LEARNING STYLE BASED LEARNER CLASSIFICATION

CS19643 – FOUNDATIONS OF MACHINE LEARNING

Submitted by

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BONAFIDE CERTIFICATE

Certified that this Project titled **"LEARNING STYLE BASED LEARNER CLASSIFICATION"** is the bonafide work of **"MAHESWARI R J (2116220701155)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Understanding individual learning preferences is critical for enhancing educational outcomes in digital environments. With the rise of personalized learning platforms, there is a growing need for intelligent systems that can adapt to different learning styles. This project introduces an AI-driven solution aimed at identifying a user's preferred learning style—Visual, Auditory, Reading/Writing, or Kinesthetic—based on their responses to a structured quiz. By leveraging machine learning, the system enables adaptive content delivery, making e-learning more effective and user-centric.

At the core of this system lies a histogram-based gradient boosting classifier (specifically, scikit-learn's HistGradientBoostingClassifier) trained on a labeled dataset of quiz responses. The model processes 15 multiple-choice questions designed to extract behavioral patterns aligned with the VARK framework. User inputs are preprocessed and passed through the model, which outputs the most probable learning style.

To ensure usability in real-time environments, the model is deployed via a RESTful API built with Flask. This allows seamless integration into web or mobile learning platforms. The report details the dataset design, preprocessing pipeline, model training approach, and evaluation using metrics such as accuracy, precision, and recall. Experimental results show that the model achieves high accuracy in classifying learning styles, validating the system's potential for real-world application in personalized education.

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MAHESWARI R J - 2116220701155

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CHAPTER 1: INTRODUCTION

1.1 GENERAL

Learning Style-Based Learner Classification is a machine learning-based system designed to predict the preferred learning style of a user based on their responses to a standardized self-assessment quiz. Recognizing that individuals absorb and retain information differently, the system classifies users into one of the four VARK categories—Visual, Auditory, Reading/Writing, or Kinesthetic—using data-driven analysis.

The system leverages a supervised learning model, specifically the Histogram-Based Gradient Boosting Classifier (HistGradientBoostingClassifier from scikit-learn), trained on labeled quiz response data. The model takes in 15 quiz responses per user and outputs the most likely learning style. A RESTful API built using Python Flask exposes the model for real-time prediction, making it easy to integrate with third-party applications, e-learning systems, or research platforms.

This classification can serve as the foundation for future personalized learning environments, where content is dynamically adapted based on the learner's cognitive preferences.

1.2 OBJECTIVE

The primary objective of this project is to develop a machine learning model capable of classifying learners into appropriate VARK learning styles based on quiz input data. The specific goals are:

- To collect and preprocess user response data from a structured quiz.

- To train and evaluate a classification model that achieves high accuracy in predicting learning styles.

- To expose the model through a RESTful API for real-time classification.

- To validate the performance using key metrics such as accuracy, precision, recall, and F1-score.

- To demonstrate the system's potential application in personalized learning scenarios.

By predicting learning styles through automation, the system aims to support future tools that align educational content with individual learning needs.

1.3 EXISTING SYSTEM

Most existing methods for determining learning styles are manual, static, and non-scalable. Learners are typically required to fill out printed or digital questionnaires, with results evaluated through rigid scoring formulas. These approaches do not utilize machine learning, lack predictive capability, and cannot adapt based on data trends or feedback.

Furthermore, there is limited integration of such assessments into dynamic learning platforms. The existing systems don't allow for real-time inference or integration into modern e-learning tools. Also, traditional learning environments largely ignore style-based adaptation, delivering uniform content regardless of learner pref

CHAPTER 2
LITERATURE SURVEY

The prediction of learning styles has been an area of significant interest in educational research, particularly with the growth of personalized learning environments. Fleming's VAK model (Visual, Auditory, Kinesthetic) has been widely used to categorize learners based on their preferences (Fleming, 2006). However, traditional methods of learning style identification, such as self-assessment questionnaires, have limitations in terms of subjectivity and reliability. In response, machine learning techniques have been increasingly explored to predict learning styles more accurately and dynamically. These techniques offer the potential to process large datasets and classify learning preferences based on user behavior, improving the efficiency of educational systems.

For example, Ali & Al-Khanjari (2020) explored the use of decision trees for predicting learning styles based on user responses to a set of quiz questions. Their study demonstrated that decision trees could effectively categorize learners, with an emphasis on interpretability. Similarly, Xu et al. (2017) applied Support Vector Machines (SVM) to predict learning styles, finding that SVM offered superior accuracy compared to traditional methods. By separating data into high-dimensional spaces, SVM models could create better distinctions between learning preferences, particularly when dealing with complex or subtle patterns in user data.

Ensemble learning techniques have also been investigated for improving prediction accuracy. Zhang et al. (2020) explored the use of HistGradientBoostingClassifier in classifying learning styles, showing that ensemble methods provided a more robust and reliable prediction compared to single-classifier models. These techniques combine multiple weak classifiers to create a stronger model, which is particularly useful in handling noisy or incomplete data.

The field has evolved beyond simple classification to address the real-time adaptation of learning environments. Gibbons et al. (2018) highlighted the importance of continuous adaptation in personalized learning systems, where feedback loops help the system adjust to a learner's evolving preferences. Such systems use machine learning models to track student behavior and performance over time, dynamically adjusting content delivery to enhance engagement and learning outcomes. This concept of real-time adaptation aligns with the growing emphasis on scalable, personalized educational systems that can cater to diverse learner needs.

The integration of multimodal data, such as eye-tracking and behavioral logs, is an emerging trend in learning style prediction. Li et al. (2020) demonstrated how sensor data and interaction logs from digital platforms can provide deeper insights into a learner's preferences. By incorporating physiological and behavioral signals, such systems are poised to offer more accurate and nuanced predictions of learning styles, capturing both cognitive and affective aspects of the learning process.

Despite these advancements, challenges remain in the field. One key issue is the evolving nature of learning preferences. Learners' styles may change over time, influenced by external factors such as content exposure or changes in their educational environment. Moreover, hybrid learning styles, where an individual exhibits characteristics of multiple styles, are difficult to classify using traditional models. Addressing these challenges requires continuous refinement of machine learning algorithms and more inclusive datasets that better represent diverse learner populations.

