Predicting Optimal Learning Approaches for Nursing Students in Morocco

Samira Fadili[1], Merouane Ertel[2], Aziz Mengad[3], Said Amali[4]
Laboratory of Education, Culture, Arts and Teaching of French Language and Literature (ECADLLF),
Faculty of Sciences of Education, Mohammed V University in Rabat, Morocco[1]
Informatics and Applications Laboratory (IA), Faculty of Sciences,
Moulay Ismail University, Meknes, Morocco[2]
Centre for Doctoral Studies "Life and Health Sciences"-Drug Sciences Formation, Laboratory of Pharmacology and Toxicology (LPTR), Faculty of Medicine and Pharmacy of Rabat (FMPh), Impasse Souissi Rabat, Morocco[3]
Informatics and Applications Laboratory (IA), FSJES, Moulay Ismail University, Meknes, Morocco[4]

***Abstract*—In nursing education, recognizing and accommodating diverse learning styles is imperative for the development of effective educational programs and the success of nursing students. This article addresses the crucial challenge of classifying the learning styles of nursing students in Morocco, where contextual studies are limited. To address this research gap, a contextual approach is proposed, aiming to develop a predictive model of the most appropriate learning approach (observational, experiential, reflective and active) for each nursing student in Morocco. This model incorporates a comprehensive set of variables such as age, gender, education, work experience, preferred learning strategies, engagement in social activities, attitudes toward failure, and self-assessment preferences. We used four multivariate machine learning algorithms, namely SVM, Tree, Neural Network, and Naive Bayes, to determine the most reliable and effective classifiers. The results show that neural network and decision tree classifiers are particularly powerful in predicting the most suitable learning approach for each nursing student. This research endeavors to enhance the success of nursing students and raise the overall quality of healthcare delivery in the country by tailoring educational programs to match individual learning styles.**

***Keywords*—Learning styles; nursing students; predictive modeling; classification; personalized education**

I. Introduction

In nursing education, discerning students' learning styles is of paramount importance to developing effective educational programs and promoting student success. Learning styles encompass the preferred methods and approaches that individuals employ to grasp, process, and retain information [1], [2], [3], [4], [5], [6]. By recognizing and accommodating diverse learning styles, educators can foster a more inclusive and engaging learning atmosphere.

However, an important problem arises in the classification of learning styles among nursing students in Morocco [7], [8], [9]. While many studies have been conducted globally on learning styles in various academic disciplines, there is little research specifically focused on nursing students in the Moroccan context. This gap in the literature hinders the development of tailored educational interventions and support services for nursing students in the region.

Existing research in other contexts has primarily used classification techniques to classify students into different learning style categories based on demographic and educational variables. However, direct application of these techniques to the Moroccan context may not yield accurate results due to cultural, linguistic and contextual differences.

Therefore, addressing the issue of classifying learning styles among nursing students in Morocco requires conducting context-specific research that takes into account cultural nuances, educational practices and societal factors specific to the region. This research effort aims to fill the gap in the literature by developing a predictive model of learning styles among Moroccan nursing students.

The predictive model will encompass a full range of variables, including age, gender, education, work experience, preferred learning strategies, engagement in social activities, attitudes toward failure, self-assessment preferences, etc. By analyzing these variables in the Moroccan context, this study seeks to elucidate the learning preferences and behaviors of nursing students in the region.

Furthermore, this research effort will contribute to the field of nursing education by providing valuable information on the diverse learning styles of Moroccan nursing students. Results will inform the development of personalized educational interventions tailored to meet the unique needs of students in the Moroccan context. Ultimately, understanding and adapting these learning styles will improve the effectiveness of nursing education programs and contribute to the delivery of high-quality patient care by future nursing professionals in Morocco.

II. Related Works

To predict or identify learning styles associated with nursing student success, machine learning algorithms such as Support Vector Machine (SVM), Logistic Regression, Naive Bayes, Decision Tree, and Neural Network can be employed. Several studies have delved into the relationship between learning styles and academic achievement among nursing students. Mahmoud et al. [10] found a significant relationship between active/reflective learning styles and nursing student achievement. Additionally, Li & Rahman [11] proposed using a tree augmented Naive Bayes approach to detect students' learning styles. Moreover, Saleh et al. [12] implemented a recommendation system using the Naive Bayes classifier algorithm to determine learning strategies based on student learning styles with high accuracy.

Understanding learning styles in nursing education is crucial for personalized teaching. Almarwani & Elshatarat [13] highlighted the prevalence of kinesthetic, accommodating, converging, visual, and active learning styles among nursing students in Saudi Arabia. Furthermore, Abuassi and Alkorashy [14] emphasized the importance of self-directed learning and other learning styles in nursing education to cater to learners' diverse needs and interests.

