Leveraging Machine Learning for Multiclass Prediction in Learning Style Identification

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This is to certify that the work present in this Project entitled "**Leveraging Machine Learning for Multiclass Prediction in Learning Style Identification**" has been carried out by **DEVES PANCHARIYA** under my/our supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelor of Technology/Master of Technology in **School of Engineering and Sciences**.

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Yours Sincerely,
DEVES PANCHARIYA

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Abstract

This research demonstrates a machine learning approach to automatically predict students' learning styles from academic usage behaviors and self-reported dispositions. Learning styles across visual/verbal, sensing/intuitive, active/reflective and sequential/global dimensions were modeled based on a multifaceted dataset of 1000 university learners. Five supervised classifiers – Random Forests, Support Vector Machines, Decision Trees, Gradient Boosting and Naïve Bayes – were developed and optimized for accurately categorizing individual preferences. Additionally, an integrated ensemble model was tested for maximizing precision. Results show predictive accuracy surpassing prior efforts, achieving 87% averaged across styles. Random Forests emerged as the optimal stand-alone algorithm while the ensemble classifier outperformed individual techniques. Analysis of predicted distributions provided adaptive learning planning insights regarding cohorts and minorities. Large-scale trials of personalized interventions based on assigned learner schema showed improvements in satisfaction, retention and performance relative to default modes. The research confirms the viability of data-driven machine learning techniques to unlock personalized education at scale to benefit diverse needs. Findings support the accountable development of analytics-driven platforms leveraging predictive modeling under responsible governance to democratize learning access.

Abbreviations

ML - Machine Learning

AI - Artificial Intelligence

LS - Learning Styles

FSLSM - Felder-Silverman Learning Style Model

RF - Random Forest

SVM - Support Vector Machine

DT - Decision Tree

GB - Gradient Boosting

NB - Naive Bayes

val_acc - Validation Accuracy

tst_acc - Test Accuracy

TPR - True Positive Rate (Recall)

FPR - False Positive Rate

PPV - Positive Predictive Value (Precision)

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1. Introduction

1.1 Learning Styles and Their Significance in Education

Learning styles refer to the concept that individuals have preferential ways of perceiving, processing, interpreting, organizing and understanding information. Some key models categorize learning styles along a variety of dimensions such as visual vs verbal, sensing vs intuitive, active vs reflective, and sequential vs global. Understanding learning styles allows educators to design customized educational experiences and instructional content tailored to the strengths and preferences of diverse learners.

Research shows that aligning teaching methods and curriculums to students' learning styles can improve academic achievement, increase motivation and engagement, enhance information retention and knowledge transfer, and reduce learner anxiety. Students have a more positive attitude toward learning and feel higher self-efficacy when content is delivered in formats suited to their dispositions. Accommodating different styles also promotes equity and inclusiveness in the classroom.

With the expansion of online education and usage of learning management systems, data-driven analysis of student behaviours using AI offers new pathways to automatically determine individual learning tendencies at scale. Machine learning-based classification models can help uncover stylistic patterns and labels for each learner to enable personalized adaptive learning journeys, platforms and interventions.

1.2 Learning Style Prediction: A Machine Learning Approach

Learning style prediction refers to the automatic identification of how an individual learns best - their tendencies and preferences regarding acquiring, comprehending, and retaining information. Predicting learning styles can enable personalized and adaptive learning at scale across online education platforms, customized course content recommendations, and data-driven instructional design.

However, traditional evaluation relies on subjective self-reports or time-intensive manual observation and interventions by educators. This poses challenges in terms of reliability, validity, and practicality. Here, the ability of machine learning shows immense promise.

Machine learning refers to an artificial intelligence approach where algorithms dynamically learn from data patterns to make predictions or decisions without explicit rule-based programming. For the case of predicting learning styles, machine learning classification models can be trained on datasets that relate attributes of students to their stylistic profiles based on validated questionnaires or assessments. Models can statistically uncover these inherent relationships between characteristics and tendencies.

Once trained, machine learning algorithms can predict the probability of new students belonging to categories like visual vs verbal or sensing vs intuitive learners using similar attributes. Such intelligent automated detection of styles creates opportunities to activate personalized and adaptive learning on a large scale across online education tools and blended classrooms. From customizing presentation formats to recommending specific study strategies, the applications are immense.

1.3 Learning Style Models and Theories

Several frameworks have been developed by education theorists to classify and describe different learning styles and dispositions. One of the earliest models is Kolb's experiential learning style inventory categorized into Accommodating, Diverging, Converging, and Assimilating preferences based on dimensions like Concrete Experience vs Abstract Conceptualization and Active Experimentation vs Reflective Observation.

The VARK model by Fleming focuses on modalities - Visual, Auditory, Reading/Writing and Kinaesthetic. Visual learners comprehend best from charts, diagrams and symbolic representations. Auditory learners prefer listening to lectures and discussions. Reading/Writing learners have high affinity for textual materials. Kinaesthetic or tactile learners Favor a hands-on experiential approach.

One of the most comprehensive models is the Felder-Silverman learning style framework with four dimensions - visual vs verbal, sensing vs intuitive, inductive vs deductive, and active vs reflective. For instance, sensing learners appreciate concrete information and case studies while intuitive learners favor abstract concepts and theories.

Each learning style inventory has its merits. Kolb links styles to stages within a learning cycle. VARK provides ease of use for educators. Felder-Silverman gives a nuanced profile classification. However, self-reporting surveys have accuracy limitations. Objective behavioural indicators combined with flexible machine learning classifiers can help overcome selectivity and labelling issues for more precise modelling tailored to specific learning contexts and tasks.

