LEARNING STYLE BASED PERSONALIZED EDUCATIONAL CONTENT DELIVERY PLATFORM

Maheswari R J,Nanditha N,Lakshanya D
220701155@rajalakshmi.edu.in
220701182@rajalakshmi.edu.in
220701140@rajalakshmi.edu.in
Department of CSE
Rajalakshmi Engineering College

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.

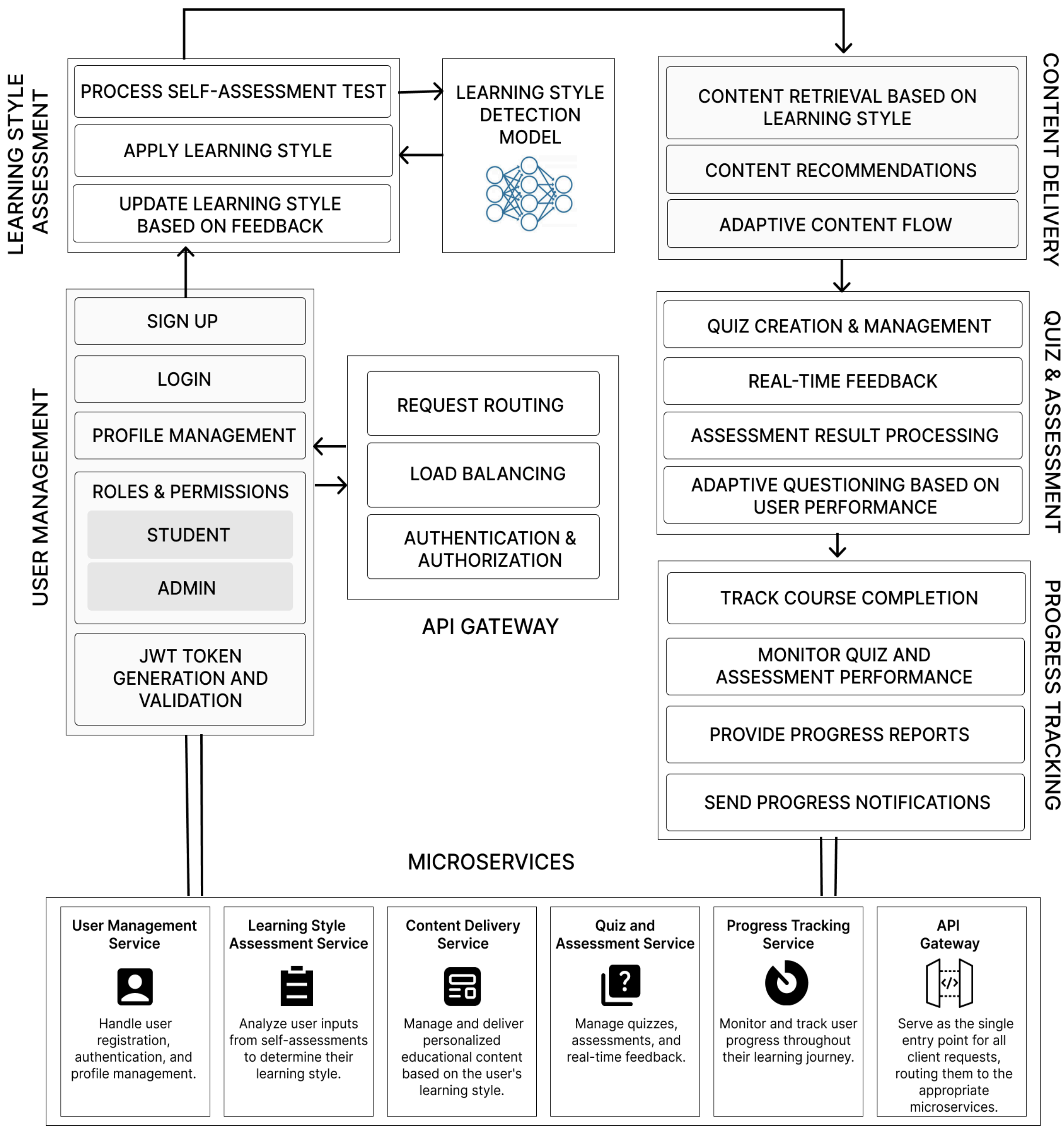

Fig.1. Architecture Diagram

ALGORITHM

For classifying our learners into 4 types namely **visual, auditory, read and write, and kinesthetic**, we have used Supervised Machine Learning models. Random forest is a supervised ML model that is found to be very effective for classification problems. Random Forest is an algorithm that is deduced from combining several Decision Trees, hence the name Forest. A Decision Tree splits the dataset recursively using the decision nodes unless we are left with pure leaf nodes. And it finds the best split by maximizing the entropy gain. Decision Trees are highly sensitive to the training data which could result in high variance. Random Forest is a collection of multiple arbitrary decision trees and it's much less sensitive to the training data.