Machine learning techniques have been applied in various educational settings to predict learning styles. Crockett et al. [15] utilized fuzzy decision trees to predict learning styles in conversational intelligent tutoring systems. Similarly, Sianturi & Yuhana [16] employed decision tree, Naïve Bayes, and K-Nearest Neighbor methods to detect learning styles in Moodle Learning Management Systems. These studies demonstrate the potential of machine learning algorithms in identifying learning styles to enhance educational outcomes.

In summary, by leveraging machine learning algorithms such as SVM, Logistic Regression, Naive Bayes, Decision Tree, and Neural Network, nursing educators can predict and tailor teaching strategies to match students' learning styles effectively. Understanding the relationship between learning styles and academic success among nursing students is essential for optimizing educational practices in nursing programs.

III. MATERIALS AND METHODS

A. Data Understanding

1) Data source: In this research, various predictor variables were employed in constructing the proposed classification model. The data for the study were acquired through the distribution of questionnaires to first-year nursing students in morrocco. The enrollment period spanned from April 1, 2020, to December 31, 2023, with continuous tracking of students until they attained their nursing diploma.

Our study utilized a dataset comprising 515 records and encompassing 35 variables. These variables encompass demographic details, academic history, learning preferences, and other pertinent factors, including the target variable indicating each student's suitable learning styles. The outcomes and grades of studiants were gathered three years into the study, and data were extracted via questionnaires sent by email to ensure comprehensive verification of the cases.

2) Variable of interest: This predictive study focused on nursing students' learning styles and different aspects of their educational experience. The table below (see Table I) covers a wide range of factors, from demographic information (such as gender and age) to academic background (honors and bachelor's degrees), to various aspects related to learning preferences, dedication and predictors related to effective learning styles that contribute to the success of nursing students throughout their education and professional growth.

TABLE I. CHARACTERISTICS USED IN THE STUDY

#	Description of features	Feaures attributes
1	Age of students	Numeric
2	Gender	Categorical
3	Baccalaureate specialty	Categorical
4	Baccalaureate Notes	Numeric
5	Level of education prior to nursing registration	Categorical
6	Professional experience	Binary
7	Nursing specialty	Categorical
8	Favorite learning strategies	Categorical
9	Preferences for educational support types	Categorical
10	Preferred learning methods	Categorical
11	Use of additional resources	Categorical
12	Preference for learning through hands-on experience	Categorical
13	Reaction to practical activities	Categorical
14	Participation in class discussions	Categorical
15	Time spent studying outside of class	Numeric
16	Preference for using specific technological tools related to nursing care	Categorical
17	Level of engagement in social activities related to nursing studies	Categorical
18	Favorite type of activities	Categorical
19	Participation in wellness activities	Categorical
20	Learning environment	Categorical
21	Collaboration	Categorical
22	Adaptability	Categorical
23	Approach to conflict resolution	Categorical
24	Leadership preferences	Categorical
25	Time management preferences	Categorical
26	Participation in research projects	Categorical
27	Rating Preferences	Categorical
28	Attitudes towards failure	Categorical
29	Reaction to failure	Categorical
30	Self-evaluation preferences	Categorical
31	Participation in volunteer activities or humanitarian initiatives	Binary
32	Preferred communication styles	Categorical
33	External support	Categorical
34	Professional objectives	Categorical
35	The learning style of nursing students	Categorical

Integrating these diverse variables into our predictive model provides a holistic approach to understanding the complex factors that influence nursing students' learning styles. Each variable, from demographic characteristics to specific preferences and experiences, contributes to a comprehensive analytical framework.

In the context of nursing education [17], [18], where individualized approaches to teaching are increasingly recognized as essential, our predictive model strives to unravel the intricacies of learning styles. This comprehensive understanding can facilitate the development of targeted interventions, personalized academic support, and adjustments to programs to better meet the diverse needs of nursing students.

Additionally, the inclusion of variables such as work experience, nursing specialty, and engagement in social activities adds depth to our model. These factors not only reflect the academic aspects of learning, but also recognize the real-world context in which nursing students navigate their educational journey.

B. Data Preparation

Data preparation is made up of several stages: Data cleaning, Data Transformation.

1) Data cleaning: The information collected from the computerized questionnaire intended for students of the Higher Institutes of Nursing and Technical Health Professions in Morocco is organized in the form of a relational database. In order to remove and reduce noise, this database has been cleaned.

- Input mistakes, missing variable values, and redundant data are the main causes of attribute noise.
- Class noise brought on by mistakes made while allocating instances to classes.

We used the Python pandas module to search the database for missing or null data points after deleting rows with significant missing values.