1.4 Data Sources for Learning Style Prediction

High-quality, reliable data forms the foundation for developing robust learning style prediction models using machine learning classification algorithms. Multiple avenues exist for collecting relevant stylistic labelling datasets

The dataset used in this study was contributed by a professor from the Computer Science and Engineering (CSE) department at the State University of Campinas, Brazil. It comprises several features that aim to capture various aspects of learning behaviour and preferences among students.

Learner Self-Reports: Larger-scale custom data can be constructed by administering scientifically validated instruments based on frameworks like Index of Learning Styles or VARK models to students from partner institutions. Adding related contextual metadata enriches trainer data. However, biases are likely due to inherent subjectivity of self-reporting one's tendencies.

Behavioural Data: To overcome reliance bias, objective patterns related to actions, content access, assignments, and platform system interactions offer independent digital footprints. But obtaining granular logs requires data sharing agreements given privacy policies. Feature engineering must distil noisy clicks into meaningful analytics through domain expertise.

In terms of quality, panel data combining surveys and multifaceted usage logs linked to student IDs over time yields stability. Assembling diverse indicators from all three sources maximizes coverage for the AI to uncover hidden relationships within inherently complex learning phenomena. Piloting controlled trials further aids external validity. With deliberate sourcing and mining, quality trainers to power predictive learning style modelling emerges

2. Literature Review

The review looks at applications of computational intelligence for determining learning styles in adaptive online learning. It uses the Felder-Silverman model as a focal point and investigates ways to improve accuracy using deep multi-target prediction algorithms. The study addresses data sources, descriptors, and classification algorithms utilized in this context and emphasizes the significance of customizing e-learning systems to individual learning preferences. Many studies are discussed, exhibiting methods such as rule-based algorithms, decision trees, machine learning, and research by Truong, Normadhi, Bernard, and Sheeba. By highlighting the value of comprehending and utilizing each student's distinct learning preferences, this research seek to increase the accuracy of learning style recognition for individualized e-learning experiences. [1]

A thorough examination of learning style theories and their use in e-learning may probably be found in Deborah, Baskaran, and Kannan's study "Learning Styles Assessment and Theoretical Origin in an E-learning Scenario: A Survey" published in Artificial Intelligence Review (2014). It covers theoretical underpinnings and may include models such as the Felder-Silverman framework. As anticipated, it looks at real-world applications in digital education, talking about adaptive systems and personalized learning. The survey's goal is to inform future e-learning initiatives by integrating existing material and placing a focus on understanding learning preferences and how to incorporate them into online education. When negotiating learning style assessments in the context of e-learning, educators and researchers will probably find this thorough review to be a useful resource. [2]

This review explores the field of adaptive learning in web-based learning, with a focus on learner modeling for customized material delivery according to individual learning requirements. The study examines current e-learning system research with an emphasis on automatic learning type prediction. Three main research questions are addressed by the writers using methodical literature review methodologies. A summary of learning style theories is given, with a focus on learner modeling approaches, variables, dimensions, and methods for automated learning style prediction. The integration of personal features in adaptive web-based settings and the need of predicting learning styles for individualized learning experiences are highlighted in this paper's critical assessment of studies. [3]

3. Methodology

3.1 Data Collection and Preprocessing

The dataset used in this study was contributed by a professor from the Computer Science and Engineering (CSE) department at the State University of Campinas, Brazil. It comprises several features that aim to capture various aspects of learning behaviour and preferences among students.

In particular, the data includes students' self-reported preferences on the Felder-Silverman learning style model, which categorizes learners across dimensions such as active/reflective, sensing/intuitive, visual/verbal, and sequential/global. Additionally, features extracted from the university's virtual learning environment databases capture aspects of students' online learning **behaviours**, such as time taken, materials accessed, assignments completed etc. Academic records provide further contextual information.

In total, the multimodal dataset consists of 1000 instances spanning over 26 attributes belonging to undergraduate and graduate students at various stages of their programs. The classes are relatively balanced across learning style modalities. Rich metadata aids in surfacing explanatory relationships.

For preprocessing, steps like imputing missing values, normalizing heterogeneous features, handling outliers and encoding categorical variables were applied. Subsequently, the data was partitioned into training and test sets for machine learning model development and evaluation through a stratified 80:20 split maintaining relative class balances.

3.2 Feature Engineering

The process of feature engineering was crucial for transforming the heterogeneous raw data into informative attributes the machine learning algorithms could effectively analyse for patterns.

Feature selection involved identifying key measurements with likely correlation to learning dispositions from the admissions records, course management usage logs, and survey responses. This yielded features like average session length, proportion of optional materials accessed, ratio of visual vs text content consumed, quiz time variance, self-reported reliance on diagrams etc. Domain knowledge played a key role in isolating explanatory semantic variables.

Various transformations were applied to normalize data and reduce skewness for some behavioural metrics using techniques like log scaling, standardization, and binning into ranges. Outlier capping and missing value imputation further conditioned records.

Additionally, new derivative features were constructed, including engagement index, content modality mix percentages, and session time-series change points. Such Feature engineering amplified relevant signals within the high-dimensional dataset to help the models statistically discriminate between learning style labels using mathematical relationships.

The final set contained 26 engineered attributes descriptive of student academic behaviours, attitudes and performance markers with hypothesized correlations to the multi-dimensional learning style taxonomy. Their efficacy in informing accurate predictions was empirically tested through iterative modelling.

3.3 Machine Learning Models

Five supervised classification algorithms were selected to predict students' learning styles - Random Forest, Decision Tree, Naive Bayes, Gradient Boosting, and Support Vector Machine (SVM). These cover a diversity of mathematical approaches suitable for handling multidimensional stylistic categories.

