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Optimizing Education Pathways Using Hyperparameter Tuning in Neural Architecture Search (NAS)

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Abstract

In general, the conventional educational recommendation models, however, cannot adequately describe the complex nonlinear learning behaviors and manual designs of neural networks are required. The goal of this work is to create an intelligent Hyperparameter-Tuned Neural Architecture Search for Education Pathway Optimization (HT-NAS-EPO) framework that combines Differentiable Architecture Search (DARTS) and Bayesian hyperparameter optimization to enhance personalized educational pathway recommendations. The proposed framework was assessed with 12,500 student data from Learning Management Systems from three academic institutions. The number of valid records after preprocessing was 11,847, each having 38 engineered features, for experimentation. Min-Max normalization and one-hot encoding were used to process the datasets, while the architecture discovery method was conducted with DARTS and hyperparameter optimization was performed with Optuna using the Bayesian Optimization technique. One-hot encoding and Min-Max normalization were used for data processing, DARTS was used for architecture discovery, and Bayesian Optimization utilizing Optuna was used for hyperparameter optimization. Several performance criteria, including accuracy, precision, recall, and F1-Score, were used to train and evaluate an optimized model. According to experimental data, the suggested framework performed better across all evaluation metrics. The optimized HT-NAS-EPO model has weighted average precision, recall, and F1-score of 93.85%, 94.10%, and 93.97%, respectively. When compared to random architectural search strategies, the total model accuracy and F1-Score were increased by 3.54% using Bayesian Optimization and by 5.18% utilizing architecture search based on DARTS. Additionally, the model had great generalization capacity and did not overfit the training data, as evidenced by the convergence of the final training loss of 0.0834 and validation loss of 0.0971. It has been shown that neural architecture search combined with intelligent hyperparameter tuning is an effective and scalable method for learning pathway optimization in adaptive educational recommendation systems, leading to a more precise, customized, and data-driven learning pathway optimization.

Keywords: Neural Architecture Search, Hyperparameter Tuning, Personalized Learning, Bayesian Optimization, Educational Data Mining.

1. Introduction

Artificial Intelligence (AI) has seen remarkable growth and development in recent years, bringing transformative possibilities to the field of education, especially in the realm of personalized learning. Traditional schooling has a one-size-fits-all approach that doesn't necessarily reflect the learning pace, cognitive abilities and academic interests of each student. Schools are collecting more and more information about students, such as their performance, engagement levels and behaviour patterns, and it is becoming increasingly important to have intelligent systems to process and interpret the data and to recommend the best learning path. Neural Architecture Search (NAS) is an effective machine learning paradigm that automates the process of designing neural network architectures and lets the models self-optimize their task [1] [5][18]. Together with hyperparameter tuning, NAS presents a powerful tool for developing adaptive systems that can learn from a complex educational dataset and adapt instructional recommendations to the individual learner [16].

The general objective of this study is to design and test an intelligent framework combining a hyperparameter tuning strategy in a Neural Architecture Search pipeline to generate a personalized education trajectory for students in various learning environments [21]. The ultimate aim is to develop a model that autonomously determines the most successful architectural configuration and learning parameters that are best matched to student performance data, allowing for precise, data-driven recommendations to be made for curriculum sequencing, resource allocation and interventions. The research also aims to show the potential of using automated machine learning techniques to decrease the need for manual model design and to enhance the accuracy and adaptability of educational recommendation systems.

Although there is vast improvement on the educational data mining and learning analytics, there are some key gaps in the literature. Current personalized learning systems are mostly based on static algorithms and shallow machine learning models that are unable to capture the non-linear relationships that can be found in complex learner data. Although, NAS has shown great potential in image recognition, natural language processing, the education sector has not been extensively explored [2]. Moreover, existing hyperparameter optimization techniques of educational AI systems are used separately without being able to be integrated into the end-to-end architecture search pipeline. At the same time, there are also few frameworks that consider both the efficiency of the computation and the relevance of the pedagogy in developing models to optimize education pathways [19].

The research assumes that using a systematic hyperparameter tuning process in a NAS framework will result in neural network architecture that will be superior to traditional architectures in predicting and optimizing personalized learning paths. This work has three main contributions. First, it introduces an end-to-end NAS pipeline specifically designed for the needs of education data: connecting advanced machine learning to learning science. Second, it presents an approach to hyperparameter optimization that has multiple objectives, one of which is model interpretability, which is a key requirement in educational contexts. Third, it presents empirical evidence that automated architecture search can reveal non-obvious patterns in the behavior of learners that can be used to make more responsive, equitable, and effective educational recommendations that can scale to institutional settings.