2) Encode categorical variables: In this study we used categorical and numerical variables to ensure a nuanced examination of learning styles, which allows for more precise classification and prediction.

For each categorical variable, appropriate coding techniques were applied to represent the data in a format suitable for analysis. Coding techniques included:

- Binary coding with “1” indicating the presence of variable disorders and “0” indicating the absence.
- Label coding "1; 2; 3, 4...." indicating the subvariables.

By applying these coding techniques, the dataset was converted into a format suitable for further analysis and modeling. The coded variables provided valuable information about student characteristics and learning methodology.

3) Data Transformation

a) Multi-label classification mode: Multi-label classification is a machine learning approach wherein a model is trained to assign multiple labels or categories to each instance in a dataset [19]. Unlike traditional classification tasks where instances are assigned to a single predefined class, multi-label classification allows instances to belong to multiple classes simultaneously [20], [21].

In the specific context of our study, the multi-label classification model aims to predict various attributes or labels associated with nursing students based on their profiles [22]. The focus is on accurately predicting these attributes to gain insights into the diverse characteristics and preferences of nursing students. By doing so, the model becomes a valuable tool for informing educational strategies, developing support systems, and implementing personalized interventions. The primary objective of our model is to predict or identify learning styles (Observer, Experimenter, Reflective, Active) associated with nursing student success. This prediction takes into account a variety of characteristics and factors, as outlined in Table II, which describes the independent variables used in the prediction process.

TABLE II. THE INDEPENDENT VARIABLE INDICATING THE LEARNING PREFERENCES LINKED TO THE ACADEMIC ACHIEVEMENT OF NURSING STUDENTS

Outcomes	Description	Code
The Effective Learning Style for Every Nursing Student	Observational	1
	Experiential	2
	Reflective	3
	Active	4

C. Modeling

1) Development model: In this study, we used a multivariate logistic regression model using as characteristics demographic data, academic background, information on preferred learning strategies, professional experience, educational preferences, social and personal engagement, Social and community involvement. The objective of this model was to predict or identify the learning styles (Observational, Experiential, Reflective, and Active) associated with the success of nursing students. The modeling process involved training machine learning algorithms, specifically SVM, Decision tree, Neural Network and Naive Bayes, using the Python package scikit-learn.

To evaluate the classifiers, we used a 10-fold cross-validation test. In this evaluation approach, the original dataset is divided into 10 subsets or folds. The model is trained on 9 of these folds and tested on the remaining fold. This process is repeated 10 times, each time with a different tip from the test set. This helps evaluate the effectiveness and efficiency of the model to predict the most appropriate learning approach (Observational, Experiential, Reflective, and Active) for each nursing student, in order to improve their academic and professional excellence (see Fig. 1).

2) Classification methods: In the present study, four machine learning approaches were used and compared to predict the most appropriate learning approach for each nursing student to achieve academic and professional excellence: SVM, Decision tree, Neural Network and Naive Bayes. The approaches are listed above, along with their results on the training and validation sets.

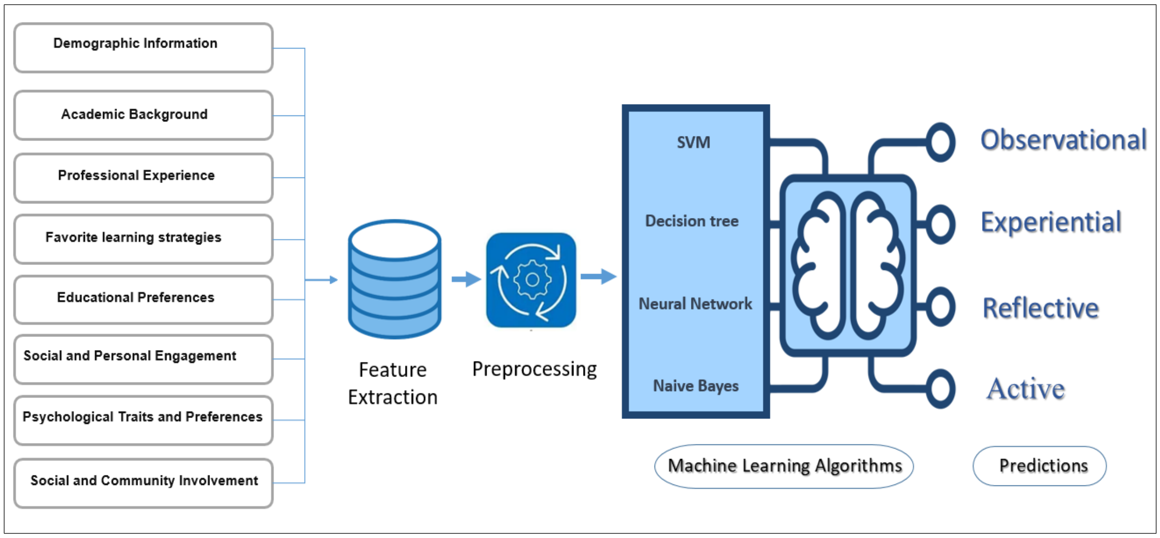

Fig. 1. Prediction model used in this study.

