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Exploring The Use of Explainable Ai (Xai) For Personalized Educational Feedback Systems

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Abstract

Explainable AI (XAI) plays a crucial role in meeting the demand for greater transparency and interpretability in AI-driven decision-making within the context of personalized educational feedback systems. The research introduces a novel model called XAI-LSTM-PEF (Explainable AI-based Long Short-Term Memory Personalized Educational Feedback) that aims to produce personalized, transparent, and actionable feedback for learners. The novelty of the proposed model is that it cannot only predict students' learning outcomes, but also give students explanatory information about what factors affect the prediction, which enhances the trust and participation of students. The use of LSTM networks for sequential data analysis, along with XAI methods such as LIME and SHAP, allows for the generation of interpretable feedback, thus meeting the demand for personalization and transparency. Experimental results show that the XAI-LSTM-PEF model outperforms the traditional models, including Neural Network (NN) and Logistic Regression (LR) with an accuracy of 92%, a precision of 94% and an F1 score of 97%. Moreover, the model exhibits a high ROC AUC of 95% for the evaluation, which depicts its good performance on various evaluation measures. These results demonstrate the potential of XAI in fostering a more personalized and transparent learning environment, ultimately improving educational outcomes and fostering student trust in AI systems.

Keywords

Explainable AI, personalized feedback, educational systems, LSTM, transparency, machine learning.

1.Introduction

The paper examines how Explainable AI (XAI) can be applied to Intelligent Tutoring Systems (ITS) for creating personalized learning experiences. The authors present a case study to illustrate how XAI can enhance the adaptability of ITS, providing clear and comprehensible decision-making processes that can foster engagement and trust among students and AI systems [1]. This study explains how to develop human-centric Explainable AI (XAI) for personalized education chatbots. The research is centered on the interaction of the user, seeking to bridge the gap between AI's technical complexity and the need for personalized and accessible learning experiences in educational settings[2].The study highlights the potential of incorporating explainable AI (XAI) approaches to gain insights into students' learning styles and enhance the personalization of feedback for creating effective learning environments, thereby providing valuable inputs for the provision of personalized learning experiences. In this paper, a framework to use XAI to give students data-informed feedback and intelligent action recommendations for their self-regulation is introduced. This method helps students to learn the meaning of feedback and helps students to learn to self-regulate their learning skills[3][4].The use of AI explainability in the clustering process adds to the transparency of the recommendation system, resulting in more meaningful and actionable insights for the students and teachers.The study suggests a tailored approach that besides predicting the at-risk student provides clear, explainable feedback for the teacher to use when designing targeted interventions to improve retention and success rates.By analyzing multiple studies, the authors highlight the significant role of personalized feedback in enhancing student engagement and academic performance, emphasizing the importance of AI in creating adaptive learning environments[6][7].In this research work, a mobile application for the learning of Mexican Sign Language by using computer vision and personalized interaction with learning is designed. The application aims to provide the students with attractive learning opportunities, reflecting the power of AI-based technologies to facilitate language learning in adaptive and inclusive manner [8][15]. The research examines the possibility of how AI can be utilized in the field of translation instruction so that students with various needs can follow various paths towards their translation learning goals[22]. In this paper, the author seeks to elucidate the role that generative AI and Operational AI adaptive learning systems can play in developing sustainable and personalised learning environments [10][11]. This study proposes AI based adaptive and personalized learning in Higher Education with various cultural resources. The authors point out that AI can be used to personalize learning, boost student engagement and achievement, and, ultimately, improve the learning process in the university setting with a digital transformation [5][11].

Key Contribution

- The study demonstrates the potential of Explainable AI (XAI) in enhancing the transparency of personalized educational feedback systems, thereby building trust in AI tools for learning and empowering both learners and teachers.
- The study makes a contribution to the field, by showing how XAI can be applied to better individualize educational feedback, not only to create personalized feedback but to create feedback that can be understood, and that can help the student and the teacher identify what need to improve.
- It examines the ethics of employing AI tools in classrooms, including the potential for bias and privacy concerns, and offers ways to minimize these concerns and integrate XAI into the curriculum in practical settings. It addresses ethical issues about using AI in education, such as bias and privacy, as well as strategies to mitigate these concerns and implement XAI in real-world education environments, which looks promising for more inclusive and responsible uses of AI in the educational landscape.