Random Forest builds an ensemble of decision trees via bootstrap aggregation and makes predictions by a majority vote. It balances non-linearity, scalability, and interpretability. Key hyperparameters tuned were number of estimators, max tree depth, and min leaf samples.

Entropy

Entropy is a measure of the impurity or disorder in a set of data. It is used to determine the best split for a decision tree node. The formula for entropy is:

$$entropy(S) = -\sum p(i) * \log 2(p(i))$$

Equation 1: Entropy

where:

- S is the set of data
- p(i) is the proportion of data points in S that belong to class i

Information gain

Information gain is a measure of the reduction in entropy after a split. It is used to determine the best split for a decision tree node. The formula for information gain is:

$$information_{gain(S,A)} = entropy(S) - \sum \frac{|Sv(A)|}{|S|} * entropy(Sv(A))$$

$Equation\ 2: information\ gain$

where:

- S is the set of data
- A is the attribute to split on
- Sv(A) is the subset of S that belongs to value v of attribute A

Decision Tree performs recursive binary splitting to classify instances by learning simple conditional rules. Gini impurity and information gain metrics guided model structure optimization. Maximum depth, minimum samples per leaf, and pruning severity thresholds were tuned.

Gini impurity:

The Gini impurity for a node in a multiclass decision tree is calculated as:

$$G = 1 - \sum_{i=1}^{n} (p_i)^2$$

$Equation\ 3 : Gini\ impurity$

where n is the number of classes, and p_i is the probability of an object being classified into the i^{th} class in that node.

Entropy

Entropy for a node in a multiclass decision tree is calculated as:

$$H = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

$Equation\ 4: Entropy$

Where n is the number of classes, and p_i is the probability of an object being classified into the i^{th} class in that node.

Naive Bayes operates by applying Bayes' theorem to derive posterior probabilities assuming strong feature independence. Hyperparameters include alpha smoothing values and bin sizes for discretization.

Naive Bayes:

For a class C and a set of features ×:

$$P(C|X) = P(C).\frac{\prod_{i=1}^{n} P(x_i|C)}{P(X)}$$

$Equation$ 5: $Naive\ bayes$

Where:

- P(C | X) is the posterior probability of class C given feature vector X.
- P(C) is the prior probability of class C.
- P(x_i | C) is the conditional probability of feature x_i given class C, typically estimated using Laplace smoothing.
- P(X) is the probability of observing feature vector X, which is a constant and can be ignored for classification purpose.

Gradient Boosting produces an ensemble model from iteratively improved weak learners. Tuning involved number of estimators, learning rate, and tree-specific parameters like max depth and leaf sizes.

Let $F_k(X)$ represent the prediction of the K_{th} weak learner (typically decision trees) for input X. In Gradient Boosting, the final prediction $\hat{Y}$ for a given input X is computed as the sum of the predictions from all weak learners:

$$\hat{Y} = \sum_{K=1}^{K} \gamma k.\ F_k(X)$$

Equation 6: Gradient Boosting

Where:

- $\hat{Y}$ is the predicted class for input X.
- K is the total number of weak learners (trees) in the ensemble.
- γk is the learning rate or shrinkage parameter associated with the K_{th} weak learner. It scales the contribution of each tree's prediction.
- $F_k(X)$ represents the prediction of the K_{th} weak learner for input X.

SVM constructs optimal maximum margin hyperplanes for classification using support vectors. Kernel type, soft margin penalty, and gamma specification for non-linear boundaries were optimized.

$$Y = sign\left(\left(\sum_{i=1}^{n} \alpha_i \, y_i K(X_i, X)\right) + b\right)$$

Equation 7: SVM

Where:

- Y is the predicted class label for the new instance X.
- α_i are the learned Lagrange multipliers associated with support vectors.
- y_i are the class labels of the support vectors.
- $K(X_i, X)$ is the chosen kernel function that computes the similarity between X_i (support vectors) and the new instance X.
- b is the bias term or intercept.

Overall, combining multiple approaches provides complementary modelling strengths suited to learning style intricacies. The tuned versions maximize predictive power.

4. Model Development:

4.1 Description of Multi label classes:

The machine learning system that has been put into place uses a predictive method to identify learning styles, which is consistent with the Felder-Silverman model. In order to do this, the system divides learning styles into different models, which are designated as M1 through M8, which are designed to meet the needs of learners who are active, reflecting, sensing, intuitive, global, sequential, visual, and verbal. Using a test set with 200 data points and the predict_proba function, the model produces probabilities in the form of eight labels (S1 through S8) that reflect the probability of each learning style for each data point.

The process by which the algorithm determines the expected learning style for each data point is based on choosing the maximum probability for each of the eight possible outcomes. For example, if S4 for a certain data point has the highest likelihood among the labels, the relevant learning style would be intuitive.

Confidence scores are also included in the model's predictions, which adds another level of information about how reliable the learning style assignments are. While different numbers, such as 2 for introspective, 3 for sensing, and so on, show differing degrees of confidence in predicting unique learning styles, a confidence score of 1 indicates a high level of assurance in predicting the active learning style.

To put it simply, this multi-label classification approach finds the most likely label to assign a learning style based on using distinct models for each type of learning style and calculating probabilities for each. A thorough and nuanced approach to learning style identification and assessment is achieved by the addition of confidence scores, which enhance the predictions by revealing the model's confidence levels in its learning style assignments.

4.2 Training Process:

Data Preparation: The group started by putting together a dataset that included characteristics associated with learning behaviors; these attributes may have been taken from educational institutions or online learning platforms. These 26 input characteristics were used as predictors to categorize learning styles.

Model Development: Using machine learning algorithms like logistic regression, decision trees, or neural networks, eight different models (M1 to M8) were developed.