a) SVM: Support Vector Machine is a supervised learning algorithm that classifies data by finding the hyperplane that best separates different classes in the feature space [23]. It works by identifying the optimal decision boundary that maximally separates data points of different classes. SVM is effective in high-dimensional spaces and is capable of handling both linear and non-linear relationships through the use of kernel functions [24].

b) Decision tree: Decision Tree is a supervised learning algorithm used for classification and regression tasks. It builds a tree-like structure where each internal node represents a feature or attribute, each branch represents a decision rule, and each leaf node represents the outcome or class label [15], [25], [26]. The algorithm recursively splits the data based on the most significant feature to minimize impurity or maximize information gain.

c) ANN: Artificial Neural Network is a class of algorithms inspired by the structure and function of the human brain. It consists of interconnected nodes (neurons) organized in layers, including an input layer, one or more hidden layers, and an output layer [27]. Each neuron receives input signals, processes them through an activation function, and passes the output to the next layer. Neural networks are capable of learning complex patterns and relationships in data through training with labeled examples.

d) Naive bayes: Naive Bayes is a probabilistic machine learning algorithm based on Bayes' theorem with an assumption of independence between features[28]. Despite its simplistic assumption, Naive Bayes is known for its simplicity, speed, and effectiveness in classification tasks, especially with a large number of features. It calculates the probability of each class given a set of input features and selects the class with the highest probability.

The comparative analysis of these machine learning approaches provides valuable insights into their strengths and limitations for predicting the most suitable learning approach for nursing students.

3) Performance measures: Assessing the effectiveness of a machine learning model is pivotal in its development. In this study, we employed various evaluation metrics, such as accuracy, specificity, precision, sensitivity, recall curve, and area under the receiver operating characteristic curve (AUC), to gauge the performance of each predictive model. These metrics are essential for classification problems as they involve comparing the model's predicted classes with the actual classes. Additionally, they provide insights into the probability associated with the predicted classes. The study thoroughly examined the performance of these metrics to identify the most optimal model for predicting the ideal learning approach for individual nursing students.

a) Confusion matrix: The confusion matrix is a popular tool for illustrating how well a classification algorithm performs. In Fig. 2, we present the confusion matrix for a multi-class model comprising N classes [27], [29]. Observations on correct and incorrect classifications are collected in the confusion matrix $C(_{Cij})$, where C_{ij} represents the frequency with which class i is identified as class j. In general, the confusion matrix provides four types of classification results with respect to a classification target k:

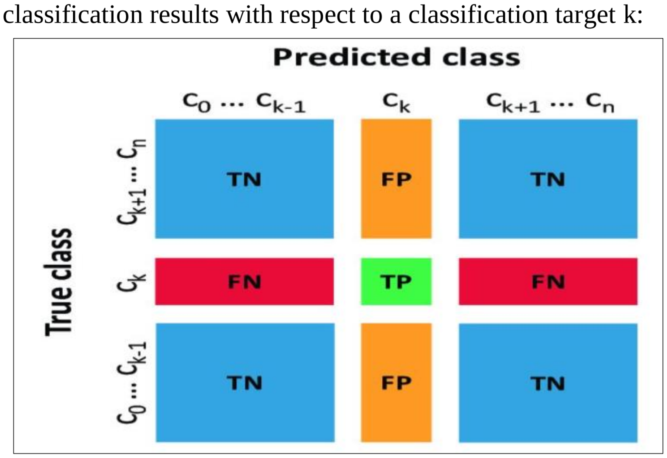

Fig. 2. Confusion matrix for multi-class classification.

- True positive (TP) : correct prediction of the positive class ($c_{k,k}$)
- True negative (TN) : correct prediction of the negative class $\sum_{i,j \in N\backslash\{k\}} c_{ij}$
- False positive (FP) : incorrect prediction of the positive class $\sum_{i \in N\backslash\{k\}} c_{ik}$
- False negative (FN) : incorrect prediction of the negative class $\sum_{i \in N\backslash\{k\}} c_{ki}$

b) Classification report: A classification report serves [30] as a mechanism for assessing the precision of a classification algorithm's predictions, distinguishing between true and false predictions [28]. The metrics in a classification report, depicted in Fig. 3, rely on parameters such as true positives, false positives, true negatives, and false negatives to quantify the accuracy of the predictions.