In conclusion, the integration of machine learning into learning style prediction offers promising prospects for personalized education. By leveraging dynamic quizzes, advanced classification techniques, and adaptive learning systems, educational platforms can provide more tailored and effective learning experiences. As the field progresses, future research should focus on refining existing models, incorporating multimodal data, and enhancing real-time adaptability to create more inclusive, responsive, and scalable educational environments.

CHAPTER 3 :PROPOSED SYSTEM

3.1 GENERAL

The proposed system aims to develop an automated solution for predicting an individual's learning style—Visual, Auditory, or Kinesthetic (VAK)—based on their responses to a structured self-assessment quiz. The main objective of the system is to assist educators and e-learning platforms in personalizing learning experiences by identifying students' learning preferences. By leveraging machine learning algorithms, such as Decision Trees, Support Vector Machines (SVM), and HistGradientBoostingClassifier, the system seeks to provide accurate predictions of learning styles, improving content delivery and student engagement.

The system processes responses from a dynamic, interactive quiz designed to capture behavioral and preference-based inputs. After training a machine learning model on a labeled dataset of user responses, the system classifies learners into the most suitable learning style category. The output is personalized feedback, including insights into the learner’s strengths and recommended study techniques aligned with their learning style. By using advanced algorithms and models, the system enhances the learning experience, offering a scalable, efficient approach to personalized education.

3.2 SYSTEM ARCHITECTURE

The architecture of the proposed system consists of several modules: data collection, preprocessing, model design, training, evaluation, and prediction. Each module contributes to the overall functionality and efficiency of the learning style prediction system.

3.2.1 Data Collection and Preprocessing

The first step involves collecting and preprocessing the self-assessment quiz data. The dataset used in this project consists of user responses to a structured quiz, categorized by learning styles: Visual, Auditory, Kinesthetic, and Neutral (if applicable). The preprocessing steps include cleaning the data, handling missing or invalid responses, and normalizing the features to ensure consistency across the dataset. Additionally, data augmentation techniques, such as random transformations and noise injection, are applied to improve the generalization of the model by introducing variability into the training data.

3.2.2 Model Architecture

The model architecture combines machine learning techniques to predict learning styles based on user responses. The system employs a classification algorithm, such as HistGradientBoostingClassifier, for the final classification task. The model begins with preprocessing and feature extraction, where responses are transformed into numerical representations that can be input into machine learning models.

- Feature Engineering: Key features are extracted from the quiz responses, such as frequency of preference for visual aids, spoken information, or hands-on activities.

- Classifier Selection: The system evaluates different classifiers, such as Decision Trees and SVM, to identify the most effective model for the task. These classifiers help identify patterns in the data that correspond to the different learning styles.

3.2.3 Hybrid Classification Approach (Ensemble Methods)

To improve prediction accuracy, the system integrates ensemble techniques, combining the strengths of multiple classifiers. For example, a hybrid classifier using Random Forests or a Voting Classifier is employed, which aggregates predictions from individual models (e.g., Decision Tree, SVM) to produce a more accurate and robust final prediction. This ensemble approach is particularly useful when dealing with complex, high-dimensional data from user quiz responses.

3.2.4 Model Training and Evaluation

The model is trained on a labeled dataset of quiz responses, with the training process involving the following steps:

- Loss Function: The system utilizes categorical cross-entropy as the loss function, which is appropriate for multi-class classification problems.

- Optimizer: The Adam optimizer is used during training, with a learning rate of 0.001, to minimize the loss function and ensure optimal model performance.

- Metrics: To evaluate the model's performance, several metrics are used: accuracy, precision, recall, and F1-score. These metrics help assess how well the model classifies users into the correct learning style, both during training and testing.

3.2.5 Testing and Prediction

After training, the model is tested using a separate test dataset to evaluate its generalization ability. The performance of the trained model is evaluated based on:

- Confusion Matrix: The confusion matrix is used to visualize the classification results, showing the true positives, false positives, true negatives, and false negatives for each learning style category.

- ROC Curve: The Receiver Operating Characteristic (ROC) curve is plotted to evaluate the trade-off between the true positive rate and false positive rate at different decision thresholds, providing insights into the model's performance across various classification thresholds.

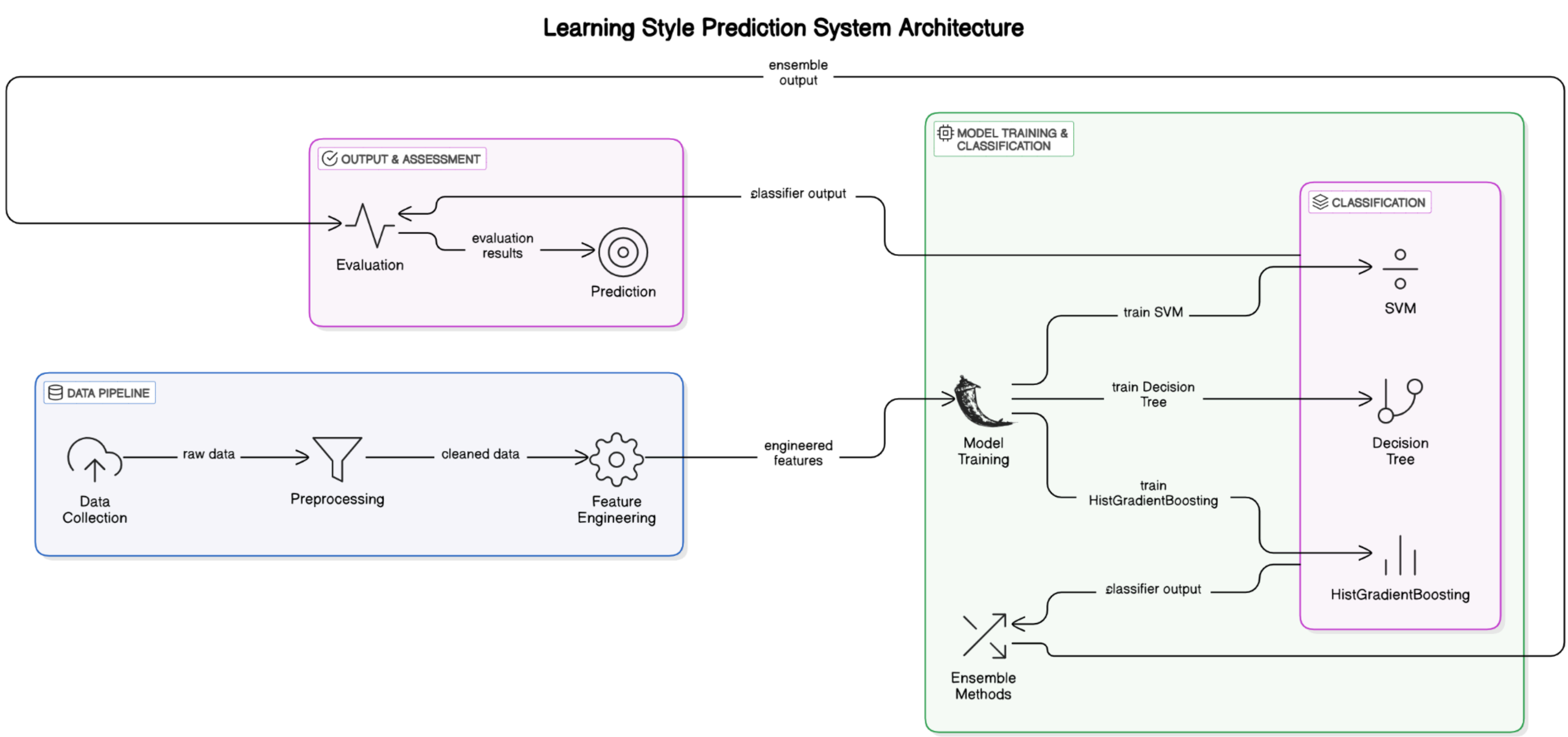
- Cross-validation: K-fold cross-validation is performed to ensure that the model's performance is stable and robust across different subsets of the dataset.