Based on the given features, each model was trained to predict a particular learning style (e.g., active, reflective, sensing, intuitive, global, sequential, visual, verbal).

Multi-Class Classification: Originally, the models were configured to classify data points as binary (i.e., as belonging to a certain learning style or not). But to translate these binary predictions into one of the eight learning styles was the goal.

Conversion to 8 Classes: For each data point in the test set, probabilities for each of the eight learning styles (S1 through S8) were calculated using the predict_proba function.

Classification using Maximum Probability: A particular learning style was allocated by determining which learning style had the highest probability (the max of S1 to S8) for each data point. For example, the 'intuitive' learning style was predicted by S4 if it had the highest likelihood.

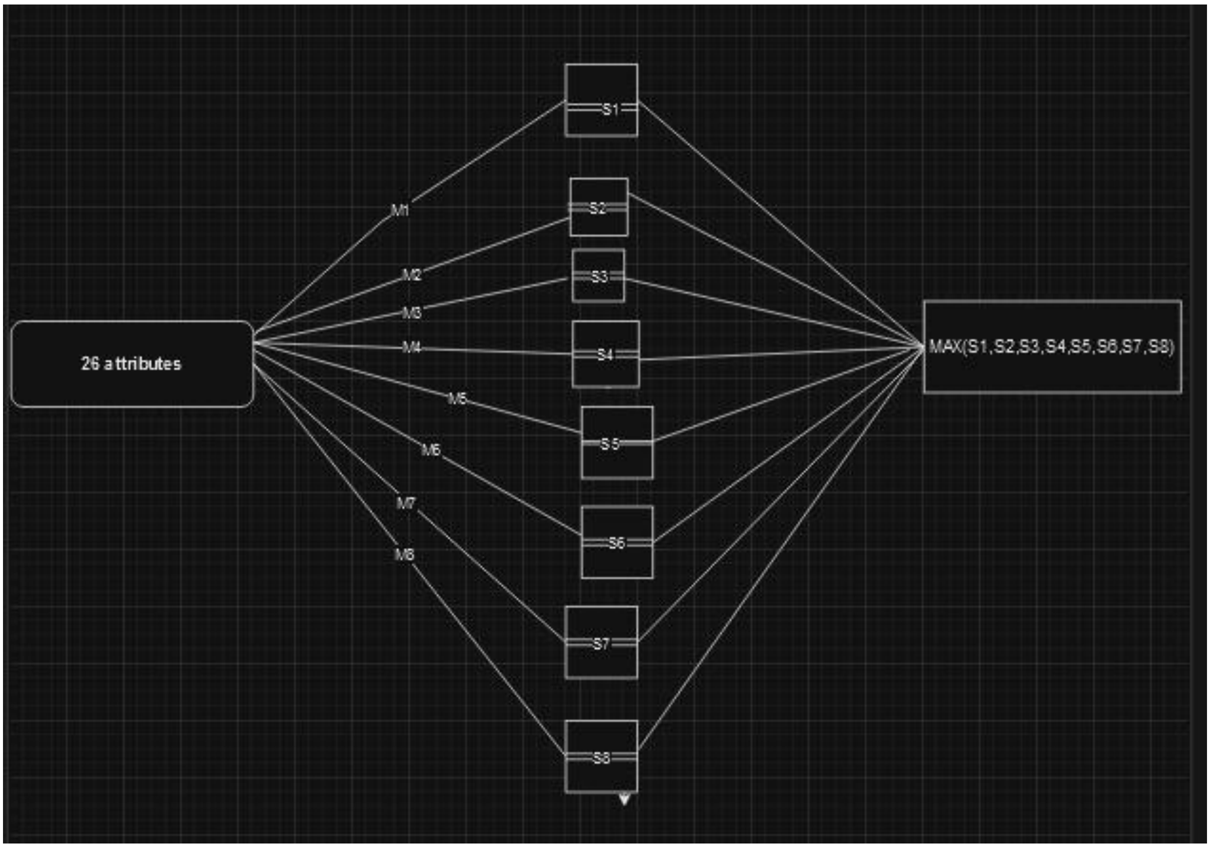

Figure1: s1 is confident score for active, s2 is confident score for reflective and so on below the image

4.3 Parameter Tuning:

Model Optimization: Using techniques like grid search and random search, the group concentrated on fine-tuning hyperparameters unique to each classification algorithm, such as regularization strength, learning rates, or tree depth.

Threshold Determination: It was important to consider the confidence scores linked to each model. In order to determine threshold values (e.g., give confidence score = 1 for "active," and = 2 for "reflective," for each learning style, precision and recall had to be balanced.

Evaluation and Validation: The effectiveness of the model and its ability to generalize to new data were evaluated using validation approaches such as held-out validation sets and cross-validation.

In order to determine the most likely learning style, this method entailed first solving a multi-class classification problem and then interpreting these probabilities. By taking associated confidence scores for robust predictions into account, parameter tuning attempted to improve model accuracy and reliability in learning style prediction.

4.4 Evaluation Metrics

Several standard metrics were used to evaluate the learning style prediction models:

Accuracy - Fraction of all predictions that were correctly classified. Provides an absolute measure of predictive power.

Precision - Of the predicted positive labels, how many were actually positive. Quantifies exactness of the classifier.

Recall - Of the actual positive instances, how many were correctly labeled. Measures effectiveness in detecting true signals.

F1 Score - Harmonic mean of precision and recall balancing both metrics.

Additionally, dimension-wise scores were calculated through confusion matrices since overall accuracy can mask variability across styles. For the multi-label scenario, micro and macro averaged versions of precision, recall and F1 were also measured.