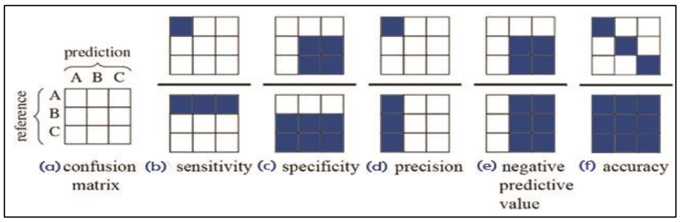

Fig. 3. (a) Confusion matrix for multiclass classification. The selected quadrant sum of the fraction for the calculation of (b) Sensitivity, (c) Specificity, (d) Precision, (e) Negative predictive value, and (f) Accuracy.

Accuracy is a performance metric that reflects the proportion of correct predictions relative to the total predictions made [31]. It is determined by dividing the total number of accurately classified instances by the overall number of instances considered [32]. Accuracy serves as an indicator of the percentage of instances correctly classified by the model [24]. The accuracy of our model is formally defined as:

$$Overall\ Accuracy = \frac{\sum_{i=1}^{N} c_{i,i}}{\sum_{i=1}^{N}\sum_{j=1}^{N} c_{i,j}} \quad (1)$$

Precision as given in Eq. (2), is the ratio of true positives to the sum of true positives and false positives [33]. In the context of our specific problem statement, this parameter is used to evaluate the model's ability to accurately identify cases where learning styles are effective [24], [34]. It is formally defined as:

$$Precision_{class} = \frac{TP_{class}}{TP_{class} + FP_{class}} \quad (2)$$

The true negative rate, also known as (Specificity) and defined by Eq. (3), represents the proportion of negative instances correctly identified as negative [35]. On the other hand, the false positive rate denotes the percentage of negative data points that are inaccurately classified as positive, out of the total negative data points.

$$Specificity_{\ class} = \frac{TN_{class}}{FP_{class} + TN_{class}} \quad (3)$$

Recall, or Sensitivity, is the true positive rate as specified in Eq. (4). It represents the proportion of positive data points that are accurately identified as positive, among all positive instances [36].

$$Recall_{\ class} = \frac{TP_{class}}{TP_{class} + FN_{class}} \quad (4)$$

Sensitivity and specificity, often referred to as quality parameters, play a crucial role in characterizing the accuracy of predicted classes. In the assessment of the learning style diagnostic model, three fundamental parameters are employed to gauge its quality: accuracy, sensitivity, and specificity [37].

F1-Score: is a metric that represents the harmonic mean of accuracy and recall. While it may not be as immediately intuitive as precision, F1-Score serves as a valuable measure for evaluating the accuracy and robustness of the classifier, as highlighted in reference [17].

$$\boldsymbol{F\,1-Score} = \frac{2 * TP_{class}}{2 * TP_{class} + FN_{class} + FP_{class}} \quad (5)$$

D. The Roc and AUC Curve

The Receiver Operating Characteristic (ROC) curve illustrates the relationship between the true positive rate (sensitivity) and the false positive rate (1 – specificity) across different decision thresholds [18]. Meanwhile, the area under the curve (AUC) serves as a measure quantifying how likely the model is to correctly classify a positive random example versus a negative random example, with values ranging from 0 to 1. Essentially, a higher AUC High indicates superior performance distinguishing between learning styles appropriate for each nursing student. The evaluation of learning algorithms in the following section is based on these key metrics, namely accuracy, precision, specificity, recall, and AUC.

IV. Results and Discussion

A. Analysis of Result

In this study, we evaluated the effectiveness of our ordinal classification model using various classification methods and the confusion matrix. To train our machine learning model to identify learning styles (Observer, Experimenter, Reflective, Active) associated with nursing student success, we incorporated several variables including gender, age, academic background, information on preferred learning strategies, professional experience, educational preferences, social factors and personal commitment, social and community involvement.

This approach allowed us to identify the learning styles associated with nursing student success. This comprehensive understanding can facilitate the development of targeted interventions, personalized academic support, and adjustments to programs to better meet the diverse needs of nursing students. The results shown in Table III derive from the results of these classification algorithms, which were obtained through a 10-fold cross-validation process. Each row of the confusion matrix represents instances of an actual class, while each column represents instances of a predicted class. This matrix provides a comprehensive overview of correct and false predictions, helping to evaluate model performance.

Based on the provided confusion matrix Table III, we can analyze the performance of each classifier (SVM, Decision Tree, Neural Network, and Naive Bayes) in predicting the most appropriate learning approach for nursing students. The confusion matrix shows the counts of true positive, false positive, true negative, and false negative predictions for each class (learning approach).