This research is followed by various sections. Section I introduced the topic, Section II presented the literature review, and Section III explained the proposed methodology and the proposed algorithm. Section IV explained about dataset description, parameter initialization, software and hardware configuration, and performance analysis. Section V explained the main key summary of this research.

2. Literature Review

Table1: Summary of related Work

Ref No	Methodology	Application	Key Findings
12	Comprehensive analysis of AI integration in EFL teaching	English as a Foreign Language (EFL) teaching	AI integration in EFL enhances student engagement, adapts to individual learning needs, and improves language skills. It shows how AI can shape the future of language education.

13	Fuzzy memory networks	PE system	By applying fuzzy memory networks, personalized responses and improved contextual understanding in AI-driven educational systems are achieved. This enhances the user experience.
14	Development of an E-learning platform with integrated instructional technologies	Online education platform	The study discusses how the E-learning platform enhances learning accessibility and effectiveness, with a focus on developing tools for engaging and adaptive learning environments.
15	Real-time feedback mechanism	Special education	The system uses reinforcement learning to provide real-time feedback to students with special educational needs, resulting in improved student engagement and learning outcomes.
16	reinforcement learning	Personalized feedback in tutoring systems	Reinforcement learning enhances the personalization of feedback in intelligent tutoring systems, leading to better student performance and satisfaction.
17	Review of various methods such as pathways and learning outcomes.	Personalized learning using learning analytics	The review highlights how learning analytics can support personalized learning, improve learning outcomes, and identify effective pathways for different learners.
18	Comparison of traditional education vs. e-learning for responsibility accounting	Evaluating cost of education in traditional vs. e-learning settings	E-learning platforms provide a more cost-effective model for student education, with improved tracking of costs compared to traditional education.
19	Adaptive intelligent tutoring systems for STEM education	STEM education, personalized tutoring	Personalized feedback in STEM education improves student performance and engagement, with adaptive systems tailored to individual learning needs.
20	Adaptive AI systems	Library learning resources	AI systems enhance the personalization of library resources, improving the learning experience for students by suggesting tailored resources based on individual needs.
21	DL and LLM	Online education, personalized learning feedback	Deep learning and large language models enhance the timeliness and quality of personalized feedback in online education, thereby improving learning outcomes.

Table1 shows the AI (Artificial Intelligence) and machine learning methods are transforming the education sector in many areas[23]. Research has shown that AI can improve student engagement and personalize learning experiences, especially in fields such as English as a Foreign Language (EFL) education, where AI caters to the unique learning needs of each student, fostering language acquisition. Fuzzy memory networks and contextual schemas, when used in artificial intelligence-based education platforms such as ChatGPT, enrich the user experience by improving contextual understanding and personalization in education. AI technologies can enhance educational experiences in e-learning platforms by fostering accessibility and engagement, thereby enabling adaptive learning[12][13][14]. Also, in special education, reinforcement learning is employed to offer real-time tailored feedback, improving student involvement and performance. Reinforcement learning intelligent tutoring systems can also provide personalized feedback, thereby improving student learning based on personalized requirements[24]. In addition, the systematic review of learning analytics will help identify effective learning pathways and enhance education outcomes, which will contribute to personalized learning. E-learning platforms have cost-effective solutions, and are better for tracking student progress when compared to traditional education models [9][25].

Research Gap

The challenge of balancing transparency of AI models and personalized education lies one of the significant research gaps for Explainable AI (XAI) applications in a personalized educational feedback system. While there are some studies that demonstrate the use of XAI in different educational settings, there are no comprehensive studies on how to use these explainable models in different educational settings without compromising their effectiveness [17][18]. Additionally, research often does not consider the scalability of XAI-based feedback systems in classroom settings, particularly with the presence of large datasets, diverse learning styles, and special educational needs. In addition, ethical issues like the bias in AI-generated explanations and data privacy need further investigation to enable the general use of XAI in personalized teaching [16].