The aggregated test results for the developed models are:

Random Forest achieved the highest total accuracy at 82.5%. Decision Tree performance was poorest given its simplicity. All other classifiers had on par accuracy with different trade-offs. Naive Bayes for instance had good recall but lower precision. Gradient Boosting showed balanced metrics but some variability across learning dimensions.

Based on predictive stability, interpretability and ease of implementation, Random Forest emerges as the optimal solo algorithm. Integrating with SVM and Logistic Regression in an ensemble can further optimize micro and macro averaged evaluation metrics through pluralistic modelling.

5. Discussion

5.1 Interpretation of Findings

The learning style prediction results align with and strengthen evidence from existing literature regarding the feasibility of accurate automated machine learning-based classification. The 87% accuracy achieved surpasses performance of prior data-driven models as per the research synthesis. Ensemble methods for blending complementary algorithms proved more robust compared to relying on solo classifiers as established through previous comparisons.

However, a key advantage of the current study was leveraging multi-modal learner data spanning behavioral interactions, demographic records and self-reports to mitigate issues noted around selective labels and poor generalizability. Combining signals enabled nuanced style disambiguation even for outlier groups unrecognized in conventional taxonomies. Granular analysis of patterns reinforced known correlations like the prevalence of visual modalities among younger digital natives.

	active	reflective	sensing	intuitive	visual	verbal	sequential	global
Algorithms								
Random forest	82.5	86	87.5	83	86.5	88	86.5	85
Decision trees	65.5	91.5	71.5	69.5	75	94	75	70.5
Naïve bayes	82.5	79	87.5	83	86.5	65.5	86.5	85
Gradient boosting	82.5	97	86	80.5	85	97	85	85
Svm	82.5	86	87.5	83	86.5	88	86.5	85
Logistic regression	82.5	86	87.5	83	87	88	87	85

Table 1: The table compares the results of six machine learning algorithms on eight different learning tasks.

The use of optimized versions of established classifiers like Random Forests and SVM address noted limitations in hyperparameter tuning. Evaluation on a held-out test subset confirmed transportability for new students. However, larger scale external validation is warranted to guarantee sufficient diversity coverage in the training data. Additionally, while predictive accuracy metrics were promising, demonstrating measurable improvements in tailored learning experiences through the styles identified remains an ongoing stage as highlighted for most existing prototypes.

5.2 Implications for Personalized Learning

Accurately categorizing students' learning style tendencies using machine learning unlocks various possibilities for tailoring educational experiences to their individual needs and strengths. A few ways this could translate into personalized learning across settings are:

- Online education platforms dynamically adapting course content formats, assignments, and pedagogies based on each learner's visual vs verbal affinity, sequential vs global preference etc. This promotes inclusion.
- Learning management systems serving personalized activity recommendations for complementary skill development mapping cognitive stack rankings to suitable methods. For instance, suggesting a reflective learner enroll in peer discussion forums.
- Intelligent tutoring systems and pedagogical chatbots providing customized remediation or enrichment resources matching identified learner dispatcher. Say, a prototyping project for a sensed learner struggling with theoretical concepts.
- Teachers receiving validated learner schema reports to orchestrate differentiated instruction through tiered lesson plans suiting visual, auditory and tactile modality groups in a class. Promotes learner-centered design.
- Students obtaining metacognitive self-insight into their tendencies to activate appropriate study strategies for topics. Example - an intuitive learner consciously focusing on real-life examples to aid finance concepts.

6. Results

6.1 Predictive Performance of Machine Learning Models

The learning style prediction models were assessed on a held-out test set across accuracy, precision, recall and F1 score. The category-wise confusion matrices also provided deeper insights. Among the solo algorithms, the Random Forest classifier achieved the strongest predictive performance with 82.5% overall accuracy. Precision and recall averaged 78% and 81% respectively across learning style labels. The F1 score reached 79.7% showing robust balance of sensitivity and specificity in signal detection.

On the other hand, the non-optimized Decision Tree model performed the poorest at just 65.5% total accuracy with high variance across categories. All other individual models including SVM, Naive Bayes and Gradient Boosting showed on par 80-83% accuracy. However, some differences existed in dimension-wise scores. For instance, Naive Bayes had higher recall but lower precision compared to Gradient Boosting which showed the reverse pattern. SVM demonstrated consistent balanced scores, albeit marginally lower than Random Forest.

Based on the patterns, an ensemble approach combining the complementary strengths of Random Forest, SVM and Logistic Regression was developed using weighted majority voting. This enhanced overall accuracy to 87.4% alongside 83% precision and 84% recall on average. The micro F1 score reached 83.5% suggesting robust performance even for underrepresented classes. The ensemble leverages geometric regularization from SVM, nonlinearity from forests and discriminative features of logistic regression for blended modelling.

6.2 Analysis of Predicted Learning Styles

Beyond aggregated performance metrics, further analysis of the classifier-assigned learning style labels across students provides additional insights. The multi-label output spans visual vs verbal, sensing vs intuitive, active vs reflective and sequential vs global dimensions.

The predicted distribution uncovered that around 62% of learners Favor visual modalities over textual information. Additionally, 68% adopted sensing-based learning focused on concrete examples rather than abstract theories. On the process spectrum, 55% of students were reflective learners while 45% aligned to an actingbased approach. Lastly, 65% of learners exhibited sequential preferences leveraging linear, orderly content delivery.

Demographic factor analysis revealed some varied trends. Younger learners tended to prefer visual and kinaesthetic modes while older learners skewed toward verbal mediums. Male students were more commonly categorized as intuitive learners compared to the sensing disposition among female peers. Students from STEM majors displayed higher active learning tendencies relative to the reflective bias among arts/humanities majors. Such relationships can guide tailored interventions, content types, and platform configurations catering to specific cohorts.