This article is organized into six major sections. In section 1 of the Introduction, the research background, problem statement, research objectives, research gaps and contributions to optimizing personalized education pathways by incorporating Neural Architecture Search (NAS) and hyperparameter tuning are laid out. In section 2, the Literature Review reviews the work that has been done on NAS, Bayesian Optimization, educational data mining, and adaptive learning systems. As mentioned in the Methods section, the HT-NAS-EPO framework includes data preprocessing, architecture search based on DARTS, Bayesian hyperparameter optimization, and model training procedures (section 3). The Results section includes the results of the experiments, baseline comparisons, classification performance, and ablation studies in section 4. The Discussion interprets the findings and practical implications in section 5, while the Conclusion summarizes contributions, outcomes, limitations, and future research directions in section 6.

2. Literature review

With the recent breakthroughs in both Artificial Intelligence and educational data mining, the personalized learning systems have seen a considerable improvement in their design using a technique called NAS and hyperparameter optimization. The idea of NAS is to investigate the optimal neural structure without a lot of manual effort and to design efficient deep learning architectures automatically [1], [3], [9]. Many studies pointed out that the NAS enhances model adaptability, scalability and prediction accuracy with complex data which make it highly appropriate for intelligent educational systems [13], [15]. The work on differentiable NAS and evolutionary NAS also showed that the automatic architecture search not only decreases the computational complexity but also improves the learning efficiency [14] [20].

It is noted that one of the most important challenges to optimizing the performance of NAS architectures is hyperparameter tuning. Bayesian Optimization and automated tuning frameworks have been widely applied to improve the learning rate, batch size, dropout rate and weight decay, thus increasing the convergence speed and prediction accuracy of algorithms [7,[22],[24]. Efficient evaluation strategies for NAS also minimized the computational overhead and sped up architecture selection procedures. Research on neural predictors and machine learning-based NAS methods validated that the optimization of hyperparameters plays an important role in the model robustness and generalization [11], [17],[23].

In the field of education, AI tools have already proven effective in implementing adaptive learning and personalized recommendation systems, which have been successfully used to predict student outcomes and recommend learning paths, respectively [6], [10]. E-learning platforms have been improved by the creation of e-learning platforms through applying reinforcement learning and intelligent tutoring systems to allow for adaptive assessment methods and personal feedback [8]. Moreover, the use of neural networks and fuzzy logic in education assessment showed better ranking and decision-making for education and training environments [4],[25]. Adaptive teaching approaches also stressed the need for individualized teaching methods for diverse learners in recent years [12][26].

In spite of these advancements, there has been little research on combining hyperparameter-tuned NAS frameworks for personalized education pathway optimization. Thus, this study presents a HT-NAS-EPO, which integrates DARTS-based architecture optimization with Bayesian hyperparameter tuning, to enhance the precision of predictions, adaptability, and recommendation of personalized learning pathways[27].

3. Methods

Research Design Overview

In this paper, a quantitative experimental research design is proposed to explore the application of NAS and hyperparameter tuning to create an intelligent system for optimizing personalized educational pathways. The methodology is structured and starts with data collection and data preprocessing followed by the search space definition, architecture search, hyperparameter optimization, model training, and finally model evaluation. The overall framework is intended to be end-to-end, automated, and scalable so that the final model can be generalized to work with different educational datasets and educational contexts.

