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Using Artificial Intelligent Techniques to Classify Students Based on Their Preferred Learning Styles

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Abstract
With the growing demand for e-learning, numerous studies have been conducted to enhance the quality of the education process. As a result of these studies, researchers have indicated that considering individual differences (learning styles) among students is a critical requirement for promoting student engagement and performance. Adaptive education systems use instruments to find out the preferences of students and hence can provide them with the materials and learning strategies that match their learning styles. The recent trend is to harness artificial intelligence classifiers to find out the learning styles of the learner automatically without disturbing the students. This study aims to present an AI-based model that can effectively predict learning styles based on key input features. And the output learning styles include verbal, visual, passive, and active. This paper used a dataset from the authors' earlier work, and four machine learning classifiers were applied: Decision Tree, Random Forest, Support Vector Machine, and Neural Network. The experimental results indicate that machine learning algorithms can effectively classify and identify students’ learning styles.
Key words: Adaptive education, Learning Style, Student Classification

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استخدام تقنيات الذكاء الاصطناعي لتصنيف الطلبة بناء على أساليب التعلم المفضلة لديهم

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ملخص البحث

مع تزايد الطلب على التعلّم الإلكتروني، أُجريت دراسات عديدة لتحسين جودة العملية التعليمية. ونتيجةً لهذه الدراسات، أشار الباحثون إلى أن مراعاة الفروق الفردية (أنماط التعلّم) بين الطلاب شرط أساسي لتعزيز مشاركتهم وأدائهم. تستخدم أنظمة التعليم التكيفية أدواتٍ لتحديد تفضيلات الطلاب، وبالتالي تزويدهم بالمواد واستراتيجيات التعلّم التي تتناسب مع أنماطهم. هناك توجه حديث نحو استخدام مصنّفات الذكاء الاصطناعي لتحديد أنماط التعلّم تلقائيًا دون إزعاج الطلاب. تهدف هذه الدراسة إلى تقديم نموذج قائم على الذكاء الاصطناعي قادر على التنبؤ بأنماط التعلّم بفعالية بناءً على خصائص الإدخال الرئيسية، وتشمل أنماط التعلّم الناتجة: اللفظي، والبصري، والسلبي، والنشط. استخدمت هذه الورقة البحثية مجموعة بيانات من عمل سابق للمؤلفين، وطُبّقت أربعة مصنّفات للتعلّم الآلي: شجرة القرار، والغابة العشوائية، وآلة المتجهات الداعمة، والشبكة العصبية. تشير النتائج التجريبية إلى أن خوارزميات التعلّم الآلي قادرة على تصنيف أنماط تعلّم الطلاب وتحديدها بفعالية.

الكلمات المفتاحية: التعليم المتكيف ، أساليب التعلم ، تصنيف الطلبة

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Introduction

Learning style

Education research has indicated that students have different methods by which they can effectively acquire, process, and retain information. For example, some students tend to gain more knowledge from educational materials that depend on visual forms of information. In contrast, the same material will be more useful for others when represented using text and audio. In the same way, some learners tend to get more through 'doing things', whereas others prefer to 'think & reflect' about these things. These preferred methods are called learning styles (Alshammari 2016, Alzain, Clark et al. 2016). According to (Alshammari 2016, Jonassen 1991) learning is a process of knowledge acquisition through receiving new information and interacting with it. Consequently, the learning style model contains 2 main dimensions. Figure 1 illustrates the dimensions and their values.

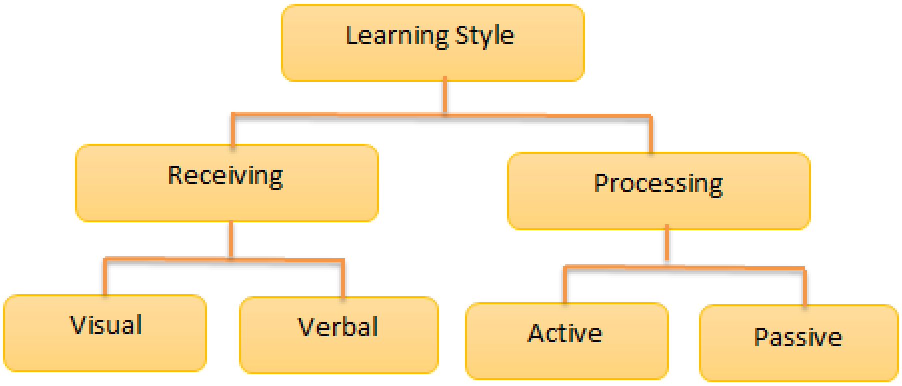

Fig1: dimensions of the LS model and its values.