Bootstrap Sampling is a statistical technique used to estimate the distribution of a sample statistic by repeatedly resampling with replacement from the original dataset. It is an important step in the Random Forest Algorithm. Because some data points may be repeated while others may not be included at all, each bootstrap sample is different. This variability is essential for training multiple models (in this case, decision trees) that capture different aspects of the data. This ensures that the model is not as sensitive to the training data like a Decision tree. Another step associated with bootstrapping is aggregation. Aggregation refers to the process of combining the predictions from multiple models to produce a final output. Bootstrap and Aggregation combined is called Bagging. Bagging reduces overfitting by training on vast datasets rather than just a single one. It also aggregates predictions from various trees thereby smoothening the variance.

Algorithm Steps:

1. Import all the necessary module like flask, scikit-learn, panda, numpy
2. Load the DataSet
3. Preprocess the data
    a. Assign scores for each answer
    b. Calculate scores for each learning style
    c. Split data into X and Y for training
4. Fit the model
    a. Import DecisionTreeClassifier
    b. Use .fit() method to fit the model
5. Training the model
    a. Get user responses from the request
    b. convert responses to DataFrame and prepare for prediction
    c. Predict the learning style (using model.predict(data))
6. Test the model for accuracy

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.

Dataset Collection

As there were no proper pre-existing datasets for classifying we curated our own dataset. The dataset was gathered using Google Forms, where multiple-choice questions and Likert scale were used to predict the outcome. Multiple choice questions involved a set of scenario-based questions that were designed to capture learner preferences and behavioral patterns.On the other hand scaled response items ranging from 1-5(strongly disagree - strongly agree) were used to quantify learner characteristics across different dimensions of learning styles. The questions were carefully selected in a way that the user's preference can be easily figured out. These data were collected from people with various educational levels.

Data preprocessing

The dataset consists of around 1000 samples. Those samples were cleaned to remove duplicate, irregular and incomplete data. Unnecessary fields like name, age, gender were removed.

Learning style Scoring

A variable called stylescores is created which is used to find the dominant learning style among others.Whenever user clicks an option the corresponding style score is incremented. Similarly, for Likert scale questions the associated style was incremented based on the user's preference level. The learning style with the highest score was identified as the user's dominant style.

Model Selection

To predict the learning style of the user accurately a deep model selection process went through. After many iterations with different algorithms finally RANDOM FOREST CLASSIFIER algorithm was chosen due to its effectiveness and its ability to handle numerical and categorical data.The dataset was split into training dataset (80%) and testing dataset (20%).The model was trained with 100 decision trees (n_estimators) and a random state of 42 for reproducibility. The question responses are stored in a variable as features (X), and the dominant learning style for each sample becomes the target label (y).The hyperparameters, including the number of decision trees (n_estimators), were tuned to optimize the model's performance and ensure reproducibility.The trained model showed a perfect balance in accuracy among various learning style paving way to accurate prediction of a user's learning style.

EXPERIMENTAL RESULT

The evaluation of the test outcomes in predicting the learning style of the users reveals the performance pattern of the model used in this study. Random Forest model shows a definitive predictive capacity achieving an accuracy of 81%. This level of precision involved in delivering personalized learning contents which aligns with the identified learning style of the user.In terms of detailed metric the model achieves great result across f1-score,precision and recall for each learning style which enables to identify and classify the users based on their learning style.The final output of the model shows the predicted learning style of the user and delivers the learning contents respective to their learning style.This outcome highlights the model's potential to predict the learning style and help to provide personalized learning based on individual needs, serves as an effective tool for enhancing learning experiences based on accurately identified learning styles.

