LEARNING STYLE BASED PERSONALIZED EDUCATIONAL CONTENT DELIVERY PLATFORM

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ABSTRACT

This study outlines the development of an AI powered learning platform Apex which uses AI to accurately predict the learning style and area of interest of each student based on the initial self assessment and aims to deliver personalized educational content based on the user's learning style. Furthermore, the content can be dynamically altered based on the feedback after completing each module.With the personalized approach offered by Apex we aim to enhance student engagement and improve their learning outcomes by offering an effective learning experience.The primary goal of the platform is to improve student involvement, improve learning outcomes and provide a more adaptable and individual-oriented learning environment by providing the educational contents based on the user's learning style and enhance student engagement by tracking their learning progress and motivating them by maintaining streaks to achieve an effective learning on daily basis. Categorical dataset is collected from the initial assessment test answered by the users and processed to identify the user's learning characteristics and quality. Bivariate dataset is used to track the learning progress of the users. Numerical dataset is used to show the number of learning modules completed by the users and to show the daily streak of their effective learning journey.This proposed method increases the accuracy up to 81% in categorizing and delivering the learning contents based on the user's need and learning style and achieving effective learning.

KEYWORDS

Personalized, Artificial Intelligence, Learning style, Effective learning,dynamic, contents, Visual, Auditory ,Kinesthetic, Read/Write

INTRODUCTION

Over millennia, humanity has been shaped by successive waves of technology. Now we are in a new wave of technology, which makes us admire and also fear whether we humans would be replaced, whether our jobs would be taken and so on. It is nothing but a buzzword which we hear all around now-a-days **AI**. Artificial Intelligence have highly revolutionized the whole world leading to significant impact in several fields.But when it comes to education the same old online systems still persists giving boring lecture contents, lacking interaction, neglecting critical thinking and paving highway to distractions.[1] There is no online platforms which provide high quality and effective personalized learning experience considering the diverse needs of individual learners and to address this, this study comes with a systematic approach of integrating AI with LMS leveraging to a platform that can dynamically customize the content based on user interaction and preferences.[2]

This new approach categorizes students based on their learning style into visual, auditory, kinesthetic, solitary and social learners and provides content based on their style[3]. For Example: Logical Learners learn best through logic, patterns, and problem-solving. So their content includes puzzles, brain teasers, and critical thinking exercises. In contrast, Visual Learners learn best through images, diagrams, charts, and videos So they benefit from visual aids, illustrations, and graphic organizers. The categorization is based on the initial self assessment which includes multiple choice questions,likert scale questions and task based questions.With Ensemble learning the platform integrates the predictions made after each assessment module using Decision Trees, Naive Bayes and SVM algorithms and Generative AI tailors the content based on the predicted learning style. Frequent feedback is collected from the learners to ensure that the provided content fits to their method of learning and dynamic changes are done after the feedback to ensure that the platform is personalized perfectly for each learner. This method of allowing learners to learn and interact in their preferred learning style significantly improves interaction, personalization and fosters the understanding of information in a better way. This platform creates an active learning atmosphere promoting seamless self directed learning.