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Learning Style Instrument

Instruments of learning style have been extensively used in the adaptive education system to determine how students prefer to learn (Alzain, Ireson et al. 2016, Özyurt, Özyurt 2015, Truong 2016). Over the last few years, many instruments of learning styles have emerged (Hawk, Shah 2007). Initially, selecting an instrument to be used is not as important as understanding how students like to learn (Fleming, Baume 2006). However, the instruments of learning style are often criticized (Alshammari 2016). In earlier work, the author mentioned that all of the previous instruments were built using only textual content, so it might be more motivating and suitable for verbal students than others. For this reason, the author claims that the previous instruments have not been designed and presented in a manner that corresponds to the different learning styles. Consequently, this situation might be leading to a bias for this type of student (verbal), more than others, such as active, passive, and visual students. As a result, the author designed a new learning style instrument (ALSI), and for the reasons explained above, the new instrument was constructed using different forms of information such as visual and active, Figure 2 shows a sample of the ALSI instrument (Alzain, Ireson et al. 2016). The instrument consists of sixteen items, each with four choices corresponding to the four learning styles. Respondents need to determine the answer(s) that best fits their preferences by selecting the priority levels from zero (least important) to three (most important) for each item, for the respective choices. The respondents are also allowed to give the same priority level for more than one choice. The highest score possible is

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forty eight, and each preference is divided into three equal categories: pure preference (from 33 to 48), moderate preference (from 17 to 32), and mild preference (less than 17). The instrument mechanism is explained below :

- The instrument consists of 16 questions;
- Each question has 4 choices;
- Participants give a priority weight from 0 (least important) to 3 (most important) for each choice;
- Each choice corresponds to one preference (Visual ,Verbal/ Active, Passive);
- Visual Preferences (VP) = $\sum_{Q=1}^{16} Visual\ items$;
- Verbal Preferences (EP) = $\sum_{Q=1}^{16} Verbal\ items$;
- Active Preferences (AP) = $\sum_{Q=1}^{16} Active\ items$;
- Passive Preferences (PP) = $\sum_{Q=1}^{16} Passive\ items$;
- Preferred Style of Receiving new information (PSR) = VP – EP;
    - ✓ If PSR > 0 then student has Visual preference;
    - ✓ If PSR < 0 then student has Verbal preference;
    - ✓ If PSR = 0 then student has equivalent preferences;
- Preferred Style of Interacting new information (PSI)= AP-PP;
    - ✓ If PSI > 0 then student has Active preference;
    - ✓ If PSI < 0 then student has Passive preference;
    - ✓ If PSI = 0 then student has equivalent preferences.