	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

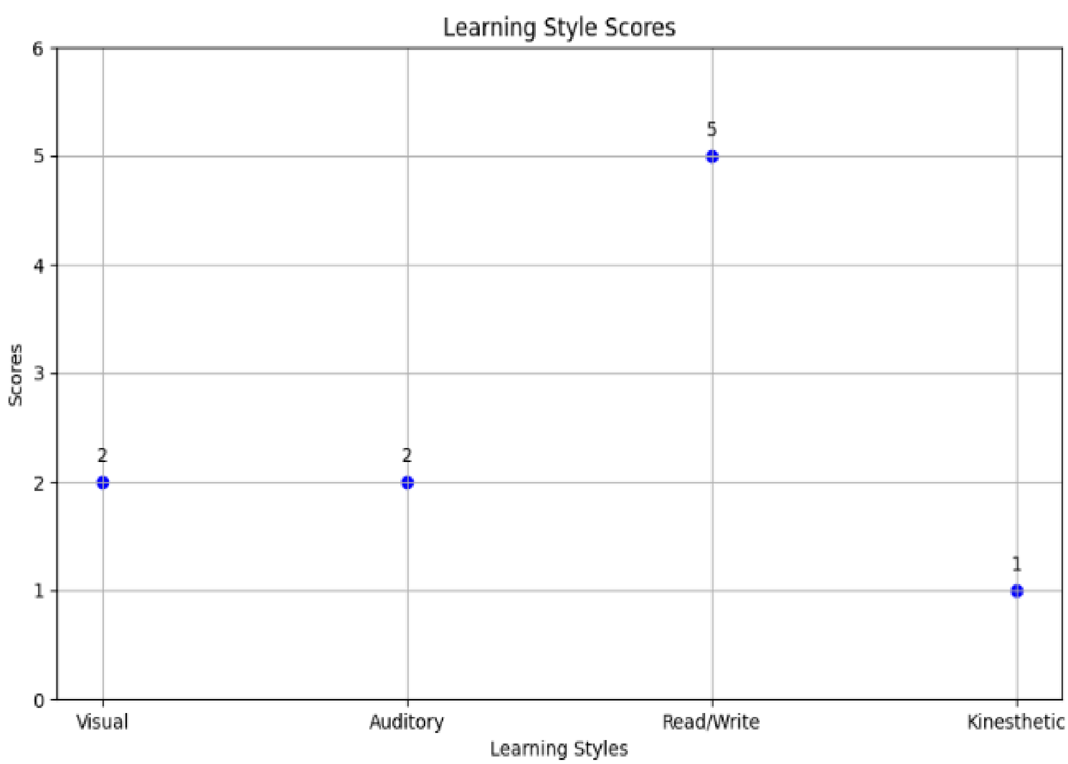

Fig.2. Scatter Plot of Learning Style Prediction

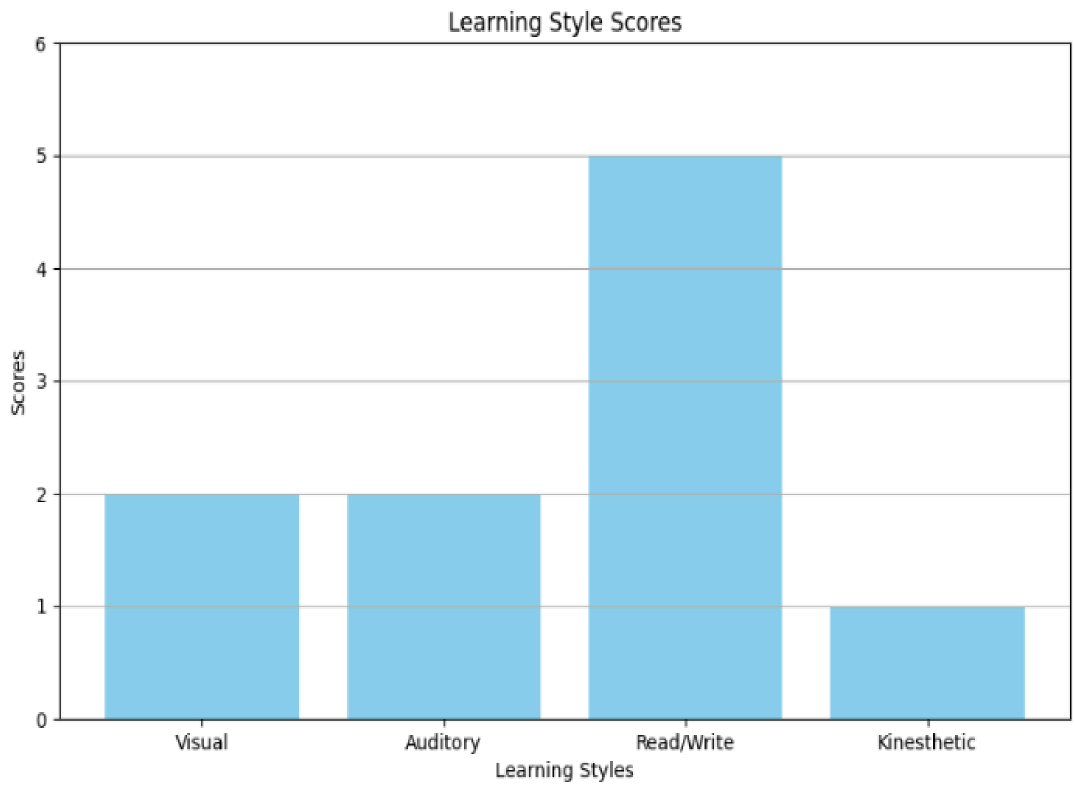

Fig.3. Bar Graph of Learning Style Prediction

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

FUTURE SCOPE

In conclusion, The Random Forest model has been used effectively in this work which demonstrates the potential of machine learning in effective personalized learning. The model trained on a dataset of user responses from the multiple choice questions and likert scale questions, accurately predicted the learning style with a success rate of 81%. By delivering learning contents tailored to the predicted learning style of the user we can significantly enhance learning engagement,motivation and overall learning outcomes. In particular, the application of the Random Forest model produced outstanding outcomes in predicting the learning style of the user by understanding the data and by analyzing the pattern between input variables and output variables effectively.

The Implementation of Random Forest model opens up a promising future for effective personalized learning. By incorporating deep learning techniques and advanced AI methods we can enhance the productivity and accuracy of the model.Personalized learning platforms can be further optimized through adaptive learning systems, intelligent tutoring systems and providing gamified versions of learning to enhance personalized self learning experiences effectively and to get better outcomes.

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