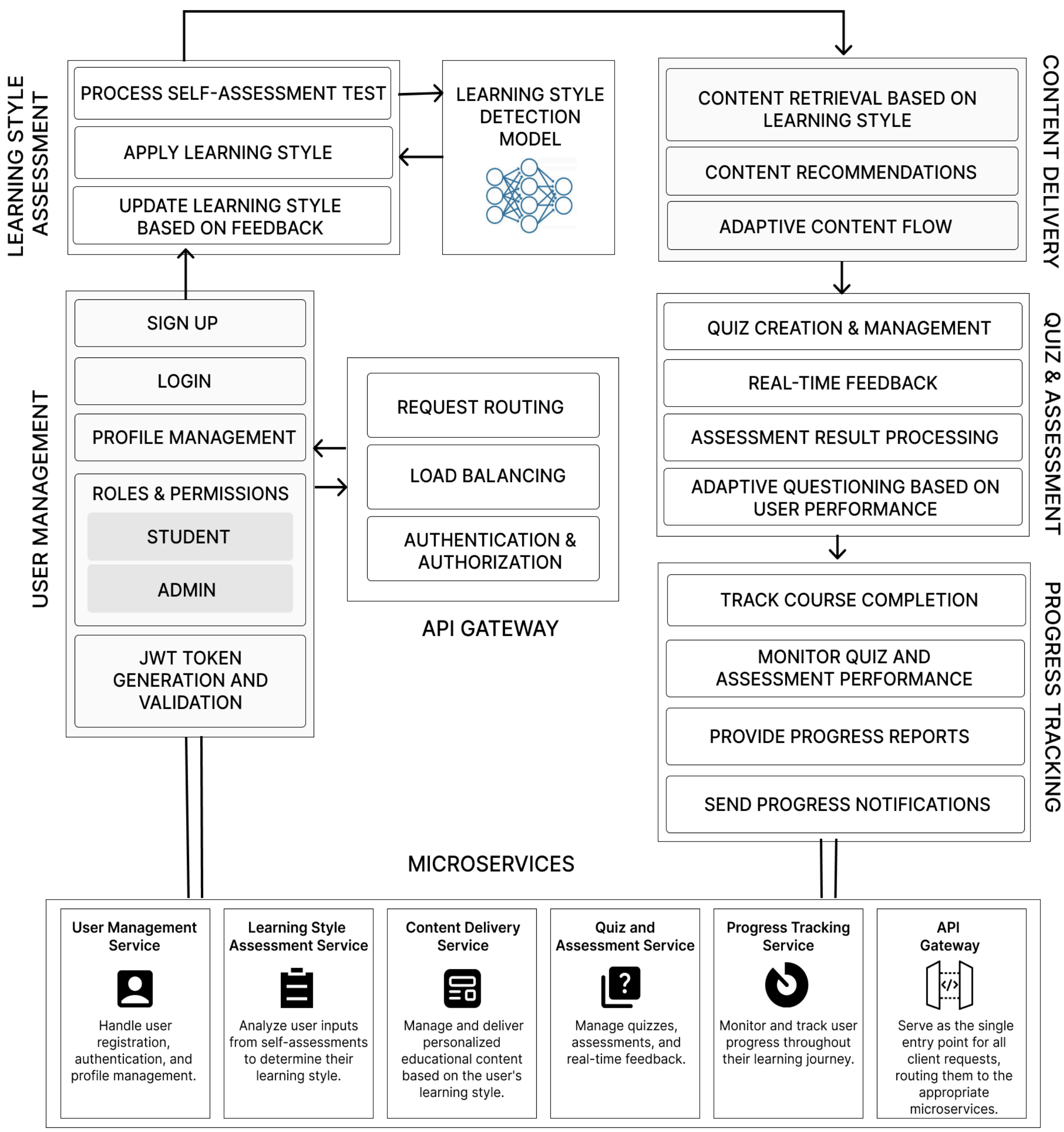

Fig.1. Architecture Diagram

ALGORITHM

For classifying our learners into four types—Visual, Auditory, Read/Write, and Kinesthetic—we have used Supervised Machine Learning models. After experimenting with multiple classification algorithms, **HistGradientBoostingClassifier** was selected due to its efficiency, scalability, and high accuracy with both numerical and categorical data. It is an ensemble-based method that builds trees sequentially, where each tree corrects the errors of the previous one, leading to improved prediction performance.

Unlike Random Forest, which relies on bagging and parallel decision trees, Gradient Boosting uses a boosting strategy that focuses on hard-to-predict instances. The model works by minimizing a loss function through gradient descent, and its histogram-based implementation (HistGradientBoosting) makes it faster and more memory-efficient by binning continuous features into discrete bins.