- The rows represent the true classes (actual learning approaches).
- The columns represent the predicted classes by each classifier.

TABLE III. THE MULTI-CLASS CONFUSION MATRIX OF THE CLASSIFICATION MODELS USED

Classifier	Predicted				n = 515	
	1	*2*	*3*	*4*		
SVM	198	0	2	5	*1*	**Current**
	3	106	3	3	*2*	
	4	7	103	4	*3*	
	11	8	1	57	*4*	
Decision tree	193	2	4	6	*1*	
	10	97	1	7	*2*	
	15	3	97	3	*3*	
	8	6	7	56	*4*	
ANN	196	2	2	5	*1*	
	2	106	2	5	*2*	
	3	3	110	2	*3*	
	5	3	4	65	*4*	
Naive Bayes	146	19	19	21	*1*	
	29	59	10	17	*2*	
	9	3	92	14	*3*	
	15	7	4	51	*4*	

Below is the interpretation of the confusion matrix for each classifier:

1) SVM:

- Observational (1): 198 correct predictions, 3 misclassified as Reflective, 11 misclassified as Active.
- Experiential (2): 106 correct predictions, 3 misclassified as Observational, 103 misclassified as Reflective, 8 misclassified as Active.
- Reflective (3): 110 correct predictions, 2 misclassified as Observational, 3 misclassified as Experiential, 4 misclassified as Active.
- Active (4): 57 correct predictions, 3 misclassified as Observational, 4 misclassified as Experiential, 4 misclassified as Reflective.

2) Decision Tree:

- Observational (1): 193 correct predictions, 10 misclassified as Reflective, 15 misclassified as Active.
- Experiential (2): 97 correct predictions, 1 misclassified as Observational, 97 misclassified as Reflective, 6 misclassified as Active.
- Reflective (3): 97 correct predictions, 7 misclassified as Observational, 3 misclassified as Experiential, 7 misclassified as Active.
- Active (4): 56 correct predictions, 2 misclassified as Observational, 3 misclassified as Experiential, 4 misclassified as Reflective.

3) Neural Network (ANN):

- Observational (1): 196 correct predictions, 2 misclassified as Reflective, 3 misclassified as Active.
- Experiential (2): 106 correct predictions, 2 misclassified as Observational, 110 misclassified as Reflective, 4 misclassified as Active.
- Reflective (3): 110 correct predictions, 2 misclassified as Observational, 3 misclassified as Experiential, 4 misclassified as Active.
- Active (4): 65 correct predictions, 3 misclassified as Observational, 3 misclassified as Experiential, 4 misclassified as Reflective.

4) Naive Bayes:

- Observational (1): 146 correct predictions, 29 misclassified as Experiential, 9 misclassified as Reflective, 15 misclassified as Active.
- Experiential (2): 59 correct predictions, 19 misclassified as Observational, 3 misclassified as Reflective, 7 misclassified as Active.
- Reflective (3): 92 correct predictions, 19 misclassified as Observational, 10 misclassified as Experiential, 4 misclassified as Active.
- Active (4): 51 correct predictions, 1 misclassified as Observational, 2 misclassified as Experiential, 4 misclassified as Reflective.

Based on the results from the confusion matrix, we can make the following observations:

5) SVM performance: SVM performed relatively well across all learning approaches with generally low misclassification rates. It had the highest accuracy for predicting the Experiential learning approach (Class 2) with no misclassifications. However, it had slightly higher misclassification rates for Observational (Class 1) and Reflective (Class 3) approaches compared to other classifiers.

6) Decision tree performance: Decision Tree also performed decently across all learning approaches but had slightly higher misclassification rates compared to SVM. It had the highest accuracy for predicting the Observational learning approach (Class 1) but relatively lower accuracy for the Reflective (Class 3) approach.

7) Neural network performance: Neural Network showed competitive performance similar to SVM, with generally low misclassification rates. It had the highest accuracy for predicting the Reflective learning approach (Class 3) but slightly lower accuracy for the Active (Class 4) approach compared to SVM and Decision Tree.

8) Naive bayes performance: Naive Bayes had mixed performance across learning approaches, with higher misclassification rates compared to SVM and Neural Network, especially for Observational (Class 1) and Reflective (Class 3) approaches. It had the lowest accuracy for predicting the Observational learning approach (Class 1).

9) Overall observations:

- SVM and Neural Network showed more consistent and competitive performance across all learning approaches compared to Decision Tree and Naive Bayes.
- Experiential learning approach (Class 2) was predicted with high accuracy by all classifiers, indicating it might have distinctive features that are easier to classify.
- Reflective learning approach (Class 3) had varying performance across classifiers, indicating it might be more challenging to classify accurately.