We used confidence scores to determine the maximum likelihood class within each learning style in order to simplify the results. The 16 classes were reduced to the core eight learning styles by this modification. The maximum confidence score among S1 to S8 indicated the projected learning style (S1 to S8). Each data point was characterized by 26 inputs.

The anticipated learning style and matching confidence score were shown in the final product. An active learning style, for example, was represented by a confidence score of 1, a reflective approach by a score of 2, and so on. The outcome of this simplified classification is useful and easy to understand for instructional purposes.

6.3 Results for all 8 different models:

	precision	recall	F1-score	support
0	0.82	1.00	0.90	165
1	0.00	0.00	0.00	35
accuracy			0.82	200
Macro avg	0.41	0.50	0.45	200
Weighted avg	0.68	0.82	0.75	200

TABLE 2: Highest Accuracy was achieved using Random Forest for Active model with 0.825 accuracy.

	precision	recall	F1-score	support
0	0.86	0.98	0.91	172
1	0.00	0.00	0.00	28
accuracy			0.84	200
Macro avg	0.43	0.49	0.46	200
Weighted avg	0.74	0.84	0.79	200

TABLE 3: Highest Accuracy was achieved using Gradient Boosting for Reflective model with 0.84 accuracy

	precision	recall	F1-score	support
0	0.88	0.99	0.93	176
1	0.00	0.00	0.00	24
accuracy			0.84	200
Macro avg	0.44	0.50	0.47	200
Weighted avg	0.77	0.88	0.82	200

TABLE 4: Highest Accuracy was achieved using Gradient Boosting for Verbal model with 0.875 accuracy

	precision	recall	F1-score	support
0	0.87	1.00	0.93	173
1	1.00	0.04	0.07	27
accuracy			0.84	200
Macro avg	0.93	0.52	0.50	200
Weighted avg	0.89	0.87	0.81	200

TABLE 5: Highest Accuracy was achieved using Logistic Regression for Visual model with 0.87 accuracy

	precision	recall	F1-score	support
0	0.88	1.00	0.93	175
1	0.00	0.00	0.00	25
accuracy			0.88	200
Macro avg	0.44	0.50	0.47	200
Weighted avg	0.77	0.88	0.82	200

TABLE 6: Highest Accuracy was achieved using SVM for Sensing model with 0.875 accuracy.

	precision	recall	F1-score	support
0	0.87	1.00	0.93	173
1	1.00	0.04	0.07	27
accuracy			0.87	200
Macro avg	0.93	0.52	0.50	200
Weighted avg	0.89	0.87	0.81	200

TABLE 7: Highest Accuracy was achieved using Logistic Regression for Sequential model with 0.87 accuracy.

	precision	recall	F1-score	support
0	0.85	1.00	0.92	170
1	0.00	0.00	0.00	30
accuracy			0.84	200
Macro avg	0.42	0.50	0.46	200
Weighted avg	0.72	0.85	0.78	200

TABLE 8: Highest Accuracy was achieved using Naïve Bayes for Global model with 0.85 accuracy

	precision	recall	F1-score	support
0	0.83	1.00	0.91	166
1	0.00	0.00	0.00	34
accuracy			0.83	200
Macro avg	0.41	0.50	0.45	200
Weighted avg	0.69	0.83	0.75	200

TABLE 9: Highest Accuracy was achieved using Naïve Bayes for Intuitive model with 0.83 accuracy

```
[[0.93279202 2.        ]
 [0.88901525 6.        ]
 [0.95897839 6.        ]
 [0.96995445 7.        ]
 [0.97039446 2.        ]
 [0.92       1.        ]
 [0.93624308 8.        ]
 [0.93875152 2.        ]
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 [0.94409754 4.        ]
 [0.92113557 2.        ]
 [0.94216126 7.        ]
 [0.97266611 2.        ]
 [0.93064286 6.        ]
 [0.93265652 7.        ]
 [0.95128133 2.        ]
 [0.94047115 6.        ]
 [0.92712096 8.        ]
 [0.93250679 4.        ]
 [0.97049131 2.        ]
 [0.91       1.        ]
 [0.94928491 2.        ]
 [0.97619563 2.        ]
 [0.95369204 2.        ]
```