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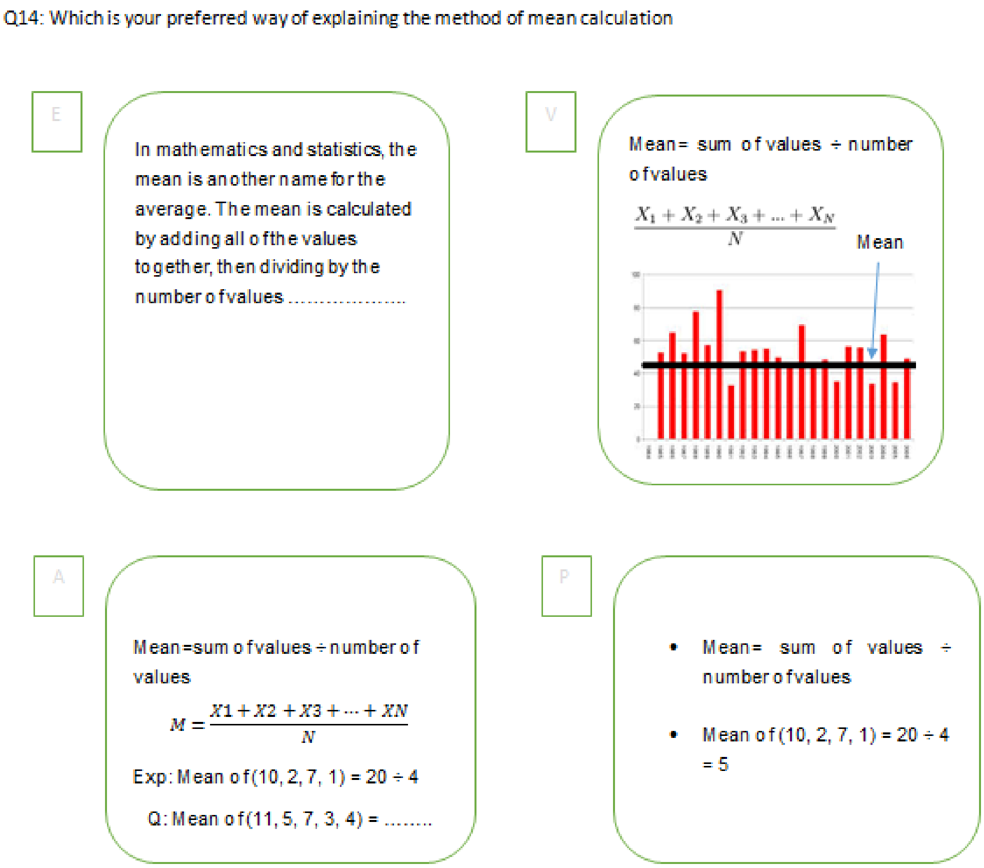

Fig2: sample from ALSI instrument

Education research revealed that learning style instruments are one of the most common and important tools that could be used to design adaptive learning environments to consider individual differences among students. in 2015 Özyurt conducted a review study within the scope of adaptive

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educational systems, 69 research papers published between 2005 and 2014 were reviewed. The results revealed that (69.6 % of studies) used learning style instruments to determine student preferences to achieve the adaptation process (Özyurt, Özyurt 2015).

Adaptive Education System

In 2012, Feighas defined adaptive systems as a “technological component of joint human-machine systems that can change their behavior to meet the changing needs of their users, often without explicit instructions from their users” (Feigh, Dorneich et al. 2012). This kind of system could be harnessed to consider the individual differences among students and match them with their preferences. Figure 3 shows the mechanism of Adaptive Educational Systems

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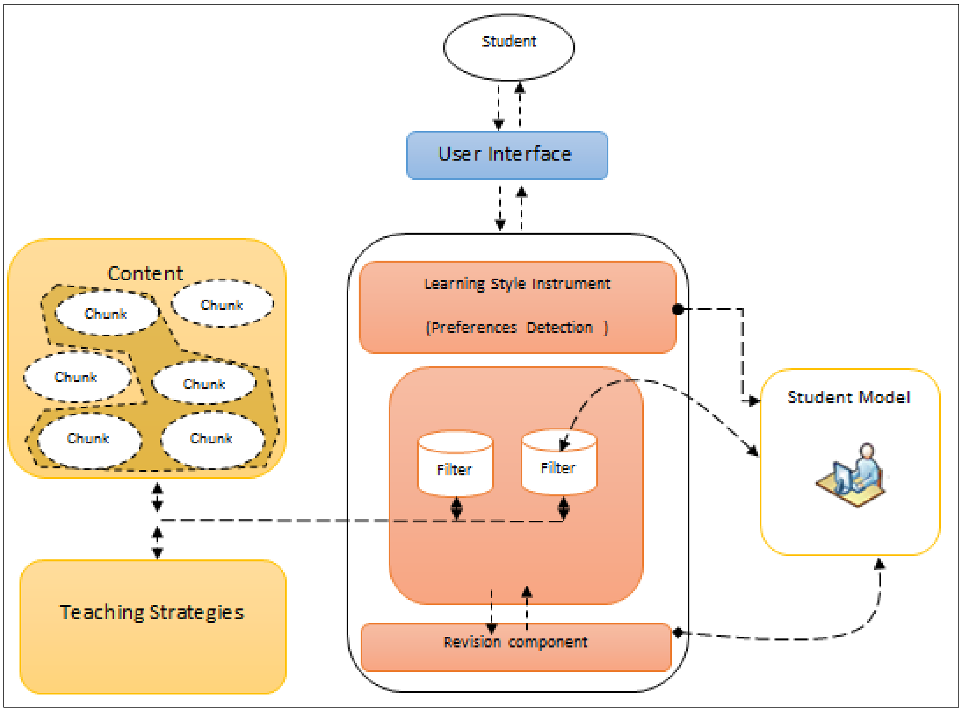