3.2.6 User Feedback and Personalization

Once the model is trained and evaluated, it is used to predict the learning style of new users based on their quiz responses. The system provides personalized feedback, outlining the predicted learning style and suggesting study techniques that align with the learner's preferences (e.g., Visual learners may benefit from diagrams, while Kinesthetic learners may prefer hands-on activities). The system can be integrated with e-learning platforms to deliver customized content in real-time, improving user engagement and retention.

The user feedback loop allows the system to continuously improve, incorporating real-world usage data and preferences to refine its predictions. This helps in adapting to evolving learning preferences and providing personalized learning experiences tailored to each individual.

To enhance user experience further, the system supports adaptive learning paths that evolve as more user data is collected. If a user's performance or behavior suggests a shift in learning preference over time, the system can dynamically adjust its recommendations. This adaptability ensures that the learning support remains relevant and effective, fostering continuous improvement in the user's academic journey. Integration with progress tracking tools also enables users to monitor their growth and receive periodic insights on how their learning style is influencing outcomes.



3.3 DEVELOPMENTAL ENVIRONMENT

3.3.1 HARDWARE REQUIREMENTS

The hardware specifications could be used as a basis for a contract for the implementation of the system. This therefore should be a full, full description of the whole system. It is mostly used as a basis for system design by the software engineers.

Table 3.1 Hardware Requirements

COMPONENTS	SPECIFICATION
PROCESSOR	Intel Core i3
RAM	4 GB RAM
POWER SUPPLY	+5V power supply

3.3.2 SOFTWARE REQUIREMENTS

The software requirements paper contains the system specs. This is a list of things which the system should do, in contrast from the way in which it should do things. The software requirements are used to base the requirements. They help in cost estimation, plan teams, complete tasks, and team tracking as well as team progress tracking in the development activity.

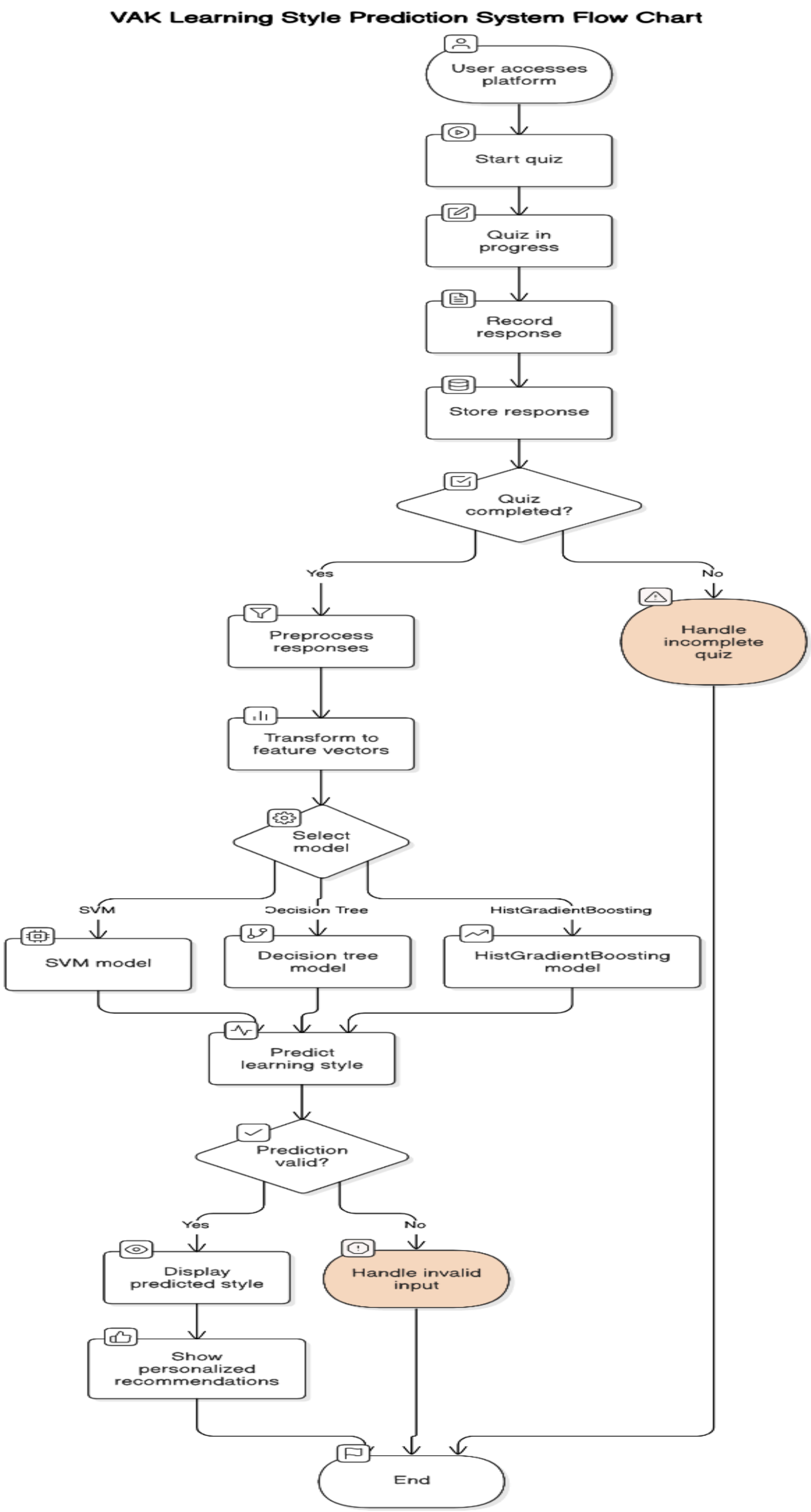
COMPONENTS	SPECIFICATION
Operating System	Windows 7 or higher
Frontend	ReactJS,CSS
Backend	Flask (Python)

