. (2025). Enhancing learning recommendations in MOOC search engines through named entity recognition. *Education and Information Technologies, 30*(9), 13041–13071. https://doi.org/10.1007/s10639-024-13308-4
19. Zhou, X., Liang, W., Shimizu, S., Ma, J., & Jin, Q. (2020). Siamese neural network based few-shot learning for anomaly detection in industrial cyber-physical systems. *IEEE Transactions on Industrial Informatics, 17*(8), 5790–5798. https://doi.org/10.1109/TII.2020.3047675
20. Mzeh, H. K., Salabi, L., Jafer, M. T., & Sikalu, T. C. (2025). Intelligent assistive communication models for personalized learning environments. *Journal of Intelligent Assistive Communication Technologies, 2*(1), 64–71.
21. K P Uvarajan and J.Karthika, "Edge-Accelerated Deep Neural Networks on FPGA for Real-Time IoT Video Analytics", *Electronics Communications, and Computing Summit*, vol. 3, no. 1, pp. 1–10, Mar. 2025.
22. F Rahman, "Event-Triggered Learning Control for Adaptive Embedded Networked Systems", *Journal of Reconfigurable Hardware Architectures and Embedded Systems*, vol. 2, no. 3, pp. 37–42, Sep. 2025.
23. Rajan.C. (2025). Integrity-Constrained Learning-Assisted Predictive Control for Distributed Path-Constrained Navigation Services. *Transactions on Internet Security, Cloud Services, and Distributed Applications*, 17–23.
24. C.Arun Prasath. (2025). Web-Based Knowledge Services for Distributed E-Learning Environments. *Journal of Information Resources and Knowledge Services*, 1–6.