Fig3: Mechanism of adaptive education system

Related Work

In the previous sections, the concept of learning style and the integration process of learning style instruments into adaptive education systems were discussed. in artificial intelligence Classification algorithms can be used to make predictions in case these algorithms have already been trained from data. Therefore these capabilities could be harnessed in the education field in terms of students' preferences prediction. Table 1 provides an overview of different machine learning algorithms that have been applied in adaptive education systems to .predict the preferred learning style of students

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Paper Title	Classification method used	Results	Reference
"Learning Styles Diagnosis Based on User Interface Behaviors for the Customization of Learning Interfaces in an Intelligent Tutoring System"	Decision Tree and Hidden Markov	The Decision Tree error rate was 28.57% in global sequential, 0% in visual aural, 22.22% in sensing intuitive, and 33.33% for active reflective dimension And Hidden Markov error rate was 14.28%, 14.28%,22.22%, 33.33% respectively	(Cha et al., 2006)
"EDUCA: A web 2.0 authoring tool for developing adaptive and intelligent tutoring systems using a Kohonen network"	Neural Network	This paper presents self-organizing maps (SOMs) to classify Felder–Silverman learning styles	(Cabada et al., 2011)
"A Framework for Automatic Identification of Learning Styles in Learning Management Systems"	Fuzzy Classification	The study presented a framework for automatic identification of learning styles. The study does not provide precision and accuracy	(Márquez et al., 2015)
"Detecting Learning styles in Learning Management Systems Using Data mining"	Decision Tree, Bayes Net, Random forest, Naïve Bayes	This research aims to predict individual learning styles by analyzing log data, and J48 decision tree classification algorithm achieves the best results. 91.25% in global sequential, 82.50% in visual aural, 84.38% in sensing intuitive, and 70.89% for active reflective dimension	(Liyanage et al., 2015)
Paper Title	Classification method used	Results	Reference

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"Learning Style Identifier: Improving the Precision of Learning Style Identification Through Computational Intelligence Algorithms"	Genetic algorithm, ant colony system, particle swarm, and Artificial neural network	The artificial neural network achieved the best results with an average precision of 80.7%	(Bernard et al., 2015)
"Model Detecting Learning Styles with Artificial Neural Network."	Artificial neural network	In this study, the authors developed Latent semantic indexing, which starts with the prior knowledge generation process, and then one can predict learning style using the artificial neural network	(Hasibuan et al., 2019)
"Automatic detection of students learning style in learning management system"	Decision Tree	This study used only two dimensions of Felder Silverman learning style model, getting student behavior from the web log files. the proposed model achieved 87% accuracy.	(Sheeba et al., 2019)
"A robust classification to predict learning styles in adaptive E-learning systems"	Fuzzy C Means Classifier	In this study, the system used Fuzzy C means classifier to analyze data captured from learners' sequences and mapped it according to Felder-Silverman Learning Style Model. The accuracy of the algorithm was 93.41%	(Azzi et al., 2019)
"An AI-based learning style prediction model for personalized and effective learning"	Random Forest, Ensemble learning, and Decision Tree.	the authors used three classifiers to prediction based on (attention, cognitive workload, facial expressions, meditation, and emotional state) features. Random Forest achieved the highest accuracy 87.5%.	(Lokare et al., 2024)

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Methodology

Machine Learning Algorithms

Decision Tree

This algorithm operates by recursively partitioning the dataset into subsets based on feature values, forming a tree-like structure. Each internal node represents a decision based on a specific feature, branches denote the outcomes of the decision, and leaf nodes indicate the final prediction or class label. The algorithm harnesses metrics such as Entropy, Gini impurity, or mean squared error to select the optimal splits, aiming to maximize information gain or minimize error. Decision Trees are intuitive, easy to interpret, and capable of dealing with both numerical and categorical data, although they can be prone to over-fitting without proper pruning or regularization. (Mahesh. 2020, Sarker 2021).