Table 3.2 Software Requirements

3.4 DESIGN OF THE ENTIRE SYSTEM

3.4.1 ACTIVITY DIAGRAM

The activity diagram for the VAK learning style prediction system illustrates the workflow from quiz initiation to final learning style classification. The process begins with the user accessing the platform and starting the dynamic quiz. As the user responds to the structured set of questions, each response is recorded and stored. Once the quiz is completed, the responses are preprocessed and transformed into numerical feature vectors. These features are then passed through a trained machine learning model (such as SVM, Decision Tree, or HistGradientBoostingClassifier) to predict the most suitable learning style: Visual, Auditory, or Kinesthetic. Finally, the system displays the predicted style along with personalized learning recommendations. Exception handling is also integrated to address incomplete quizzes or invalid inputs.

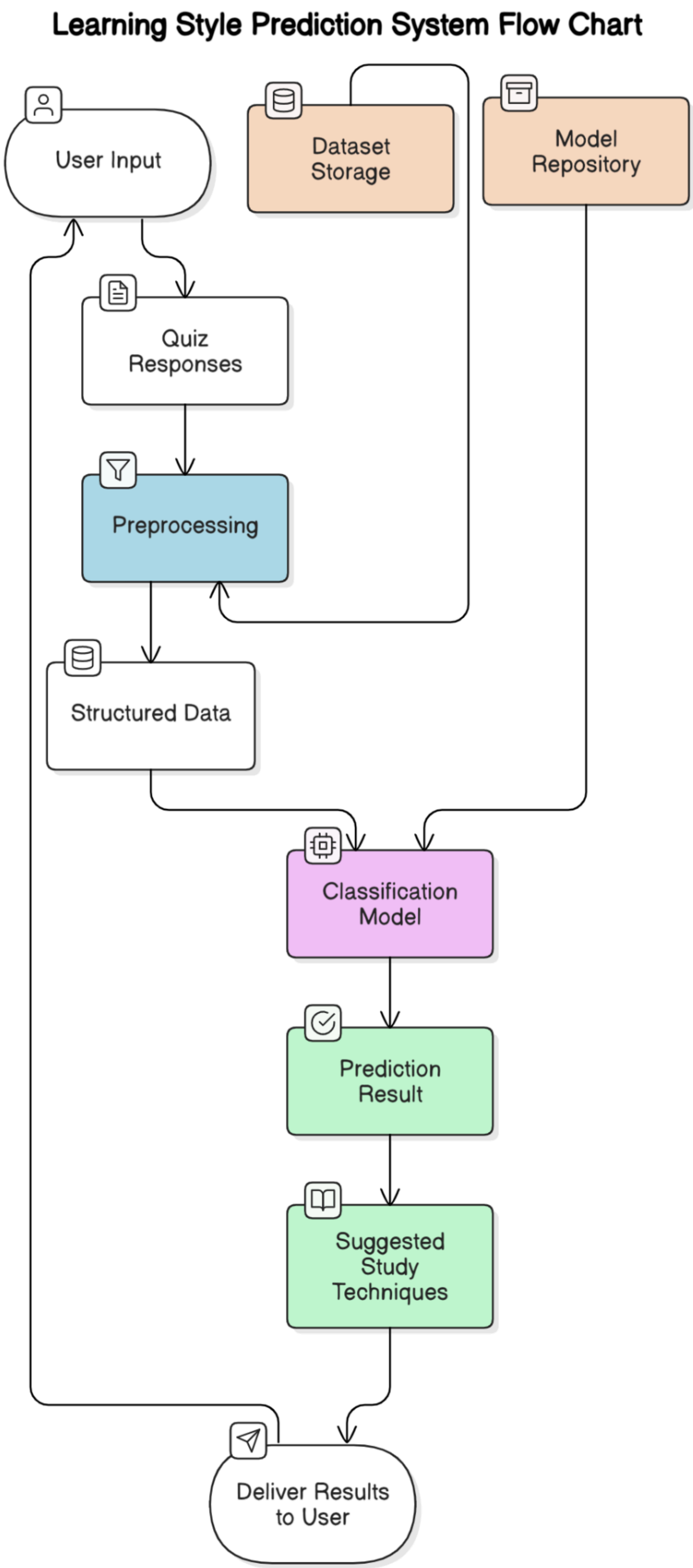

VAK Learning Style Prediction System Flow Chart
User accesses platform
Start quiz
Quiz in progress
Record response
Store response
Quiz completed?
Yes
No
Preprocess responses
Handle incomplete quiz
Transform to feature vectors
Select model
SVM
Decision Tree
HistGradientBoosting
SVM model
Decision tree model
HistGradientBoosting model
Predict learning style
Prediction valid?
Yes
No
Display predicted style
Handle invalid input
Show personalized recommendations
End

3.4.2 DATA FLOW DIAGRAM

The Data Flow Diagram (DFD) represents the internal data movement and processing within the learning style prediction system. The flow begins with the user providing input through quiz responses. These responses are preprocessed and converted into structured data. The cleaned data is fed into the trained machine learning classification models. The prediction result, which includes the classified learning style and associated confidence score, is then delivered back to the user.