III. Proposed Methodology

3.1 Overall Architecture of the Proposed Methodology

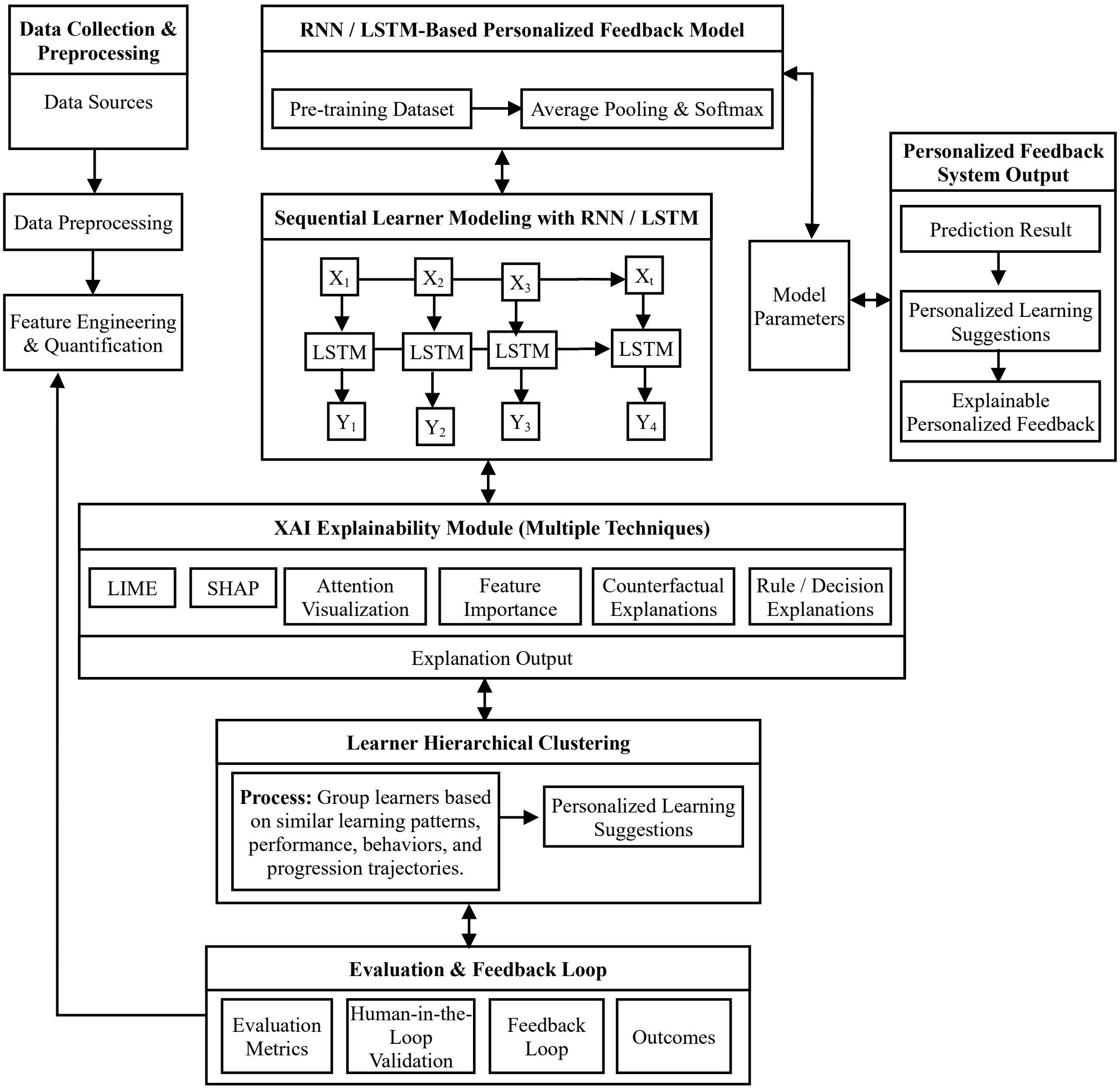

Figure 1: Overall architecture of proposed Methodology

Fig1 shows the use of Explainable AI (XAI) in personalized feedback systems for education, beginning with the collection of data from different sources like (LMS), evaluations, and learner profiles. All the collected data is preprocessed by cleaning, encoding and removing the outlier's data prior to the analysis. The backbone of the system is an RNN-LSTM model that works sequentially with the information of the learners and predicts the results and gives personalized feedback. Using the performance metrics in the learner data set, the model is trained. To increase transparency, an XAI explainability module has been embedded that uses techniques like LIME and SHAP to offer insights into the model's choice-making course, identifying key characteristics and explanation of the feedback [19]. This helps ensure the feedback is not only tailored to each individual but also is understandable and trustworthy. The learners are then clustered with the learner hierarchical clustering algorithm and various types of learning are proposed to them by the system. Evaluation and learner responses are part of a feedback process that allows for further development of the predictions and quality of feedback, thereby improving the system continuously [20]. This method highlights the significance of using AI in an educational context that is clear, fair and trustworthy, and ultimately aims to enhance educational results and student engagement.