Random Forest

The Random Forest algorithm is an ensemble learning method primarily used for classification and regression tasks. It operates by constructing many decision trees during training and outputs either the mode of the classes (classification) or the individual trees' mean prediction (regression). Random Forest leverages the concept of bagging (Bootstrap Aggregating), where each tree is trained on a random subset of the data, and features are selected randomly at each split, reducing over-fitting and enhancing generalization. This approach ensures robustness, scalability, and high accuracy, making it

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suitable for handling large datasets and high-dimensional spaces. (Mahesh. 2020, Sarker 2021).

Support Vector Machine (SVM)

SVM is widely used for (classification / regression) tasks. It works by identifying the optimal hyperplane that separates data points of different classes in a feature space. This hyperplane is determined by maximizing the margin, defined as the distance between the hyperplane and the nearest data points from each class, known as support vectors. SVM can effectively handle linear and non-linear problems by employing kernel functions, which map input data into higher-dimensional spaces. Its ability to manage high-dimensional data and maintain computational efficiency makes it a robust choice for diverse machine-learning applications. (Mahesh. 2020, Sarker 2021).

Neural Network

The Neural Network algorithm is a computational framework modeled after the structure and functionality of the human brain. It comprises interconnected layers of units, or neurons, arranged in an input layer, one or more hidden layers, and an output layer. Each neuron computes outputs by performing a weighted sum of inputs, followed by an activation function, allowing the model to identify complex, non-linear patterns in data. Training neural networks involves optimizing a loss function, often using gradient descent, while backpropagation updates the weights through iterative adjustments. These models are highly effective in applications such as image processing, natural language understanding, and time-series prediction, though they demand considerable computational power and large datasets for optimal performance. (Mahesh. 2020, Sarker 2021).

Dataset

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This study used a new dataset, which was designed by the author in previous work. Where ALSI instrument was used to collect learners' preferences (see section 1.2). The dataset contains 632 samples, and 48 features. All students in the dataset are at least 17 years old. There are two dimensions: Visual-verbal or active-passive. the proposed research methodology is given in Figure 4.

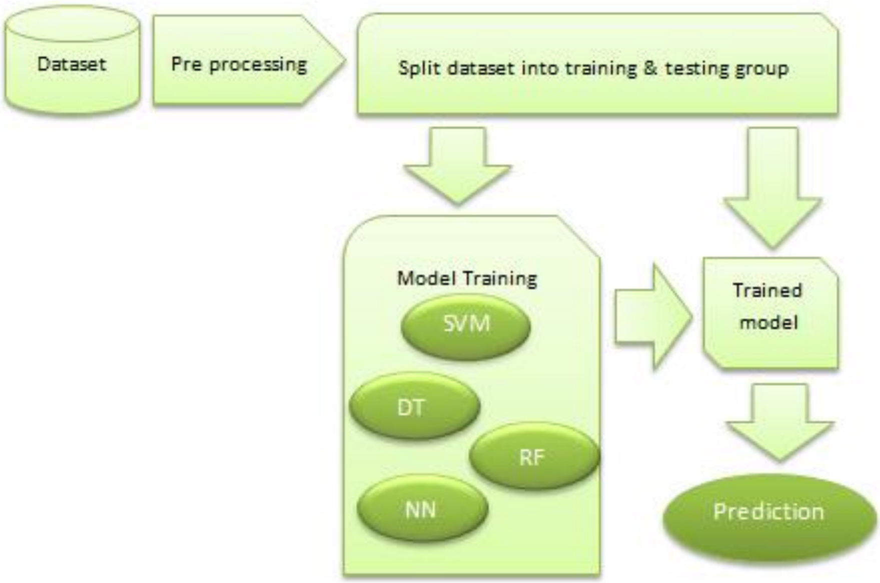

Fig4: The proposed research methodology

Data prepressing

Missing values

To increase the reliability and accuracy of machine learning models, the missing values have to be processed in a good manner. The missing values can arise due to various factors, such as data entry errors, or incomplete data collection. Techniques for managing missing values include deletion

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methods, such as removing rows or columns with a high proportion of missing data, and imputation methods, which replace missing values with estimated ones. Common imputation techniques include mean, median, or mode substitution and more sophisticated methods like k-Nearest Neighbors (k-NN) imputation or predictive modeling. The method choice depends on the data's nature and the proportion of missing values. Proper handling of missing values prevents biased model predictions and ensures the integrity of the dataset for analysis. In this study, the missing values were filled using the average value. (Acock, A. C. 2005)