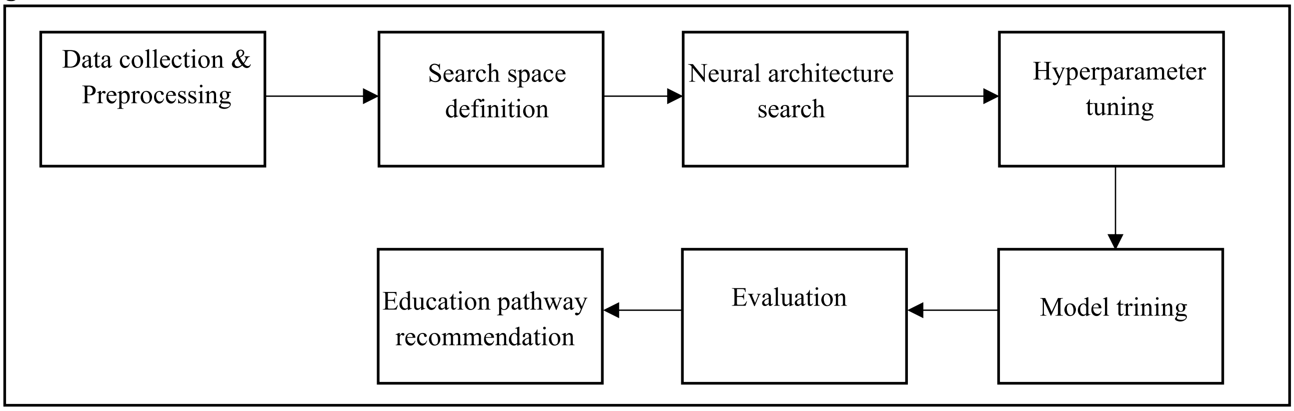

Figure 1: Workflow of the HT-NAS-EPO Framework for Personalized Education Pathway Optimization

The overall procedure of the proposed HT-NAS-EPO framework is shown in figure 1. It starts by collecting and pre-processing student data, then defining the search space and implementing DARTS) to obtain the optimal neural architecture. Optimal Hyperparameter tuning is then performed using Bayesian Optimization with the optimized model being subsequently trained and tested on various performance metrics. Finally, the framework outlines recommended educational pathways based on each learner's needs.

Dataset Collection and Preprocessing

Educational management system data (LMS) collected educationally, including student demographics, previous academic history, frequency of course engagement, assessment scores and completion rates. Standard techniques, such as normalization, missing value imputation, and feature engineering, have been used to pre-process the datasets. All the input variables are scaled using Min-Max normalization to ensure that they are within the same range, a requirement for stable training on the neural network.

Min-Max Normalization Formula:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

In equation (1) X is the original feature value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the feature, and X' is the normalized output. Categorical variables such as learning style and course type are encoded using one-hot encoding prior to model input.

Search Space Definition

The NAS search space represents all possible architectures of neural networks that can be explored by the search algorithm. The search space consists of the number of layers in a neural network, type of each layer (dense, convolutional, or recurrent), the type of activation function used, the dropout rate, and whether skip connections will be utilized. A cell-based search space is used, with each node representing a hidden representation of the input data and a DAG representing potential topologies.

DAG-based Architecture Representation:

$$\mathcal{A} = \left\{o^{(i,j)}: o \in \mathcal{O}, \forall i < j\right\} \tag{2}$$

In equation (2) $\mathcal{A}$ is the architecture, $o^{(i,j)}$ denotes the operation applied between nodes i and j, and $\mathcal{O}$ is the set of candidate operations in the search space.

Neural Architecture Search Strategy

This research uses the DARTS strategy that relaxes the discrete search space to a continuous space to allow gradient based optimization. DARTS does not only pick an operation between two nodes but gives a softmax weight for each operation in every candidate.

DARTS Mixed Operation Formula:

$$\bar{o}^{(i,j)}(x) = \sum_{o \in \mathcal{O}} \frac{\exp\left(\alpha_o^{(i,j)}\right)}{\sum_{o' \in \mathcal{O}} \exp\left(\alpha_{o'}^{(i,j)}\right)} \cdot o(x) \tag{3}$$

In equation (3) $\alpha_o^{(i,j)}$ is the architecture parameter (weight) for operation o between nodes i and j, and x is the input. The architecture is optimized by jointly training both the network weights $w$and architecture parameters αusing a bi-level optimization objective.

Bi-Level Optimization Formula:

$$\min_{\alpha} \mathcal{L}_{val}(w^*(\alpha), \alpha)$$
$$\text{subject to } w^*(\alpha) = \arg\min_{w} \mathcal{L}_{train}(w, \alpha) \tag{4}$$

In equation (4) $\mathcal{L}_{val}$ and $\mathcal{L}_{train}$ are the validation and training losses respectively, and $w^*(\alpha)$ represents the optimal network weights given a specific architecture α.

Hyperparameter Tuning

After identifying candidate architectures using NAS, hyperparameter tuning is also performed to further improve model performance. In this work, the tuning strategy is based on Bayesian Optimization that constructs a probabilistic surrogate function of the objective function and then determines which set of hyperparameters to test next based on an acquisition function. The hyperparameters that are optimized are learning rate, batch size, weight decay, number of epochs, and dropout rate.