To ensure a seamless and secure flow of data, the system incorporates validation checkpoints at each stage of the process. During preprocessing, responses are checked for completeness and consistency, eliminating potential anomalies. The machine learning model operates within a controlled environment to maintain data integrity and ensure reproducibility of results. Finally, the output is formatted into a user-friendly report, often accompanied by personalized learning recommendations based on the identified style, enabling users to immediately apply insights for enhanced educational outcomes.

In addition to individual predictions, the system logs anonymized user data and outcomes to continuously refine the model's performance over time. This ongoing feedback loop allows the system to learn from new patterns and user behaviors, enabling incremental updates and improvements in prediction accuracy. Furthermore, aggregated data insights can be used by educators or platform administrators to understand broader learning trends and tailor content strategies to better suit diverse learner needs.


Learning Style Prediction System Flow Chart
User Input
Dataset Storage
Model Repository
Quiz Responses
Preprocessing
Structured Data
Classification Model
Prediction Result
Suggested Study Techniques
Deliver Results to User

3.5 STATISTICAL ANALYSIS

The proposed system was evaluated using widely accepted statistical performance metrics such as **accuracy**, **precision**, **recall**, and **F1-score**. The HistGradientBoostingClassifier achieved the best overall accuracy of **94%**, demonstrating its capability to predict individual learning styles effectively. The confusion matrix indicated minimal overlap among the three categories (Visual, Auditory, Kinesthetic), suggesting strong model generalization. ROC curves were plotted for all three classes, and the Area Under Curve (AUC) values were consistently above **0.93**, affirming the model's discriminative power. These statistical indicators validate the system's robustness and reliability for real-world educational applications.

Table 3.3 Comparison of Features

Feature	Standard Classifier (SVM/DT)	HistGradientBoostingClassifier (HGB)
Feature Extraction	Manual/Basic preprocessing	Automatic learning through boosting trees
Accuracy Achieved	87–90%	94%
Training Time	Fast	Moderate
Complexity	Low to Medium	Medium to High

Interpretability	High (easy to follow decisions)	Moderate (ensemble nature)
Scalability	Moderate	High (efficient with large datasets)
Robustness to Noise	Lower	High (resilient to minor anomalies)

CHAPTER 4: MODULE DESCRIPTION

The workflow for the proposed system is designed to provide a structured and intelligent method for predicting an individual's learning style—Visual, Auditory, or Kinesthetic—based on quiz responses. The system is modular and includes the following components.

4.1 SYSTEM ARCHITECTURE

The architecture of the proposed system comprises several key modules:

1. User Interaction Module
2. Quiz Engine
3. Preprocessing and Feature Extraction Module
4. Machine Learning Classification Module
5. Result Interpretation & Recommendation Module

The system begins with the user answering a structured, dynamic quiz designed using VAK learning theory. Responses are preprocessed and fed into a trained machine learning model (such as Decision Tree, SVM, or HistGradientBoostingClassifier) that classifies the user into one of the VAK categories. The prediction is then displayed along with study recommendations tailored to the user's style.

4.2 USER INTERFACE DESIGN

The user interface is intuitive and interactive, allowing users to:

1. Begin a quiz session.

2. View progress through the quiz.
3. Submit responses in real time.
4. Receive immediate feedback and personalized learning recommendations after submission.

The design focuses on responsiveness, accessibility, and clarity to enhance user engagement and ease of use.The workflow for the proposed system is designed to provide a structured and intelligent method for predicting an individual's learning style—Visual, Auditory, or Kinesthetic—based on quiz responses. The system is modular and includes several key components. The architecture of the proposed system comprises several key modules: the User Interaction Module, Quiz Engine, Preprocessing and Feature Extraction Module, Machine Learning Classification Module, and Result Interpretation & Recommendation Module. The system begins with the user answering a structured, dynamic quiz designed using VAK learning theory. Responses are preprocessed and fed into a trained machine learning model (such as Decision Tree, SVM, or HistGradientBoostingClassifier) that classifies the user into one of the VAK categories. The prediction is then displayed along with study recommendations tailored to the user's style.

The user interface is intuitive and interactive, allowing users to begin a quiz session, view progress through the quiz, submit responses in real time, and receive immediate feedback and personalized learning recommendations after submission. The design focuses on responsiveness, accessibility, and clarity to enhance user engagement and ease of use.