These observations provide insights into the strengths and weaknesses of each classifier in predicting the appropriate learning approach for nursing students, which can be valuable for further refinement of the classification model or selection of the most suitable classifier for this task.

Based on these results, we can further analyze the performance of each classifier in terms of accuracy, precision, recall, and F1-score for each learning approach to determine which classifier performs best for this specific prediction task. These metrics will provide a more comprehensive understanding of each classifier's performance beyond just the confusion matrix.

B. Performance Evaluation

Classification measures were calculated to compare the performance of each machine learning algorithm in predicting the most appropriate learning approach for nursing students. Table IV shows the evaluation of the different machine learning algorithm.

TABLE IV. EVALUATION OF THE DIFFERENT MACHINE LEARNING ALGORITHMS USED

Model	AUC	CA	F1	Precision	Recall
SVM	0.939	0.860	0.859	0.861	0.860
Decision tree	0.978	0.901	0.900	0.901	0.901
ANN	0.985	0.926	0.926	0.926	0.926
Naive Bayes	0.881	0.676	0.676	0.684	0.676

- Classification Accuracy (CA) measures the overall correctness of the predictions. Neural Network (ANN) has the highest accuracy (92.6%), followed closely by the Decision Tree (90.1%), SVM (86.0%), and Naive Bayes (67.6%).
- F1 Score is the harmonic mean of precision and recall. Neural Network (ANN) and Decision Tree have the highest F1 Scores (92.6% and 90%, respectively).
- Precision is the ratio of true positive predictions to the total predicted positives, while Recall is the ratio of true positive predictions to the total actual positives. Decision Tree, Neural Network (ANN), and SVM have similar precision and recall values, indicating a good balance between precision and recall.
- Naive Bayes shows the lowest performance in terms of Classification Accuracy, F1 Score, Precision, and Recall among the four models.

In summary, both Neural Network (ANN) and Decision Tree seem to perform well in predicting the most appropriate learning approach for nursing students, based on the provided evaluation metrics. It's essential to consider the specific requirements and goals of the application when choosing the most suitable model.

C. Roc and AUC curve

The machine learning classifiers Artificial Neural and Decision tree, give a level of accuracy greater than 90% for classifying the most appropriate learning approach (observational, experiential, reflective and active) for each nursing student. This indicates that the performance of these classification techniques is excellent for prediction. Based on the ROC curves of the models (see Fig. 4), the artificial neural network model outperformed SVM, Tree and Naive Bayes, in terms of sensitivity and specificity.

Fig. 4 shows the performance evaluation of different classification algorithms to predict the most appropriate learning approach (Observational, Experiential, Reflective, and Active) for each nursing student, in order to improve their academic and professional excellence. Performance is assessed using ROC (Receiver Operating Characteristic) curves, which represent the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity).

The ROC curves are presented for four target values, representing the four learning approaches: Observational, Experient, Reflective, and Active. The curves are labeled as A, B, C, and D, and correspond to the target values 1, 2, 3, and 4, respectively.

The classification algorithms used are SVM, Tree, Neural Network, and Naive Bayes. The performance of each algorithm is compared for each target value. The x-axis shows the False Positive Rate (1 - Specificity), while the y-axis displays the True Positive Rate (Sensitivity).

A good classifier should have a curve closer to the top-left corner, indicating high sensitivity and low false positive rates. Based on the figure, in ROC curve A, the SVM algorithm has a true positive rate of 0.9 and a false positive rate of 0.1 for target value 1 (Observational). Similarly, the Neural Network algorithm has a true positive rate of 0.8 and a false positive rate of 0.2 for target value 2 (Experiential).

Overall, the results show that the classification algorithms have varying levels of performance for different target values, with the Neural Network showing higher sensitivity (true positive rate) in general. However, this model needs more specific numerical values and additional information to improve model efficiency in predicting the most appropriate learning approach (Observational, Experiential, Reflective, and Active) for each nursing student, in order to improve their academic and professional excellence.