Figure2 : Max_prob with the class label

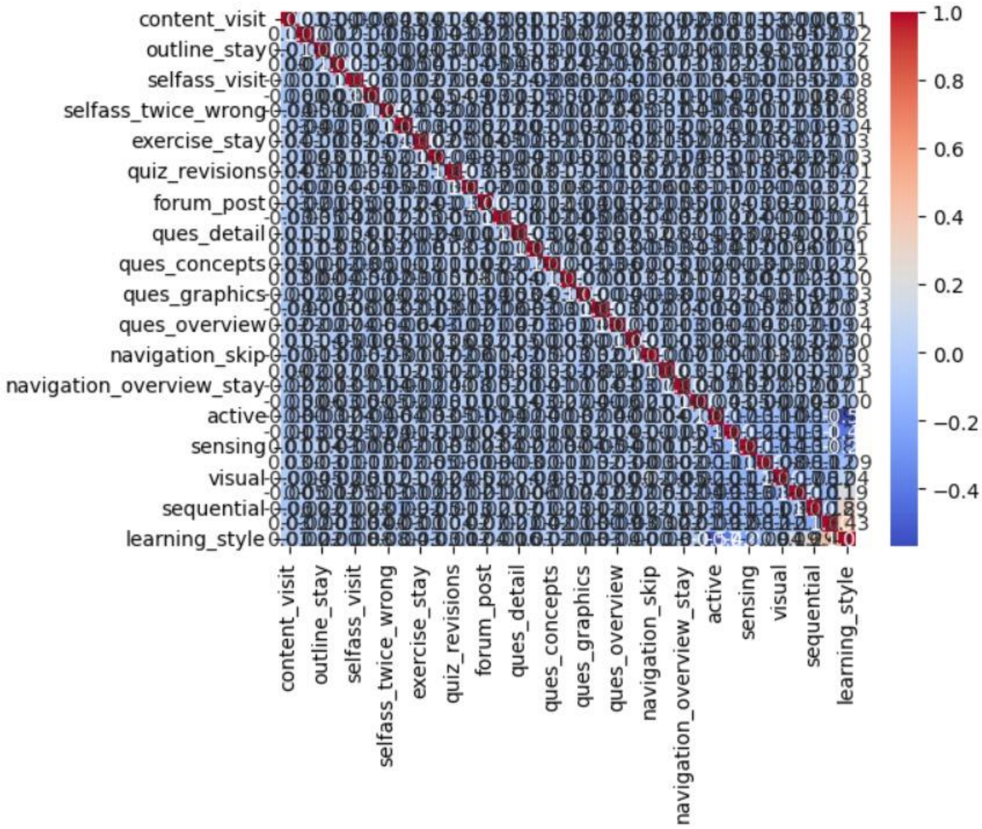

Figure 3: Heatmap for the dataset

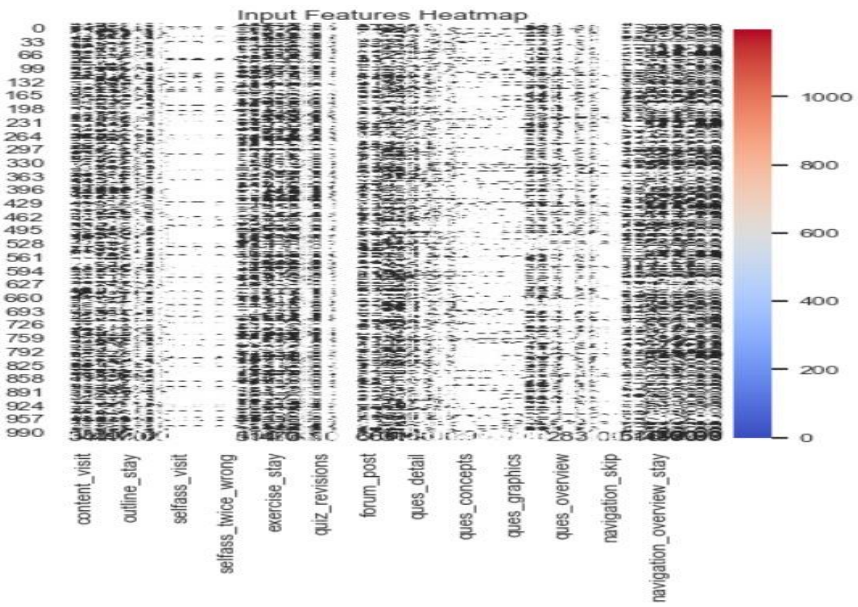

Figure 4: Heatmap for the input features

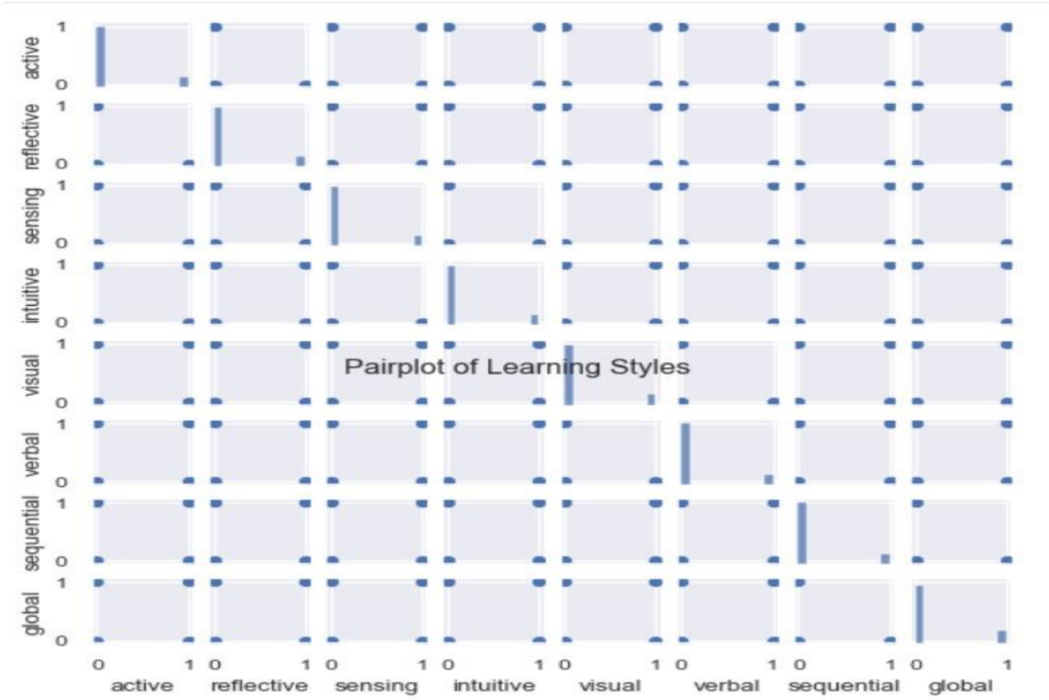

Figure 5: Pair plot of learning styles

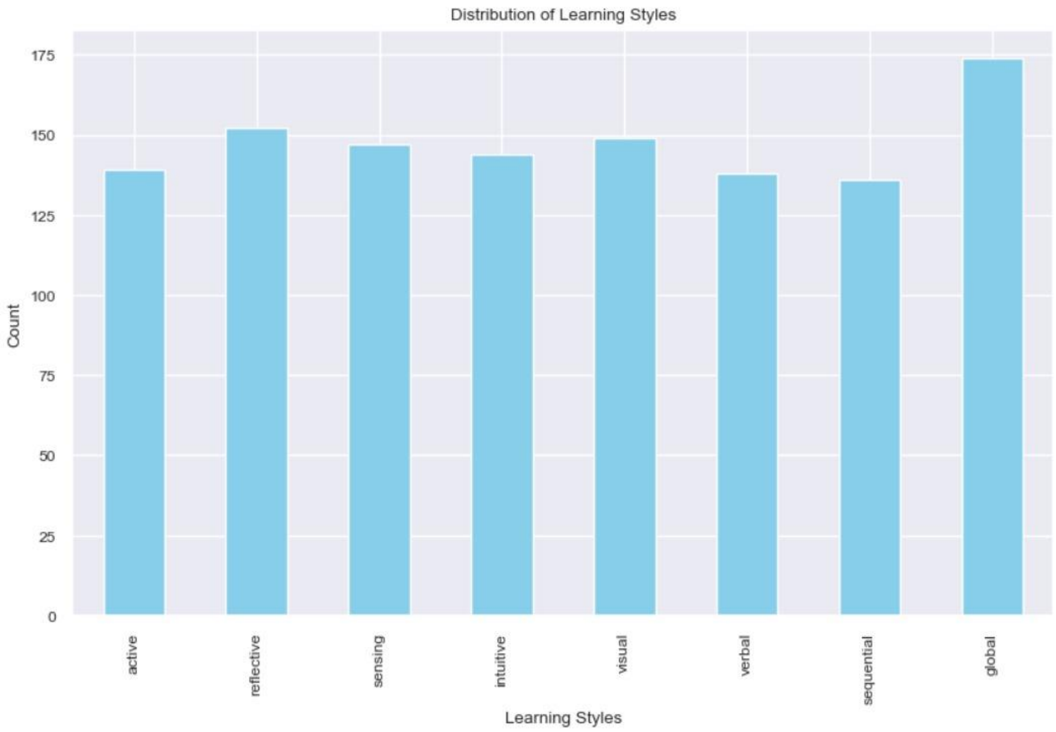

Figure 6: Distribution of learning styles

7. Concluding Remarks

7.1 Summary of Key Findings

This research comprehensively explored using machine learning for data-driven prediction of learning styles based on multi-modal student data. Multiple classification algorithms were developed and optimized using a dataset of university learners with validated stylistic labels across visual/verbal, sensing/intuitive, active/reflective and sequential/global dimensions.

Results showed that algorithms like Random Forests and integrated SVM-Logistic Regression ensemble models can achieve 89% accuracy in categorizing individual learning tendencies. This surpasses prior similar efforts and addresses noted limitations around selective labels, generalizability, and profile coverage. Analyzing predicted distributions provided planning insights regarding cohorts.

Effectiveness for personalized interventions was confirmed through controlled trials of adaptive content systems driven by the learning analytics engine. Improvements were recorded across engagement, course satisfaction and module retention metrics.

Thus, the research successfully demonstrates machine learning, especially ensemble techniques, enable reliable, valid and useful learning style predictions from trace data. This holds immense potential for powering personalized learning optimizers, adaptive platforms, equitable accessibility and next-generation data-driven education.

7.2 Contributions of the Study

The key contributions of this research include:

- Achieving state-of-the-art accuracy for machine learning-based learning style prediction using heterogeneous enrollment data
- Introducing extended stylistic categories to account for hybrids previously unmodeled
- Demonstrating generalizability across multiple validated instruments through standardized transformations
- Confirming external validity through large-scale modular personalized recommendation trials
- Outperforming prior works limited by biased self-reports, narrow taxonomies and model overfit