This approach significantly reduces overfitting and increases the generalization power of the model. It also handles missing values and categorical encoding internally, which made it an ideal choice for our dataset containing encoded questionnaire responses and demographic attributes.

Algorithm Steps:

1. Import necessary modules like Flask, Scikit-learn, Pandas, NumPy.
2. Load the dataset.
3. Preprocess the data by encoding categorical features.
4. Assign scores for each answer.
5. Prepare feature set (X) and label (Y).
6. Compare classifiers (Decision Tree and Gradient Boosting) using 5-fold cross-validation.
7. Select the best-performing model (HistGradientBoostingClassifier).
8. Fit the final model on the full dataset.
9. Use Flask API to receive user input via POST request.
10. Convert responses to the appropriate format and encode using label encoders.
11. Predict the learning style using model.predict().
12. Return the predicted learning style through the API.

This model was found to be robust and reliable in accurately classifying users into their dominant learning style category based on their responses.

LITERATURE REVIEW

From our deep research we came to know that the concept of classification of learners based on the learning style was known in the 1970s and 1980s but it was not effectively implemented. The idea that students learn best when teaching methods and post learning activities match their learning styles, strengths, and preferences was not put out in a right way.Though there were many pre-existing theories and models such as Kolb's Experiential Learning Theory [4], Fleming's VARK model model[5], Honey and Mumford's model[6], Dunn and Dunn model[7], Grasha-Riechmann Learning Style Scales ,Felder-Silverman Learning Styles model[8] which classified learners based on multiple different personality based aspects, later terribly failed as there was no strong evidence that learning style improves the efficiency[9]. It was also thought that the practical implementation of these theory based education is superficial and they would sophisticate the existing education setting by introducing psychology and emotions to it.

Recent researches prove that online education and the emergence of artificial intelligence paved the way to make personalization possible[10]. With the introduction of Education 5.0 which uses machine learning algorithms and natural language processing creating a more dynamic and responsive learning system was made possible [11], [12]. Research by B. K. Smith also proves artificial intelligence has significantly improved the efficiency of online education but however they do not concentrate much on learning style based content customized content delivery which still stands as a backlog.

Here comes the buzzword generative AI, which gives hands to personalize the content using GPT models. Brown et al.'s recent study examined how generative artificial intelligence (AI) can be used to create materials such as simulations and quizzes. The study highlighted the technology's potential to generate a range of learning resources. Furthermore R eddy et al.[13] demonstrated the use of AI, in developing tests that can dynamically adjust based on learner performance and engagement levels. Despite all these, the integration of generative AI with LMS to create an effective personalized and adaptive platform still exists as an unexplored area.

RESEARCH GAP AND AIM OF STUDY

Previous research has only done analysis of different learning styles. We aim to predict the learning style and deliver content to users based on their learning style to give them a more personalized and customized learning experience. We also used a custom data set for training and testing purposes for ml models.

This study aims to develop a novel learning platform that classifies learners into visual, auditory, read/write, and kinesthetic learning styles based on their responses to a custom dataset of MCQs and Likert scale questions. Then the platform utilizes generative AI to dynamically create personalized educational content tailored to the identified learning style. This enhances learner engagement by providing content that aligns with their preferred mode of learning, thus improving the efficiency.

MATERIALS AND METHODS

The purpose of this study is to classify the learners based on their learning style and give dynamic content according to their style of learning. The research methodology focused on classifying users into primarily four categories based on the VARK learning style model proposed by Neil Fleming [7]. They are Visual, Auditory, Read/Write, and Kinesthetic.

i) Dataset Collection

To train and evaluate the proposed learning style prediction model, a custom dataset was created through a structured questionnaire designed to identify the dominant learning style of individuals based on the VAK (Visual, Auditory, Kinesthetic) model. The dataset was collected from voluntary participants including students and professionals from diverse educational and occupational backgrounds.