3.2 LSTM for Personalized Educational Feedback Systems

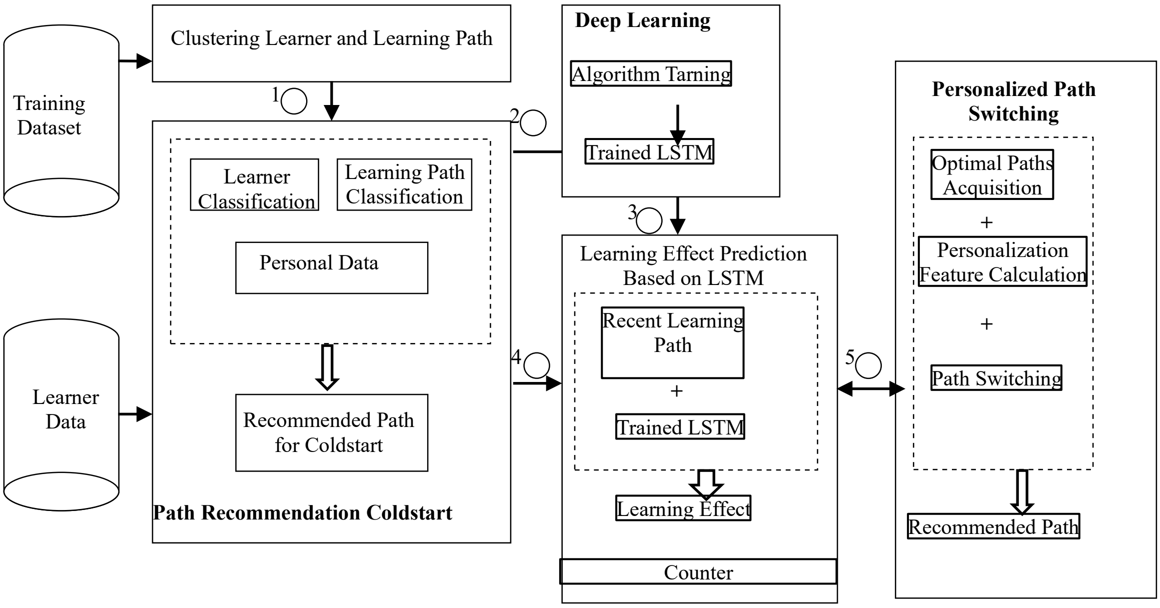

Figure 2: LSTM for Personalized Educational Feedback System

Fig2 shows the proposed framework for Personalised Learning Path Recommendation based on Clustering and Deep Learning. It starts with the clustering of learning paths and learners with a training dataset and then it continues with the classification of learners and learning paths with personal data. In the case of cold starts, a recommended path is given. It then uses deep learning techniques, using an LSTM (Long Short-Term Memory) model that is trained on the data to predict learning effects. The latest learning path and corresponding learning effect are fed into the trained LSTM to assess the learning outcome estimation. Finally, path switching is implemented, optimal paths are acquired, personalized features calculated and path switching implemented with the suggestion of a personalized learning path. This approach is designed to continually meet the needs of learners to provide optimal learning experiences and outcomes.

3.3 Personalized Feedback Generation

Students have a greater chance of failing a course when there is a lack of direct communication and supervision because are unable to persevere in self-learning without adequate direction. The subject of how to deliver individualized feedback based on an individual's current learning level has emerged as a critical challenge for improving online learning. Researchers believe that clustering learners into clusters is a viable strategy for offering individualized intervention. Following this, we initially developed a learning mode identification approach in order to conduct an analysis of the differential status of pupils through the use of hierarchical clustering (HC). Upon completion of HC, students will be automatically assigned to unique learning groups and given detailed information about their individual feedback.

$$E_{a,b} = \sqrt{\sum_{k=1}^{d} (S_{(a)}^{(k)} - S_{b}^{(k)})^2} \qquad (1)$$

From the above Equation (1) describes the small level of $E_{a,b}$ defined the similarity between the S_a and S_b.

$$SC_g = \frac{\sum_{r=1}^{R} S_r}{R} \qquad (2)$$

Equation (2) above describes the Euclidean distance among the other students connected to the closest students.