Normalization

Normalization is a fundamental technique in data preprocessing that involves scaling numerical features to a specified range, typically [0, 1] or [-1, 1]. This process ensures that all features contribute equally to the model, preventing bias due to differences in magnitude or scale. By transforming data into a uniform range, normalization improves the performance and convergence speed of gradient-based learning algorithms and reduces sensitivity to the choice of metric in distance-based models like k-Nearest Neighbors. Common normalization methods include Min-Max scaling and Mean Normalization, which adjust feature values relative to their minimum, maximum, or mean. Equation 1 is a normalization formula. (Ali, P. J. M., Faraj, R. H., Koya, E. 2014).

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$$Xnorm = \frac{X - Xmin}{Xmax - Xmin} \qquad (1)$$

Standardization

Standardization is a crucial data preprocessing technique used to transform features so they have a mean of zero and a standard deviation of one. Unlike normalization, which scales data to a specific range, standardization focuses on ensuring that each feature contributes equally to the analysis, irrespective of its original scale. This is achieved by subtracting the mean and dividing by the standard deviation of the feature. Standardization is particularly beneficial for algorithms that assume normally distributed data, such as linear regression and principal component analysis, or those sensitive to feature scaling, like gradient descent-based models. By standardizing features, the technique reduces biases caused by varying scales and enhances model performance, especially in datasets with features of diverse magnitudes. Equation 1 is a normalization formula. (Ali et al., 2014)

$$Xstand = \frac{X - Mean\ (X)}{Standard\ Deviation\ (X)} \qquad (2)$$

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Results

four machine learning algorithms were utilized in this research to classify whether learners had visual or verbal, and active or passive preference. These algorithms are random forest, decision tree, neural network, and SVM. The dataset was split at a ratio of (70% for training), and (30 % for testing the model). The results obtained are explained below in Table 2,3.

Dimension	Visual – Verbal			
Algorithm	D T			
Classification:				
	Pre	Rec	f1-score	support
Visual	0.99	0.96	0.98	111
Verbal	0.78	0.93	0.85	15
Acc	0.96			126
Algorithm	R F			
Classification:				
	Pre	Rec	f1-score	support
Visual	0.99	0.99	0.99	111
Verbal	0.93	0.93	0.93	15
Acc	0.98			126
Algorithm	SVM			
Classification:				
	Prec	Rec	f1-score	support
Visual	0.99	1.00	1.00	111
Verbal	1.00	0.93	0.97	15
Acc	0.99			126
Algorithm	Neural Network			
Classification:				
	Prec	Rec	f1-score	support
Visual	0.99	1.00	1.00	111
Verbal	1.00	0.93	0.97	15
Acc	0.99			126

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Dimension	Active – Passive			
Algorithm	D T			
Classification:				
	Pre	Rec	f1-score	support
Active	0.99	1.00	1.00	110
Passive	1.00	0.94	0.97	16
Acc	0.99			126
Algorithm	R F			
Classification:				
	Pre	Rec	f1-score	support
Active	0.99	1.00	1.00	110
Passive	1.00	0.94	0.97	16
Acc	0.99			126
Algorithm	SVM			
Classification:				
	Pre	Rec	f1-score	support
Active	0.96	1.00	0.98	110
Passive	1.00	0.69	0.81	16
Acc	0.96			126
Algorithm	Neural Network			
Classification:				
	Pre	Rec	f1-score	support
Active	0.99	1.00	1.00	110
Passive	1.00	0.94	0.97	16
Acc	0.99			126

The results showed that the SVM and Neural network algorithm achieved the best results in Verbal-Visual, followed by Random Forest, and finally the Decision Tree algorithm. Regarding the second dimension, the Passive-Active Decision Tree, Random Forest, and Neural Network algorithms achieved the best results, followed by the SVM algorithm.

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5 Discussion and Conclusion

During this researchers made the following observations :

1. In general, individual differences among learners should be considered in our teaching strategies.
2. Learning preferences are not static. Therefore, it might be changed over time by exposing the students continually to educational content that does not match their weaknesses.
3. In comparison with the results of the previous the results of this study were quite high, and this could be interpreted by the size of the dataset, as well as the balanced data nature of the dataset that avoids bias.

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