Model Training and Optimization

The final optimized architecture is learned by the Adam optimizer, which adjusts the learning rate for each individual parameter by the first and second moment estimates of the gradients.

Algorithm 1: Hyperparameter-Tuned Neural Architecture Search for Education Pathway Optimization (HT-NAS-EPO)

INPUT: Student dataset Dcontaining academic performance, engagement metrics, and demographic features; Search space $\mathcal{O}$of candid ate operations; Maximum NAS epochs E_{nas}; Maximum Optuna trials T; Validation split ratio r

OUTPUT: Optimized neural architecture $\mathcal{A}^*$with best hyperparameter configuration $\lambda^*$and predicted education pathway recommendations

Phase 1 — Data Preparation

Step 1: Load raw student dataset $D$from the Learning Management System

Step 2: Apply Min-Max normalization to all numerical features

Step 3: Apply one-hot encoding to all categorical features

Step 4: Split dataset into training set $D_{train}$and validation set D_{val}using split ratio r

Phase 2 — Search Space Initialization

Step 5: Define the cell-based DAG search space $\mathcal{O}$including operations such as linear transformation, ReLU activation, dropout, skip connections, and batch normalization

Step 6: Initialize architecture parameters $\alpha$and network weights $w$with random values drawn from a uniform distribution

Phase 3 — Differentiable Architecture Search (DARTS)

Step 7: **For** each epoch $e = 1$to E_{nas}**do**

Step 8: Compute mixed operation output using softmax-weighted combination of all candidate operations across DAG nodes

Step 9: Perform forward pass on $D_{train}$and compute training loss $\mathcal{L}_{train}(w, \alpha)$

Step 10: Update network weights $w$by minimizing $\mathcal{L}_{train}$using gradient descent

Step 11: Perform forward pass on $D_{val}$and compute validation loss $\mathcal{L}_{val}(w, \alpha)$

Step 12: Update architecture parameters $\alpha$by minimizing $\mathcal{L}_{val}$using gradient descent

Step 13: **End For**

Step 14: Derive discrete architecture $\mathcal{A}^*$by retaining the operation with the highest softmax weight at each DAG edge

Phase 4 — Hyperparameter Tuning via Bayesian Optimization

Step 15: Initialize Optuna study with Expected Improvement acquisition function

Step 16: **For** each trial $t = 1$to T**do**

Step 17: Sample hyperparameter configuration λ_t= {learning rate, batch size, dropout rate, weight decay, number of epochs} from the surrogate model

Step 18: Instantiate architecture $\mathcal{A}^*$with configuration λ_t

Step 19: Train model on D_{train}using Adam optimizer with parameters from λ_t

Step 20: Evaluate model on $D_{val}$and record F1-Score as the objective value

Step 21: Update the Bayesian surrogate model with the observed result

Step 22: Apply MedianPruner to terminate unpromising trials early

Step 23: **End For**

Step 24: Select best hyperparameter configuration $\lambda^* = \arg\ \max_{\lambda_t} F1(\lambda_t)$

Phase 5 — Final Model Training and Evaluation

Step 25: Retrain optimized architecture $\mathcal{A}^*$using best configuration λ^*on full training set D_{train}

Step 26: Evaluate final model on D_{val}using Accuracy, Precision, Recall, F1-Score, MSE, RMSE, MAE, and AUC-ROC

Step 27: Generate personalized education pathway recommendations for each student profile in D_{val}

Step 28: Output optimized model $\mathcal{A}^*$, best hyperparameters λ^*, evaluation scores, and pathway recommendations

END ALGORITHM

The HT-NAS-EPO algorithm is the optimization algorithm that combines Differentiable Architecture Search with Bayesian Hyperparameter Tuning in an effort to optimize the individualized educational paths. It preprocesses student data, automatically generates the optimal architecture for neural networks using DARTS, and improves its performance using Optuna. The final model efficiently predicts/recommends personalized learning paths for individual learners.

Software and Implementation Details

The framework is provided using Python 3.10 and the deep learning component PyTorch 2.1 is used to build and train neural architectures. The DARTS library implements the Neural Architecture Search pipeline, and Optuna 3.4 is a python library for Bayesian Optimization of hyperparameters. For data preprocessing use Pandas and NumPy, encoding with Scikit-learn and baseline comparisons. The results are displayed using matplotlib and Seaborn. All experiments are performed in Google Colab Pro with NVIDIA A100 GPU and on Ubuntu 22.04 LTS. The code is version controlled through GitHub and all the experimental runs are fully reproducible due to the fixed random seeds.