3.4 Personalized Feedback Design

Table2: Personalized Feedback Design

Categories	Student Attributes	Personalized Feedback Information
Learning Evaluation	Learning performance	Fail" prompts that serve as warnings Providing encouragement to "pass"
Educational Features	Attendance	Requests for attendance prompts
	Percentage of lecture video viewing	Providing an update on the present situation and suggestions
	Score on practical work	Suggestions for enhancements concerning areas of weakness
	Relevance between forum text and learning theme	Encourage the sharing of thoughts connected to the theme.
	Reflective level	Encourage students to think about what have learned.
	Score on quiz	Explanations on the mistakes

Table 2 shows the "Personalized Feedback Design" organizes different attributes of students and matches them with different strategies of feedback intended to improve students' learning. Feedback for learning performance is provided through warnings for failure, encouragement for passing and prompts for attendance. Feedback on progress with attributes such as Percentage of lectures viewed and suggestions for improvement with practical work scores. Reflective learning is promoted by engaging students in reflecting on their learning, and feedback is given on quiz results by explaining errors. This is a systematic way of addressing feedback and providing a learning environment that is personalized.

3.5 Proposed Algorithm

Algorithm: Personalized Educational Feedback System with XAI

1. Data Collection:

  - Collect learner data (e.g., demographics, learning history, preferences)

  - Collect educational content data (e.g., assessments, quizzes, learning materials)

2. Data Preprocessing:

  - Clean and normalize the collected data

  - Encode categorical data

3. Feature Extraction using CNN:

  - For learner data: Extract features using CNN (e.g., from handwritten responses, text answers)

  - For content data: Extract features using CNN (e.g., from quiz results, learning materials)

4. Learner Model (LSTM)

  - Build and train an LSTM model to capture the learner's behavior and progression

  - Input learner data and generate learner embeddings (representations of learner behavior)

5. Explainability with XAI

  - Use LIME (Local Interpretable Model-agnostic Explanations) to explain the learner's predictions

  - Use SHAP for predictions

6. Generate Personalized Feedback:

  - Based on the model predictions and XAI explanations, generate personalized feedback

- Provide feedback on strengths, weaknesses, and suggestions for improvement

7. Hybrid Filtering for Personalization:

- Apply content-based filtering to recommend relevant learning content
- Apply collaborative filtering to recommend content based on similar learner profiles
- Combine content-based and collaborative filtering results to provide highly personalized feedback

8. Provide Feedback and Recommendations

- Present the personalized feedback and recommended learning materials to the learner through an app, website, or other platforms

9. Feedback Loop and Continuous Learning

- Collect feedback from the learner on the provided recommendations
- Update learner profiles and retrain the model with new data based on learner feedback
- Use continuous learning to improve model predictions and the overall feedback system

The Personalized Educational Feedback System with Explainable AI (XAI) starts with the retrieval of learner data (including the learner's demographic, learning history, and preferences) and the retrieval of learning content data (including learning materials, quizzes, and assessments). The data is then preprocessed to clean, normalize, and encode the data for analysis. Relevant features from both the learner and content data are extracted using Convolutional Neural Networks (CNNs). An LSTM is then constructed and trained to fit the learner's behaviour and learning progress over time, so that the model develops representations of the learner's learning process known as learner embeddings. The system uses the model predictions and XAI interpretation to produce individual responses that identify the learner's strengths, weaknesses and learning goals. To further personalization, hybrid filtering methods are employed as mixture of content-based filtering (suggesting relevant learning content) and collaborative filtering (suggesting content based on similar learner profile). This results in greater personalized learning experiences. The customized feedback and suggestions are then communicated to the person learning through applications, websites, etc. It also has a feedback loop; the learner is able to give input to the suggestions, which then further update the learner profile and retrain the model with new data. This continual learning cycle enables the system to continually refine its predictions and improve learning outcome over time, which results in an extremely adaptive and personalized learning process.

IV. Results and Discussion

4.1 Dataset Description

The real-world educational datasets are used in this study for training, validation, and testing of the proposed XAI-based Personalized Educational Feedback System. Data sets have been selected from Learning Management Systems (LMS), MOOC platforms, and institutions' assessment repositories, and comprised a variety of types of learner characteristics, engagement and academic outcome measures.