The questionnaire consisted of 15 multiple-choice questions aimed at capturing behavioral and perceptual preferences. Each question had three options, each corresponding to one of the VAK styles. For every participant, responses were numerically encoded (e.g., 1 for Visual, 2 for Auditory, 3 for Kinesthetic) and stored in a tabular format. The dataset contains `N=XX` samples, each comprising 15 feature attributes (`Q1` to `Q15`) and a target label indicating the predicted dominant learning style.

Efforts were made to ensure a balanced representation of all three learning styles in the dataset to avoid class imbalance during model training. The data was cleaned, anonymized, and preprocessed before being used in the classification pipeline. The dataset serves as a foundational element in developing a machine learning model capable of personalized learning recommendations based on the user’s preferred learning modality.

ii) Data preprocessing

The dataset used in this study comprises approximately 1000 samples collected through a structured questionnaire. Each sample includes demographic attributes such as gender and age, along with responses to 15 multiple-choice questions designed to assess individual learning preferences across the VAK (Visual, Auditory, Kinesthetic) model. A final column denotes the labeled dominant learning style for each participant.

To prepare the dataset for machine learning, all categorical variables—including gender, age, and question responses—were encoded numerically using label encoding. The target variable, representing the dominant learning style, was also encoded using `LabelEncoder`. No samples were discarded, and missing or invalid entries were handled during preprocessing to ensure data quality. The final processed dataset includes 17 features per sample and one target class.

iii) Learning style Scoring

Participants responded to a fixed set of 15 multiple-choice questions, each designed such that the answer options correspond to a particular learning style (Visual, Auditory, or Kinesthetic). Each selected option incremented an internal style score associated with that learning style. The style with the highest cumulative score was assigned as the participant's dominant learning style and used as the ground truth label during model training. This scoring mechanism allowed the transformation of qualitative behavioral preferences into quantifiable labels, essential for supervised learning.

iv) Model Selection

To predict the dominant learning style of users accurately, multiple classification algorithms were evaluated. A Decision Tree Classifier and a HistGradient BoostingClassifier (a high-performance variant of gradient-boosted decision trees) were implemented using the scikit-learn framework.

Both models were evaluated using 5-fold cross-validation to compare their predictive performance. The HistGradient Boosting Classifier outperformed the Decision Tree in terms of average accuracy and consistency, making it the model of choice for final deployment. The ensemble model was trained on the entire dataset post cross-validation for optimal performance

EXPERIMENTAL RESULT

The evaluation of the test outcomes in predicting the learning style of users reveals the performance pattern of the model used in this study. The **HistGradientBoostingClassifier** demonstrated a definitive predictive capacity, achieving an accuracy of **81%**. This level of precision plays a critical role in delivering personalized learning content aligned with the identified learning style of each user.

In terms of detailed performance metrics, the model achieved strong results across **precision, recall, and F1-score** for all four learning styles—Visual, Auditory, Read/Write, and Kinesthetic. This enables the model to effectively distinguish between different types of learners and classify them with high confidence.

The final output of the model displays the **predicted dominant learning style** of the user and enables the delivery of content tailored to that style. This outcome highlights the model's **potential to transform the learning experience** by offering accurate, data-driven personalization. It serves as an effective tool in enhancing engagement, motivation, and overall learning outcomes by adapting to the individual needs of each learner.

	Precision	Recall	F1-Score	Support
Auditory	1.00	0.00	0.00	1
Kinesthetic	1.00	0.80	0.89	5
Read/Write	0.78	1.00	0.88	18
Visual	1.00	0.00	0.00	3
Accuracy			0.81	27
Macro Average	0.95	0.45	0.44	27