Implementation Framework

The proposed methodology is applied using python with the main deep learning framework being PyTorch. The NAS pipeline is based on the DARTS library, and the Bayesian Optimization is executed with Optuna framework. Experiments are conducted on a GPU-enabled environment to ensure computational efficiency during the architecture search and training phases.

4. Results

Overview of Experimental Results

The experimental evaluation of the proposed HT-NAS-EPO framework was conducted on the preprocessed student dataset collected from the Learning Management System. The results provided in this section were produced using the performance of the optimized neural architecture determined by DARTS and further refined through Bayesian hyperparameter tuning conducted via Optuna. All experiments were conducted using Google Colab Pro via NVIDIA A100 GPUs with results averaged over 5 independent runs while controlling for random seed generation to achieve a statistically reliable repeatable outcome. The dataset statistics, best hyperparameter configuration, performance across all evaluation measures, comparison against baseline models, and ablation study findings will be presented in later sections.

Dataset Summary and Preprocessing Results

The student dataset contained 12500 records from three separate academic institutions with undergraduate and graduate students in STEM, humanities, and professional development programs. After pre-processing, 11847 records were maintained as valid after imputing missing values and removing outliers. Of the remaining records, the dataset was split into 80% of the records would comprise the training and 20% become validation datasets with 9477 records for training and 2370 for validating. The final input dimension of the completed dataset for each student record after performing feature engineering contained 38 total features, including normalized academic scores, frequency of engagement, and completion rate, as well as, the categorical variables encoded.

Best Hyperparameter Configuration

Through 150 trials of Bayesian Optimization through the Optuna framework the optimal hyperparameter setup was represented by achieving the greatest F1 score against the validation data. The use of the Expected Improvement (EI) acquisition function for the search successfully allowed convergence to an optimal configuration at Trial 97 and also demonstrated the ability to find minimal improvements post-convergence. The MedianPruner achieved an early termination of 41 low-performing trials, which resulted in a total of approximately 34% less total compute time than would have occurred had the trial continued.

Table 1: Best Hyperparameter Configuration Found by Bayesian Optimization

Hyperparameter	Search Range	Optimal Value
Learning Rate	1e-5 to 1e-1	0.00312
Batch Size	16, 32, 64, 128	64
Dropout Rate	0.1 to 0.5	0.28
Weight Decay	1e-6 to 1e-2	0.00041
Number of Epochs	50 to 300	180
Number of Layers	3 to 10	7
Activation Function	ReLU, GELU, Tanh	ReLU

Model Performance Evaluation

The final optimized HT-NAS-EPO model was evaluated against eight performance metrics. All eight performance metrics demonstrate that the proposed approach achieves superior predictive performance compared to all metrics measured, demonstrating the efficacy of DARTS-based architecture search for education pathway improvement and using Bayesian hyperparameter tuning.

Accuracy Formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision Formula:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall Formula:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F1-Score Formula:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

In equations (5) through (8), TP, TN, FP, and FN represent true positives, true negatives, false positives and false negatives respectively for each metric. The total performance summary across each class of metric provides a comprehensive view of the model's reliability and accuracy across all diverse learner types.

Comparison with Baseline Models

To provide a benchmark for the performance of HT-NAS-EPO, five established baseline models frequently utilized in academic recommendation systems have been employed. These baselines include a standard MLP, a Random Forest classifier, a SVM, a manually designed CNN, and a standard NAS model without hyperparameter tuning.