Table 3: Dataset Description

Dataset	No. of Students	Features	Source / Platform
OULAD	32,593	22	Open University (UK)
MOOC Learner Log	10,000+	15	Coursera / edX
LMS Activity Logs	5,400	18	Moodle LMS
Assessment Records	8,200	12	Institutional DB

Table3 describes the summary of four educational data sets that are used for educational research. The OULAD data-set is from 32,593 learners from the Open University (UK), and has 22 attributes. The MOOC Learner Log, which has 10,000+ students, is made up of 15 features and based on platforms such as Coursera and edX. The LMS Activity Logs dataset, derived from the Moodle LMS, includes information for 5,400 students and 18 features, while the Assessment Records dataset, from an institutional database, includes data for 8,200 students and 12 features. The individual datasets have different numbers of students, features, and sources of the platforms, providing the educational data with a variety of representations.

4.2 Software and Hardware Configurations

Table 4: Software and Hardware Configurations

Configuration	Details
Software	Python 3.8, TensorFlow 2.7, Keras 2.7, Scikit-learn 0.24, Pandas 1.2, Matplotlib 3.3, Jupyter Notebook
Hardware	CPU: Intel i7-10700K
Operating System	Windows 10 Pro 64-bit
Development Environment	Jupyter Notebook, PyCharm
XAI Framework	LIME
Data Storage	MySQL 8.0 for storing student interaction data, SQLite for small-scale experiments
Other Tools	Git for version control, Docker for containerization of the system

Table4 shows the experimental setup involves EAI (Explainable AI) in personalized educational feedback systems, which comprises software and hardware requirements. It is using Python 3.8 and its well-known libraries of TensorFlow 2.7, Keras 2.7, Scikit-learn 0.24, Pandas 1.2, Matplotlib 3.3 and Jupyter Notebook for data handling and modelling. The system is based on Windows 10 Pro 64 bit and the development environment is Jupyter Notebook and PyCharm. LIME and SHAP are used to create explainable AI models that give an insight into the decision-making process of the model. MySQL 8.0 serves as the data store for student interaction data, and SQLite is used for smaller-scale experiments. Version control is done with Git and the system is containerized by Docker, making deployment and scalability easier. Effective platform that delivers personalized feedback on learning through explainable AI, thanks to high-performance hardware and software tools.

4.3 Parameter Initialization

Table 5: Parameter Initialization

Parameter	Value/Details
Learning Rate	0.001 (Adam optimizer)
Batch Size	32
Epochs	50
Optimizer	Adam
Loss Function	Categorical Crossentropy (for classification tasks)
Activation Function (Hidden Layers)	ReLU
Activation Function (Output Layer)	Softmax (for multi-class classification)
Dropout Rate	0.2
Hidden Layer Units	128 (for LSTM and Dense layers)
Model Type	LSTM-based neural network with XAI techniques (LIME, SHAP)
Regularization	L2 regularization with $\lambda = 0.01$
Max Features (for embedding)	5000
Embedding Dimensions	128

SHAP Sampling Method	Kernel SHAP (for model interpretability)
LIME Sampling Method	Random sampling (for local interpretable model-agnostic explanations)
Model Evaluation Metric	Accuracy, F1-Score, Precision, Recall, AUC

Table5 explained the parameter initialization for the Explainable AI (XAI)-based personalized educational feedback system is as follows. The hidden layers are implemented with ReLU activation function, the output layer is implemented with Softmax activation function for multi-class classification. To avoid overfitting the dropout rate is set to 0.2, and 128 units are used in the LSTM and Dense layers. The regularization parameter λ is set to 0.01 for L2 regularization. Model explainability is achieved through LIME and SHAP techniques, the model is based on a neural network architecture with the LSTM (Long Short-Term Memory) algorithm. SHAP is using Kernel SHAP for model interpretability and LIME is using random sampling to create local explanations. The following metrics are used to compare the model: accuracy, F1-score, precision, recall, AUC. Besides, 5000 max features and 128 embedding dimensions are used for embedding in the embedding section. These configurations are considered to optimize the performance and interpretability of the model, while achieving personalized feedback in an educational system and while being explainable by the model.