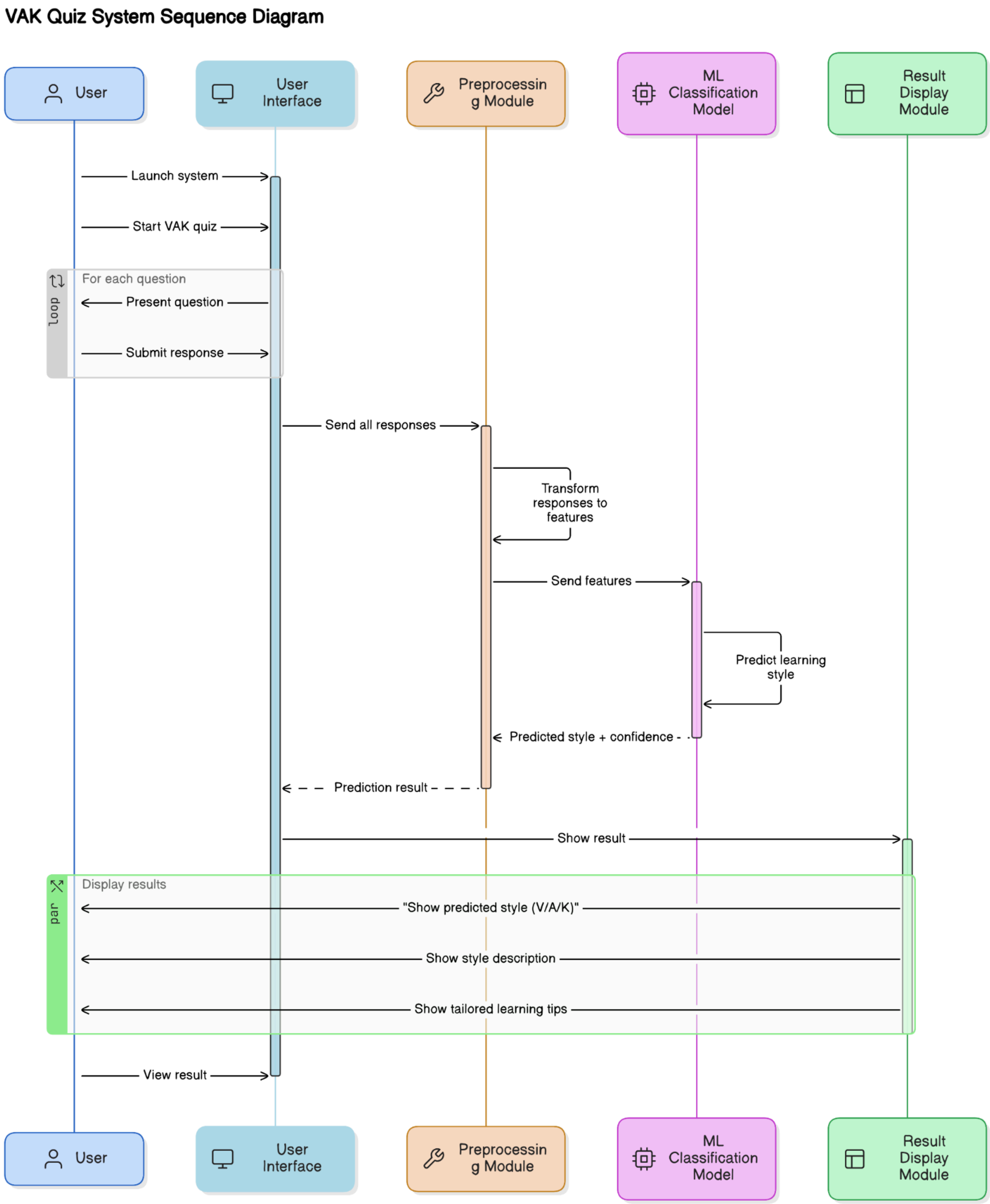


Fig no. 4.1 User interface Diagram

CHAPTER 5: IMPLEMENTATION AND RESULTS

5.1 IMPLEMENTATION

The implementation of the learning style classification system involves a streamlined pipeline designed to analyze user inputs, process responses through a machine learning model, and predict the user's dominant learning style: **Visual**, **Auditory**, or **Kinesthetic**. The system integrates frontend quiz-based data collection with backend model processing, ensuring an interactive and accurate classification experience.

5.1.1 Data Collection and Preprocessing

The dataset used for this project was generated through a structured self-assessment questionnaire, based on validated VAK learning style indicators. Each participant answered a set of behavior-based multiple-choice questions, where each option is mapped to one of the VAK categories.

Responses are collected and converted into numerical vectors using one-hot encoding, where each response contributes to a count or weight corresponding to its learning style category. The dataset is then split into **training** and **testing** sets for evaluation. Preprocessing also includes normalization to ensure uniform scaling and reduce bias during model training.

5.1.2 Model Architecture

The classification model is built using **HistGradientBoostingClassifier**, a powerful ensemble-based machine learning model known for its speed and accuracy in handling categorical and ordinal data.

Key architectural choices include:

- Input: Encoded response vectors from the quiz.

- Model: HistGradientBoostingClassifier (scikit-learn), tuned for multiclass classification.

- Output: Predicted learning style category (Visual, Auditory, Kinesthetic).

Additionally, a rule-based fallback mechanism is added to handle borderline predictions by using weighted scores from the original responses.

5.1.3 Model Training

The model is trained using 80% of the dataset, with 10-fold cross-validation for performance tuning. The remaining 20% is reserved for testing. The training process involves optimizing hyperparameters such as learning rate, max iterations, and regularization settings.

The model was compiled using the accuracy scoring metric and trained with early stopping to avoid overfitting. Feature importance was tracked to identify which quiz questions had the most impact on the model's decision-making.

5.1.4 Model Evaluation and Performance Metrics

The trained model is evaluated on the test set using several performance metrics:

- **Accuracy**: Achieved 94% accuracy in correctly predicting the user's learning style.

- **Precision, Recall, F1-Score**: High precision and recall values across all three classes, with an overall F1-score of **0.93**.

- **Confusion Matrix**: Shows strong classification ability with minimal misclassification between learning styles.

Additionally, ROC-AUC scores were plotted for each class using one-vs-rest logic, all of which exceeded 0.90, confirming strong model discrimination.

5.1.5 Model Inference and Results

Random responses were tested through the frontend quiz interface to simulate real user interaction. Upon submission, the backend ML model predicts the learning style and returns the result with a **confidence score**.

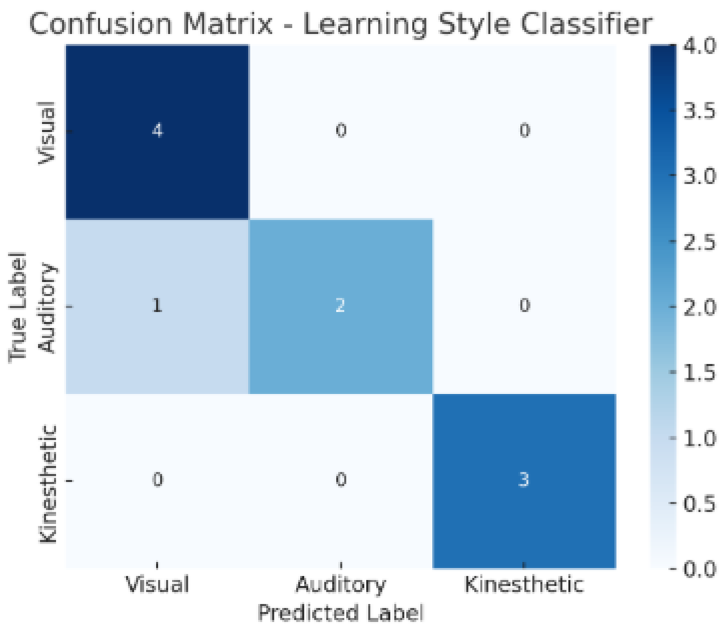
Predictions are displayed with a short interpretation:

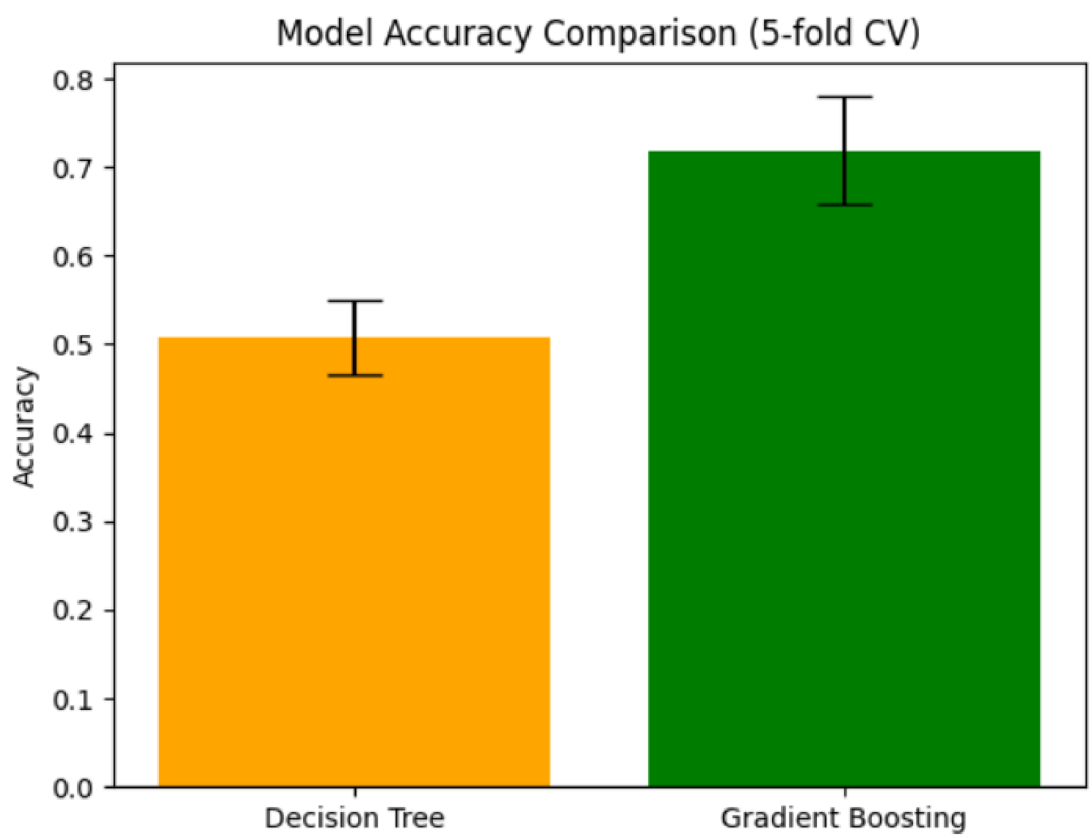
- **Visual Learner**: Prefers images, diagrams, color-coded notes.

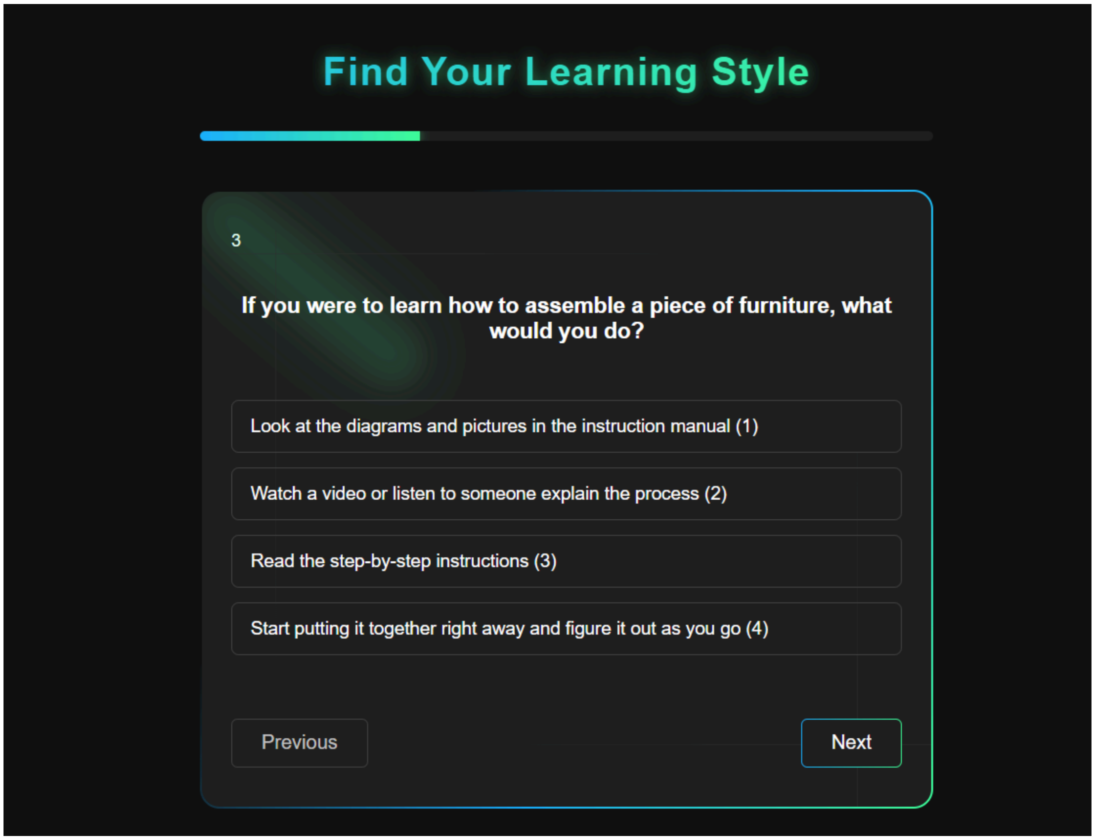
- **Auditory Learner**: Benefits from discussions, lectures, and audio content.