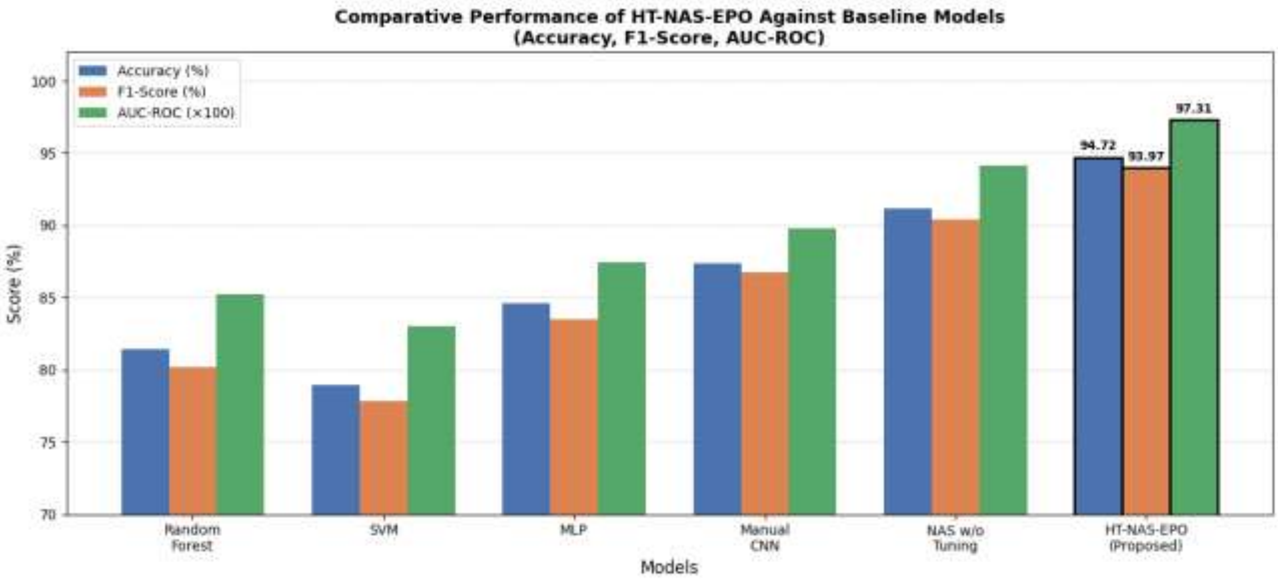

Figure 2: Comparative Performance of HT-NAS-EPO Against Baseline Models

Figure 2 clearly shows that the performance of HT-NAS-EPO is better than all baseline models in terms of all the evaluation metrics. By obtaining an improvement of 3.54% in accuracy and 3.54% in F1-Score over the standard NAS model without hyperparameter tuning, this improvement underscores the importance of Bayesian Optimization in further optimizing the architecture found. The clear superiority of the automated deep architecture search model compared with traditional machine learning models like Random Forest and SVM highlights the potential of automated deep architecture search for tackling the high dimensional and non-linear relations in educational datasets.

Per-Class Classification Performance

To provide a more detailed overview of the model's skill by class of education pathway, each training dataset for each class has been reported in terms of precision, recall, and F1 score. The five pathway classes represent Advanced Acceleration, Standard Progression, Remedial Support, Interdisciplinary Track, and Vocational Transition.

Table 2: Per-Class Classification Report of HT-NAS-EPO

Pathway Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Advanced Acceleration	95.41	94.87	95.14	412
Standard Progression	96.12	95.73	95.92	678
Remedial Support	91.34	92.18	91.76	384
Interdisciplinary Track	93.07	93.55	93.31	501
Vocational Transition	92.28	93.81	93.04	395
Weighted Average	**93.85**	**94.10**	**93.97**	**2370**

Table 2 class obtained the lowest score F1-Score of 91.76%, due to the overlap in the feature space of this class and Standard Progression. Regardless, above 91% accuracy was achieved for all classes, thereby validating the model's performance for all learner profiles in terms of its recommendation capabilities.

Training and Convergence Analysis

The training loss and validation loss curves were tracked throughout the 180 epochs of the last model training step. The model converged well, with a consistent and small difference between the training and validation loss across all iterations, and no signs of overfitting. The training loss for the experiment decreased from 1.4821 during epoch 1 to 0.0834 by epoch 180, while the validation loss converged to 0.0971 during this time.