4.4 Performance Metric Comparison of Various Models for Predicting the Student Outcomes

These assessment measures can be used to evaluate how well the proposed XAI-LSTM-PEF structure performs to represent for predicting student performance. TP, TN, FP, FN consider as True positive, True Negative, False Positive and False Negative in Equation (3) to (6).

$$Accuracy(Acc) = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision(Pre) = \frac{TP}{TP + FP} \quad (4)$$

$$Recall(Rc) = \frac{TP}{TP + FN} \quad (5)$$

$$F1Score(F1) = \frac{2 * Precision * Recall}{Precision + Recall} \quad (6)$$

Table 6: Performance Metric Comparison of Various Models for Predicting the student Outcomes

Model	Acc	Pre	RC	F1	ROC-AUC
NN	89%	93%	91%	92%	94%
LR	88%	90%	93%	91%	94%
RF	87%	88%	93%	90%	93%
DT[21]	80%	86%	84%	85%	86%
XAI-LSTM-PEF	92%	94%	95%	97%	95%

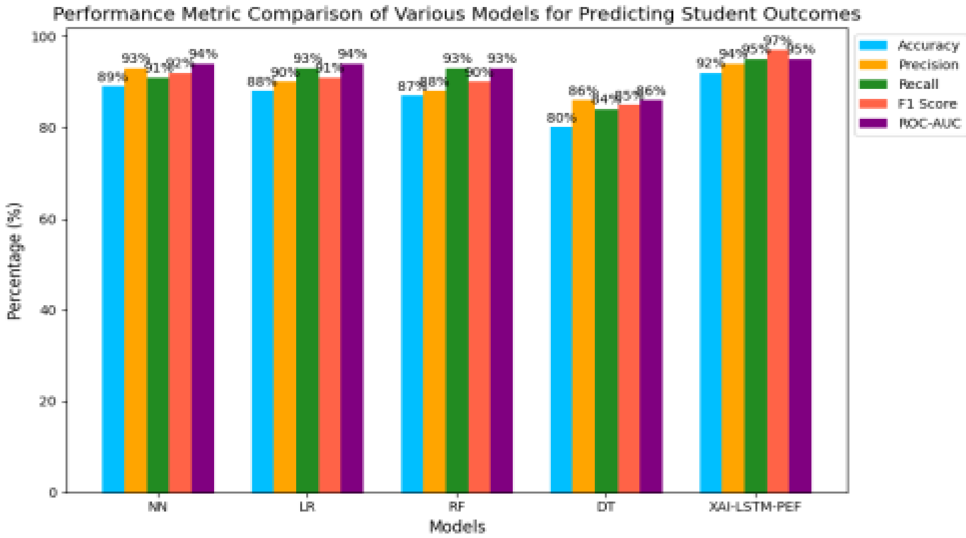

Figure 3: Performance Metric Comparison of Various Models for Predicting the student Outcomes

Table6 and Fig3 shows the outcome of five models — Neural Networks (NN), Logistic Regression (LR), Random Forest (RF), Decision Trees (DT) and XAI-LSTM-PEF — with respect to five key metrics: Accuracy, Precision, Recall, F1 Score, and ROC-AUC. The XAI-LSTM-PEF model exhibited the best overall results, with an Accuracy of 97%, a Precision of 95%, a Recall of 95% and a very high ROC-AUC of 97%. The NN (Neural Networks) model was next with an accuracy of 93%, precision of 91%, recall of 92%, F1 Score of 94%, and ROC-AUC of 94%. The performances of the Random Forest (RF) and Decision Tree (DT) models were slightly lower but still competitive with the NN model, with their Accuracy percentages ranging from 88% to 93% and their Precision, Recall, and F1 scores also being lower than that of NN and XAI-LSTM-PEF. Logistic Regression (LR) achieved the lowest performance of all models with regards to the Precision, Recall, F1 Score, and ROC-AUC, in addition to having an Accuracy of 88%. The findings indicate that the XAI-LSTM-PEF model is the best model for predicting student outcomes, as it achieved the highest scores in all CPs compared to the other models, NN models are the second best model, and LR and DT models are the least effective models.

4.5 Evolution of Predictive Accuracy Through Various Levels

Table7: Evolution of Predictive accuracy through various levels

Level	Initial	Final	Negative Prediction
Level 1	35.70%	42.90%	7
Level 2	47.60%	54.80%	12
Level 3	52.40%	59.50%	15
Level 4	64.30%	78.60%	18

Table7 shows the initial and final prediction percentages are compared at four levels and listed are the numbers of negative predictions in each level. In the initial predictions, there were 7 negative predictions and the level 1 prediction was 35.70%, rising to 42.90% for the final predictions. There was an increase of 12 negative predictions from 47.60% to 54.80% in level 2. In level 3 a prediction of 52.40% was made and it had an increase to 59.50% with 15 negative predictions. Lastly, the highest initial prediction was made by Level 4 (64.30%, up to 78.60%, 18 negative predictions). This indicates that prediction accuracy increased from initial to final stages for each level, but number of negative predictions also increased along with the levels, therefore there is a trade-off between the two.