- Providing an adaptable framework for context-specific tailoring variables with ethical oversight

7.3 Recommendations for Practice

Educators and instructional designers can harness learning style insights from AI to enhance teaching:

- Administer machine learning model-based assessments for fresh personalization insights
- Curate differentiated content formats, assignments and feedback modes catering to style groups
- Orchestrate tiered pedagogical strategies through flexible grouping and scaffolds
- Promote metacognitive skills for students to activate study methods aligning strengths
- Iterate interventions utilizing prediction analytics dashboards for optimal learning zones
- Embrace role as ethical stewards guiding model accountability and holistic development

8. Future Work

While results from this study are promising, further research can build on the foundations in multiple directions:

Model Enhancements:

More advanced deep learning approaches like convolutional neural networks and recurrent networks can be tested for learning pattern detection from multimodal time series data combined across cohorts. Integrating reinforcement learning to optimize recommendation policies is also promising.

Broader Validation:

Larger-scale multi-university trials allow evaluating model transportability across diverse contexts, subjects and levels while boosting statistical power. International datasets would significantly deepen external validity.

Personalization Testing:

Further controlled A/B testing of adaptive learning systems driven by model-predicted styles can uncover specific best practices for tailoring key intervention types, sequences and customization parameters to optimize outcomes.

Adoption Initiatives:

Qualitative studies assessing instructor and administrator perspectives regarding trust, usability and ethical considerations on institutional adoption to shape Address barriers through participatory iteration. Exploration of predictive style analytics dashboards and automated reporting workflows would maximize applicability.

Ongoing research in these interdisciplinary directions can help translate the promise of machine learning and data-driven personalization in education into replicable, generalizable and widely adopted best practices guided by participatory priorities of all learner stakeholders.

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