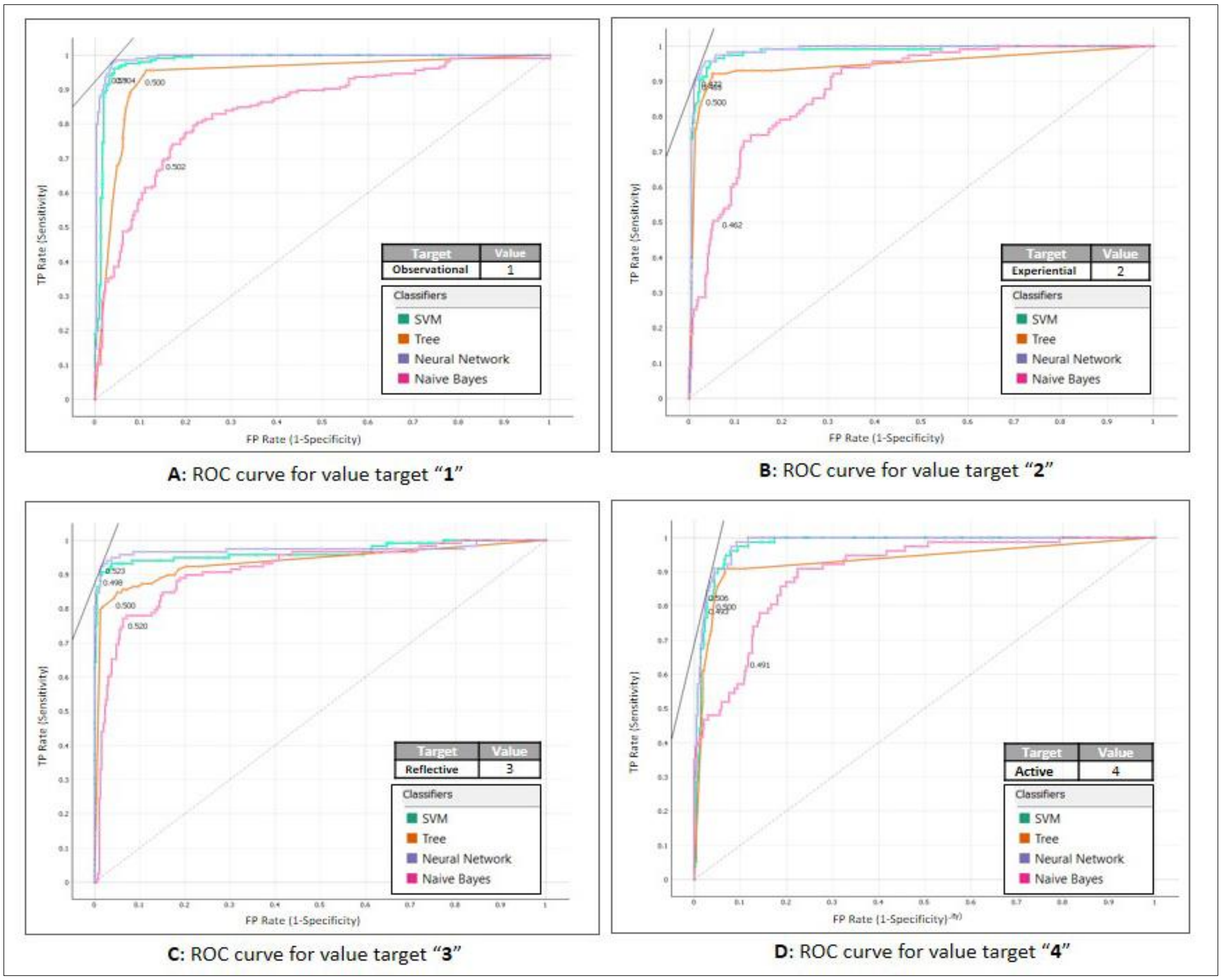

Fig. 1. ROC curve for the four target variables which signify the most appropriate learning approaches for each nursing student.

V. Conclusion

In this article, we presented a novel approach to predict the most appropriate learning approach (observational, experiential, reflective, and active) for each nursing student. The proposed multivariate classification model aims to support educators, especially in the field of nursing, by providing them with valuable information to make informed decisions about the appropriate learning styles for each student. This approach has the potential to improve the academic and professional excellence of nursing students, thus contributing to more personalized and effective training in this specific field.

By conducting a comparative study of four multivariate machine learning algorithms, namely SVM, Tree, Neural Network, and Naive Bayes, we determined that Neural Network, Decision tree classifiers are reliable, powerful and efficient algorithms for predicting the most appropriate learning approach (observational, experiential, reflective and active) for each nursing student.

As future directions of our research, we intend to expand our study by incorporating additional parameters including individual student characteristics, academic performance metrics, and contextual factors to further enhance the predictive accuracy of the model. Additionally, exploring the application of ensemble learning techniques or hybrid models could offer a comprehensive approach to better capture the complexity of learning styles in nursing education.

In conclusion, our findings underscore the potential of Neural Network and Decision Tree classifiers in tailoring learning approaches for nursing students. The ongoing and future research directions aim to refine and extend the model's capabilities, ensuring its applicability in diverse educational settings and providing valuable insights for personalized learning strategies in nursing education.

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