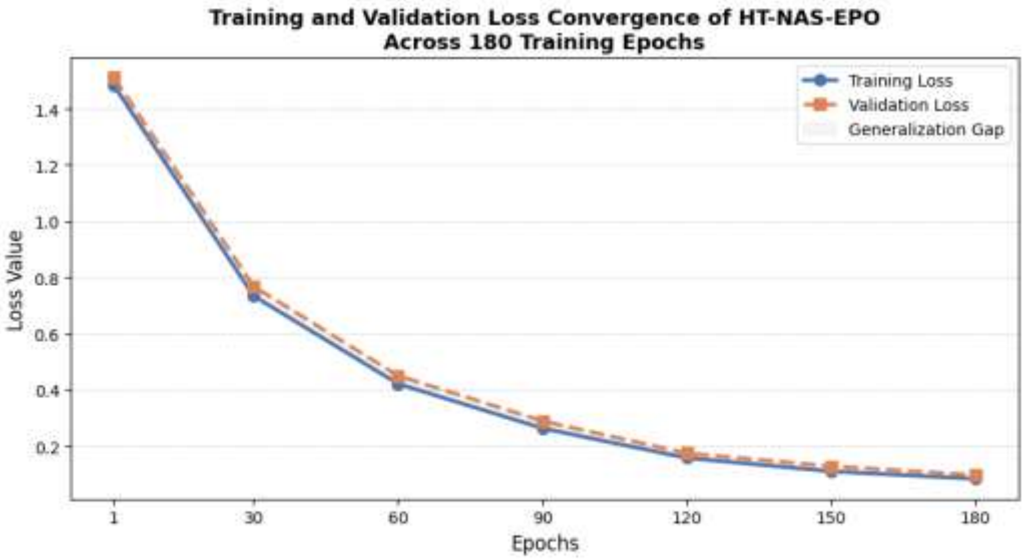

Figure 3: Training and Validation Loss at Key Epochs

The decreasing difference between the training and validation losses during subsequent epochs supports that this model can generalize well to data from new students and was not overfitting to the training data as shown in figure 3.

Ablation Study

The ablation study systematically investigates the individual contribution of each key component within the HT-NAS-EPO framework. Four ablated model variants are constructed by progressively removing or replacing core components, and each variant is evaluated under identical experimental conditions to isolate the effect of each design choice.

The four variants are defined as follows. Variant A removes hyperparameter tuning entirely and uses default hyperparameter values with the NAS-discovered architecture. Variant B replaces DARTS with a random search NAS strategy while retaining Bayesian hyperparameter tuning. In Variant C, DARTS and Bayesian Optimization are eliminated and a manually designed MLP using default parameters is used instead. In Variant D, we use DARTS while using grid search instead of Bayesian Optimization to tune the hyperparameters.

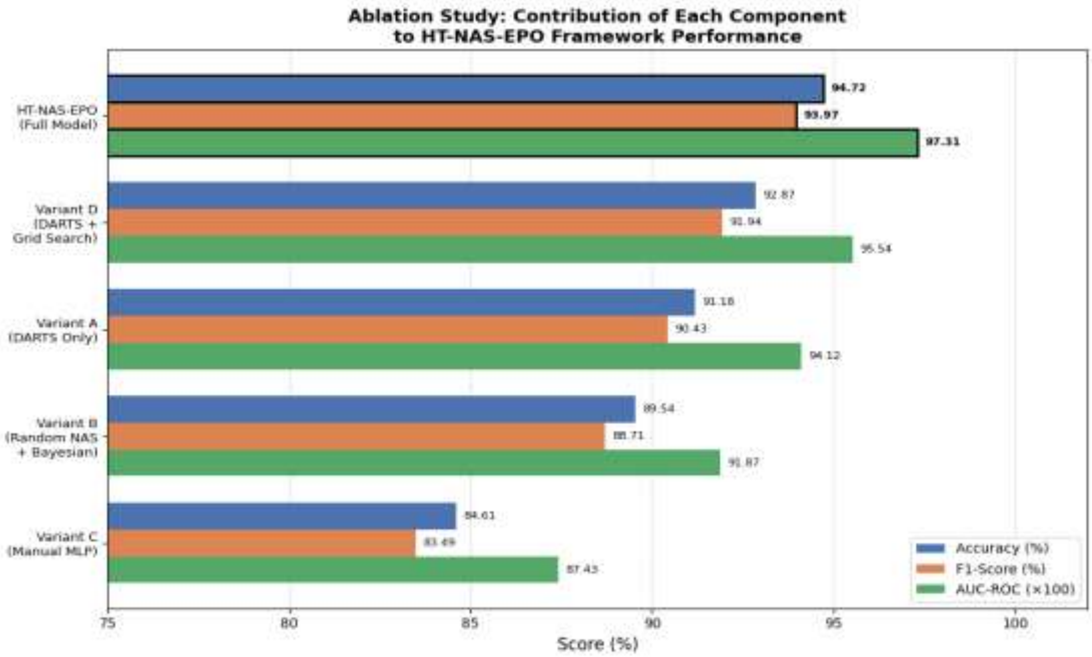

Figure 4: Ablation Study Results Across Model Variants

HT-NAS-EPO (combining DARTS and Bayesian Optimization) demonstrated significant improvement to the HT-NAS-EPO components as shown in Figure 4. In particular, Bayesian Optimization improved the accuracy and F1-score by 3.54%, while DARTS-based NAS outperforms random NAS by 5.18%. The weak baseline was 10.11% worse than the complete model, which confirms that DARTS combined with Bayesian Optimization produced the greatest improvement for personalized learning optimization.