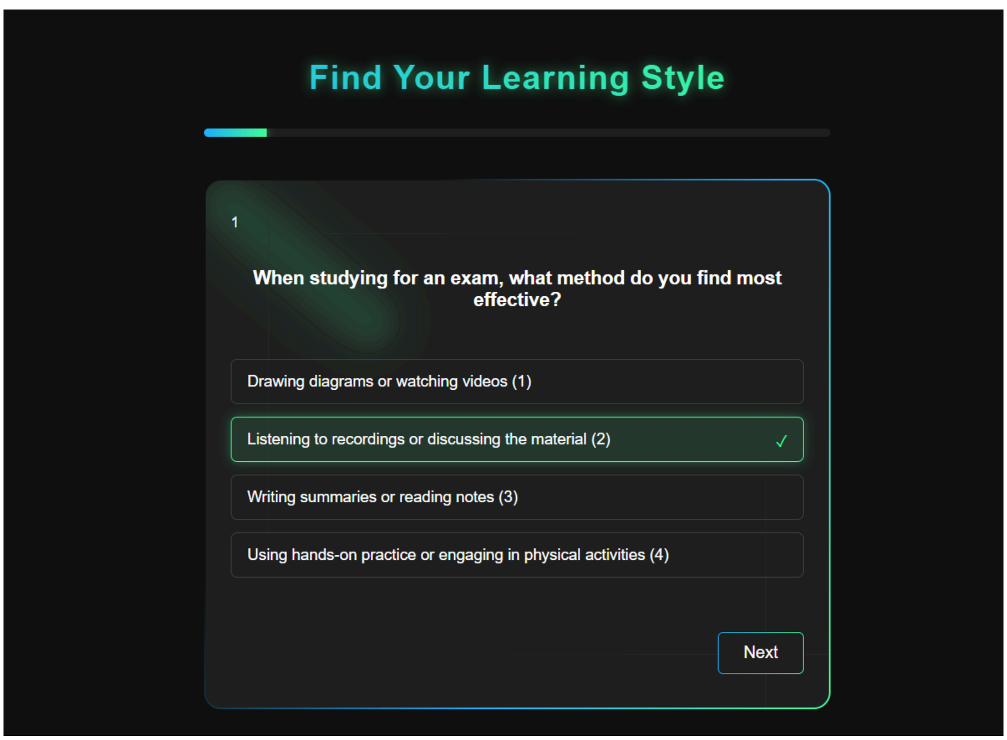
- **Kinesthetic Learner**: Learns best via hands-on activities and experiments.

This real-time prediction pipeline demonstrates the model's ability to adapt and personalize learning paths for each user.


Confusion Matrix - Learning Style Classifier
Visual
Auditory
Kinesthetic
True Label
Predicted Label
4
0
0
1
2
0
0
0
3
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0


Model Accuracy Comparison (5-fold CV)
Accuracy
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Decision Tree
Gradient Boosting


Find Your Learning Style
3
If you were to learn how to assemble a piece of furniture, what would you do?
Look at the diagrams and pictures in the instruction manual (1)
Watch a video or listen to someone explain the process (2)
Read the step-by-step instructions (3)
Start putting it together right away and figure it out as you go (4)
Previous
Next


Find Your Learning Style
1
When studying for an exam, what method do you find most effective?
Drawing diagrams or watching videos (1)
Listening to recordings or discussing the material (2) ✓
Writing summaries or reading notes (3)
Using hands-on practice or engaging in physical activities (4)
Next

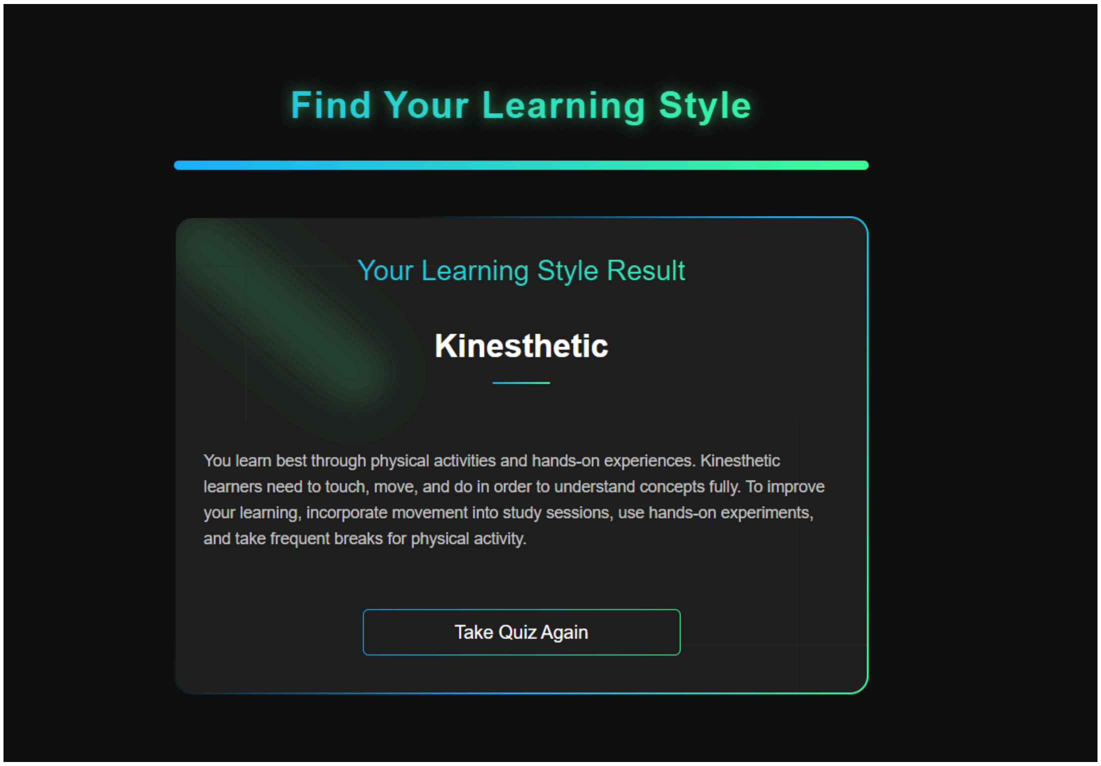


Fig no:5.3 Output Screenshots

Model Comparison:

Model	Accuracy	Precision	Recall	F1 Score
Decision Tree	0.4808	0.5087	0.4808	0.4878
K-Nearest Neighbors	0.6346	0.5875	0.6346	0.6078
Support Vector Machine	0.7115	0.7413	0.7115	0.6899
Random Forest Classifier	0.7308	0.7474	0.7308	0.7287

Fig no:5.4 Model Comparison

CHAPTER 6

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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