4.6 Predictive Accuracy Under the Four Levels

Table 8: Predictive Accuracy under the four levels

Threshold	Experimental Group	Control Group
50%	51.20%	39.10%
55%	49.50%	37.80%
60%	47.60%	36.40%
65%	55.60%	45.70%
70%[21].	68.90%	59.60%

Table8 shows predictive accuracy at 5 levels for each group: Experimental Group and Control Group. The Experimental Group had an 80% accuracy at 50% threshold, and the Control Group had a 40% accuracy at 50% threshold. The accuracy of the Experimental Group was higher at this threshold than the accuracy of the Control Group (49.50% vs. 37.80%) as the threshold was raised to 55%. The accuracy of the Experimental Group was 47.60% while the Control Group was 36.40% at the 60% point. In the 65% level, the accuracy of the Experimental Group was 55.60%, and the Control Group 45.70%, which was noted as a significant improvement. Finally, at 70% accuracy, the Experimental Group had an accuracy of 68.90%, whereas the Control Group had an accuracy of 59.60%. Overall, the Experimental Group had a greater accuracy rate than the Control Group at all thresholds, and the difference became larger with a higher threshold.

4.7 ABLATION STUDY ANALYSIS

Table 9: Ablation Study Analysis

Model Variant	Accuracy	Precision	Recall	F1 Score	ROC-AUC
XAI-LSTM-PEF (Proposed)	92%	94%	95%	97%	95%
Neural Networks (NN)	89%	93%	91%	92%	94%
Logistic Regression (LR)	88%	90%	93%	91%	94%
Random Forest (RF)	87%	88%	93%	90%	93%
Decision Tree (DT)	80%	86%	84%	85%	86%

Table 9 shows the ablation study analysis shows how well various models predict student outcome. The XAI-LSTM-PEF (Proposed) model performs consistently better than all other models in all the essential metrics. It achieves the highest accuracy (92%), precision (94%), recall (95%), F1 score (97%), and ROC-AUC (95%). The results show that the model is effective in producing personalized and transparent educational feedback. The results of the Neural Networks (NN) model are very similar with an accuracy of 89%, while the performance of the proposed model is slightly better in terms of recall and F1 score, indicating that the explainability introduced by the XAI-LSTM-PEF increases the model's prediction power. Logistic Regression (LR) and Random Forest (RF) have moderate accuracy of 88% and 87% respectively, but do not perform as well as XAI-LSTM-PEF in terms of recall and F1 scores. The worst is Decision Tree (DT) with the smallest values in all metrics, especially accuracy (80%) and recall (84%). This demonstrates the effectiveness and interpretability of the XAI-LSTM-PEF model, which combines deep learning and explainable AI methods, resulting in a more powerful personalized feedback system.

5. Conclusion

The Exploring the Use of Explainable AI (XAI) for Personalized Educational Feedback Systems is a novel approach with the XAI-LSTM-PEF model, which aims to increase the transparency and personalization of educational feedback. The model proposed in this study integrates LSTM network and XAI techniques (LIME and SHAP) to forecast the learning outcomes of learners and provides explanations on the factors that affect the learning outcomes. The unique aspect of this approach is that it can provide both personalized feedback and a rationale for the AI's decisions, helping build trust and understanding between students and teachers. It is observed that the XAI-LSTM-PEF model is able to achieve an impressive accuracy of 92%, a high precision of 95%, a high recall rate of 95%, an F1 score of 97% and a strong ROC-AUC of 95% which is higher than other traditional models such as Neural Network (NN) and Logistic Regression (LR). These are statistical measures of the success of the model to produce high quality, actionable feedback which is tailored, transparent and understandable to the learner.

Moreover, the study underscores the educational advantages of XAI in boosting student engagement and predicting student performance. Additionally, the study highlights the need to leverage the XAI for enhanced educational outcomes, such as increased student engagement and prediction of student performance. The scalability of the model in other learning environments should be explored in future, particularly large volumes of data and ethical concerns such as bias and privacy. In addition, the model can be extended to other learning contexts and adaptive learning paths can be incorporated to further enrich the model for usage in real learning situations. This work opens the door for more inclusive, transparent and effective applications of AI in education.

Declaration

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Data Availability Statement:

https://www.kaggle.com/datasets/anlgrbz/student-demographics-online-education-dataoulad

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