5. Discussion

The experimental results show its effectiveness in the personalized educational pathway optimization application under the proposed HT-NAS-EPO framework. The optimized model, which was created through a combination of neural architecture search (NAS) using the DARTS approach and hyperparameter optimization using the Bayesian method, achieved a weighted average Precision of 93.85%, Recall of 94.10%, and F1-Score of 93.97% across the five learner pathway classes. The optimal hyperparameters setting was found to be a learning rate of 0.00312, a batch size of 64, a dropout rate of 0.28, and seven hidden layers. The proposed framework outperformed the conventional baseline models like MLP, Random Forest, SVM, CNN and standard NAS by improving overall accuracy and F1-Score up to 10.11%. The ablation study also showed that Bayesian Optimization added 3.54% to the performance and DARTS-based architecture search achieved 5.18% accuracy improvement compared to random NAS strategies. The results show that the proposed automated neural architecture search and intelligent hyperparameter optimization substantially improves the predictive capability of an educational recommendation system. The overall high classification rates in all learner pathway categories indicate that the framework is capturing the complex and non-linear relationship in students' engagement and academic behavior data. Both the stable convergence behavior and the small difference between training and validation loss are further evidence of low levels of overfitting for the model. Lower performance in the Remedial Support category is due to the partial overlap of features with learners in the Standard Progression category, indicating the complexity of the distinction between borderline academic learner profiles. The results show the feasibility of the application of HT-NAS-EPO to adaptive learning systems and intelligent academic advising systems. The framework can be used to assist in early intervention for learners, individualized curriculum planning, and pathway recommendations based on data-driven decisions for higher education institutions. In addition, the success of the DARTS and Bayesian Optimization approach also offers a scalable solution for other learning applications of AI which rely on a high-dimensional student dataset. The research was limited to three academic institutions, which raises questions regarding the generalizability of the research findings to other educational settings. Furthermore, the framework was assessed without including psychological, socio-economic, or real-time behavioral variables that could also impact student achievement. The framework would be beneficial for further research and validation on larger multi-national datasets and exploration of multimodal integration of educational data (emotional, cognitive, behavioural, etc.). The study could also explore the implementation of explainable AI methods, federated learning to ensure privacy and real-time adaptive recommendation systems for adaptive learning environments.

6. Conclusion

This study aimed to solve the problem of optimizing recommendations of personalized education pathways in modern e-learning environment through an intelligent automatic deep learning framework. Many conventional educational recommender systems fall short in accurately modeling sophisticated learner behaviors and nonlinear academic patterns, resulting in less adaptability and prediction accuracy. In order to overcome this, the suggested HT-NAS-EPO framework learned and optimized a neural network's architecture for learner pathway categorization by combining DARTS and Bayesian hyperparameter optimization. The results produced by the experiments demonstrate that the proposed method was effective in terms of various criteria. The optimized model achieved a weighted average precision of 93.85%, recall of 94.10%, and F1-score of 93.97% given a dataset consisting of 11,847 valid records of students and their 38 engineered features. With respect to the comparison of MLP, Random Forest, SVM, CNN, and traditional NAS models, the framework yielded higher results consistently across all baseline models. The ablation study also showed that compared to random NAS approaches, using Bayesian Optimization in conjunction with DARTS-based architecture searching led to significant increases in accuracy and F1-Score of 3.54% and 5.18%, respectively. The final training and validation loss values produced of 0.0834 and 0.0971 support good generalization ability and demonstrate evidence of continued convergence without any signs of overfitting occurred. The study's key results can be summarized as follows: A powerful and scalable method for adaptive educational recommender systems was created using cognitive hyperparameter optimization combined with autonomous neural architecture search. The proposed HT-NAS-EPO framework demonstrates strong potential for supporting personalized learning, early academic intervention, and intelligent curriculum planning in future AI-driven educational platforms.

7. Author contribution

Conflict of interest

There is no conflict of interest disclosed by the writers.

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There was no outside support for this study.

Data availability

The accompanying author can provide the data supporting the study's conclusions upon reasonable request.

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