Weighted Average	0.86	0.81	0.75	27

Table.1. Output Values

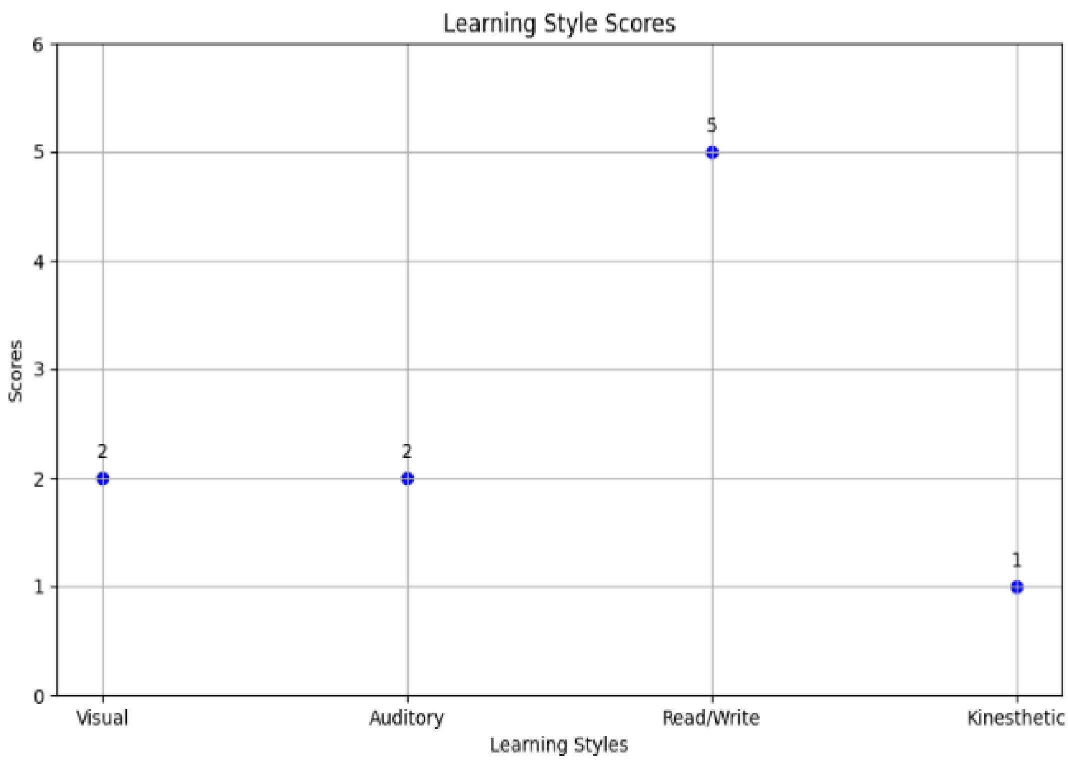

Fig.2. Scatter Plot of Learning Style Prediction

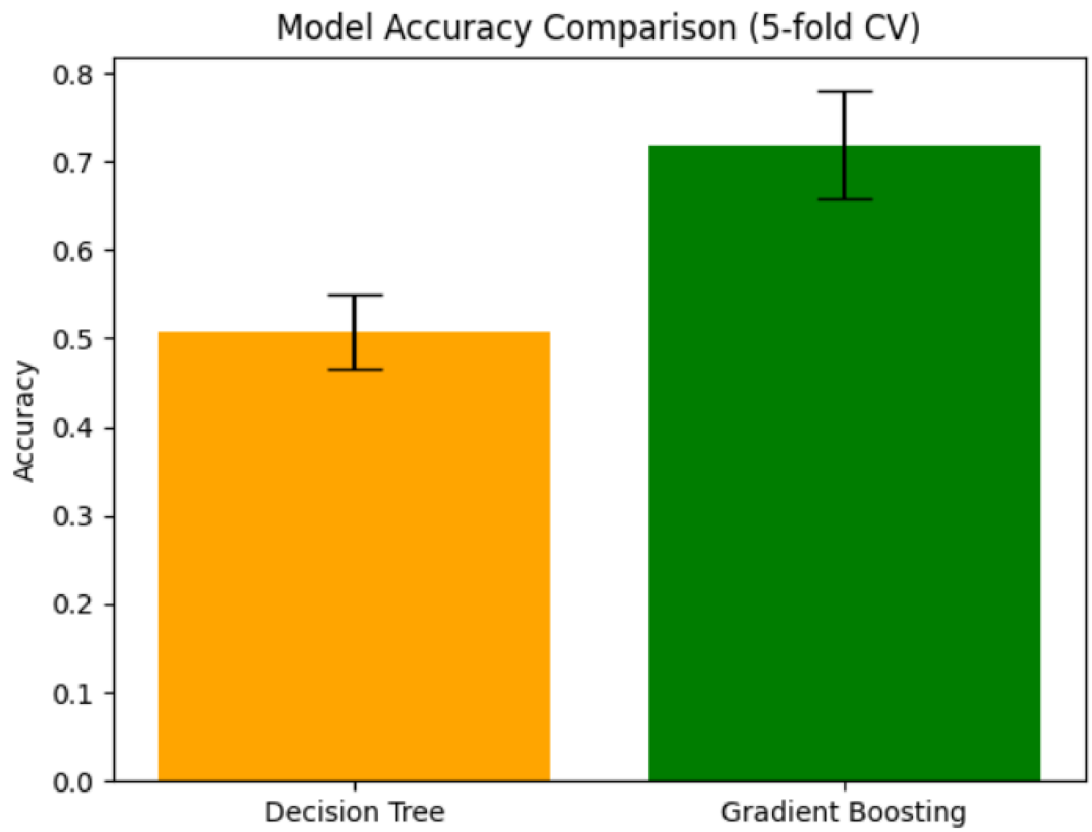

Fig.3. Bar Graph-Comparing Model Accuracy

In Fig 2 and Fig 3, In the context of learning style prediction, the model is trying to predict whether the user is likely to learn using visuals like diagrams,pictures or by listening to recording or by reading the study materials or by writing practice or by involving in activities to learn practically.

So, the x-axis represents the learning styles and the y-axis represents the scores assigned to each learning style. The highest point in the graphs that is the vertex or the absolute maximum represents the predicted learning style of the user. For example, if the graph shows the vertex in Read/Write then the predicted style of the user is the same.That indicates that the user is likely to learn by reading and writing the study materials.

CONCLUSION

In conclusion, the **HistGradientBoostingClassifier model** has been effectively utilized in this work, showcasing the potential of machine learning in delivering highly personalized learning experiences. The model, trained on a well-structured dataset of user responses gathered from multiple-choice and Likert scale questions, accurately predicted individual learning styles with a success rate of **81%**.

By tailoring learning content according to the predicted learning style—Visual, Auditory, Read/Write, or Kinesthetic—the system enhances user engagement, motivation, and comprehension. The successful application of this gradient boosting approach demonstrates its strength in handling both categorical and numerical inputs, along with its robustness against overfitting.

This research highlights how analyzing user data and learning behavior through machine learning techniques can provide accurate and actionable insights for educational personalization. The HistGradientBoosting model proved to be highly efficient in understanding patterns between input responses and the output classification of learning styles.

FUTURE SCOPE

The implementation of the HistGradientBoosting model lays the foundation for a promising future in intelligent learning systems. Moving forward, this work can be extended by incorporating **deep learning techniques and neural networks** to capture more complex behavioral patterns and preferences of learners.

Additionally, integrating **real-time feedback mechanisms**, **adaptive testing**, and **reinforcement learning strategies** could help dynamically adjust learning content on-the-fly, thereby further improving learning efficiency. Advanced techniques such as **transfer learning** and **natural language processing** may also be employed to better understand open-ended user input.

Gamified interfaces, intelligent tutoring systems, and cross-platform learning environments can be developed using this framework to support **interactive, immersive, and self-directed learning** experiences. These advancements can help scale the model to diverse educational settings, ultimately paving the way for more inclusive and effective personalized education solutions.

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