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Classification of learning styles in a personalised multi-agent system using machine learning frameworks for stem education

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Abstract: The learning style and distinct needs of each student cannot be fulfilled through the traditional teaching methods where personalized adaptive learning helps user to understand, retain and monitor its framework based on its subjective needs as discussed in Nouman et al. [1].The main aim of intelligent systems in a multiagent framework is to classify and learn various methods and styles accurately that is discussed in Ni, et al. [2].It uses Visual, Auditory and Kinesthetic in a STEM based approach which personally analyze the contents enhancing the outcomes through the feedback from the learners as discussed in Ayyoub and Al-Kadi [3].we classify each learners style through student inputs. In proposed method, we use variety of multiagent systems such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Multinomial Naive Bayes consisting of four agents: Teacher, Concept Mapping, Content Analysis, and Sentiment Analysis. Here, Multinomial Naive Bayes Framework achieves best results with accuracy of 98% where insighted analysis on sentimental and engagement level of disabled is discussed in Chang and Lin [4]. In this study, the personalized individual learning styles are promoted and engaged in STEM education where the expansion of the various learning styles pays the way for a student-centered approach in real time involved in Gonçalves [5].

Keywords: *Learning style classification, Introduction, Machine learning, Multi-agent systems, Personalized education, STEM-based learning.*

1. Introduction

The learning styles of individuals vary in different ways, such as acquiring, processing, and retaining information, which are categorized into several models acquired through various educational content discussed in Villegas-Ch et al. [6]. Here, we use the VARK model, which identifies four types of learners: visual learners, who prefer drawing diagrams and charts; auditory learners, who prefer gaining information through listening; reading and writing learners, who prefer interacting through text; and kinesthetic learners, who learn through practical exercises. Additionally, Kolb's experiential learning theory includes four categories: divergent students, who reflect through different viewpoints; assimilative students, who learn by using logic; convergent students, who learn by applying theory to real-world issues; and accommodative students, who learn through action and instinct. This model enhances the learning experience, especially in online environments, in Gm et al. [7]. Different types of learning approaches have been proposed by Gardner's Multiple Intelligences, such as diverse intelligences, linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic. Based on the interaction with experiences, the Honey and Mumford model helps to align closely with learning methods and various styles of learning activities, including reflectors, theorists, and pragmatists. VARK has an expansion model known as Fleming's model, which

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exposes preferences for processing information, whereas the theory of right-brain dominance implies that creative, intuitive right-brain learners are in contrast to rational, analytical left-brain learners. In addition, social learners prefer group surroundings, and lone students prefer independent study. An engaging and mobile learner who is adapted to the technology-driven environment through gamified-based learning experience in Cui et al. [8], through the emergence of various digital learning styles. The importance of an individual learning preference can be highlighted through these diverse models by understanding the importance of individual learning for more effective education and its application in various fields, which are discussed in Chen and Sun [9].

The various methods of learning are influenced by numerous factors that are complex to identify. Among the principal difficulties is determining what subjects individuals are engaged in, as they may be unaware of their own inclinations or might exhibit a variety of learning methods involved in Zhao et al. [10] that don't fall under the established categories, such as The Gardner's or VARK intelligence educators and learners think that learning through a single style is the best method, whereas researchers suggest that the combination of methods would be more effective and can also be technology-assisted through [11]. Due to a lack of empirical evidence, the effectiveness of this tailoring and learning styles is complicated to identify. On the other hand, diverse teaching methods would be beneficial for all kinds of learners equally. The dynamic nature of learning could be another challenge, as it can change over time or vary depending on subjective matters, environment, and context of learning. Another factor, such as cultural and contextual influences, could also impact learning methods, including cultural backgrounds, educational experiences, and socioeconomic circumstances, which could influence how an individual processes all of their information based on the application of technologies implemented in Mittal et al. [12]. Some of the assessment tools have been designed for various learning styles, such as self-reporting questionnaires, which are biased, making them untrustworthy, or misinterpretations of the inquiries by implementing the various Differentiated Instruction methods, which are predicated on recognized learning preferences which as discussed in He et al. [13], which could be resource-intensive for teachers. It makes it challenging for them to maintain equilibrium in their individualized education within realistic classroom limitations. These are the various difficulties that help to identify the difficulties and apply continuously in educational settings.

The classification of Multi-Agent System (MAS) is based on the cooperation of multiple intelligent agents that gather information to examine learning behavior and facilitate the adoption of experiences in education according to personal choices by implementing tutorial-based learning in Wu et al. [14]. An information-gathering agent typically collects data for this system; a learning behavior agent analyzes the data using machine learning techniques to discover patterns, and an agent that classifies learning styles maps the actions of models such as VARK or Gardner's intelligences. After classification, the agent providing feedback offers a resource for individualized learning or adapts the classroom setting in real time discussed in Hang et al. [15]. This collaborative approach has numerous benefits, including scalability, real-time decision-making, and ensuring communication between the agents, which integrates their outputs for cohesive decision-making, creating issues such as data privacy, integrity, intricacy, and preferences among Dynamic Education should be sent to increase the effectiveness of the framework, as discussed in Hou and Dong [16].

Among several challenges, one of the main issues is the absence of standardization in extensive datasets through self-reported questionnaires. Another major challenge is feature selection, which is used to represent abstract learning behavior in a deep learning (DL) format that may be trained in one learning environment across different contexts which as discussed in Jiang et al. [17]. The costs associated with DL models used in real-time are comparatively high, especially in resource-limited educational settings.

1.1. The Problem Statement

Using the conventional approach, the type of each unique approach to learning is frequently ignored, which leads to a lack of engagement and a variation in the level of comprehension among students. This results in the need for an integrated system that is adaptive and can be classified among learners as visual, auditory, and kinesthetic, particularly in STEM education. Today's approaches lack robustness and neglect to use machine learning techniques that could efficiently determine learning preferences and contributions.

1.2. Contributions

1. Multi-Agent Framework Development: For dynamic learning styles in STEM education, an intelligent multi-agent framework including a teacher agent, idea mapping agent, and sentiment analysis agent is proposed.
2. Personalized educational interventions are made possible by the framework's integration of four machine learning methods: SVM, DT, RF, and Multinomial Naive Bayes. These algorithms accurately determine learners' styles from their comments.
3. Sentiment Analysis Implementation for Engagement Assessment: The framework offers more profound insights into learners' attitudes and engagement using sentiment analysis, which facilitates more sophisticated comprehension and better learning type categorization.
4. Thorough Performance Evaluation: We use statistical measures to assess the classification algorithms' efficacy, and the system's predictions are dependable and flexible enough to accommodate a range of learning contexts.

2. Literature Survey

E-Learning is a method that can be used as an alternative to traditional learning methods, allowing it to serve several pupils in a normal classroom environment. First, a Multi-Labeled Labeling Framework (LSDFA) based on fusion is utilized to gather information from two data sets to obtain the labels, which are measured and indicated in Zou et al. [18]. Furthermore, the two-layer consumable Model (SRGSML) is used to learn behavior from online data and address the predicted issues caused by imbalance. Generally, the traditional way of teaching involves delivering the same course material, whereas Learning Management Systems encourage teachers and help create innovative teaching methods, which increase productivity as an outcome which as discussed in Wang et al. [19]. To overcome traditional teaching methods, the semi-supervised machine learning (ML) approach is used to identify and help solve related problems. In research, improving learning experiences through gaming acts as a motivation for learning, resulting in increased efficiency. Nevertheless, a variety of learning approaches are employed, including convolutional neural networks (CNN), generative adversarial networks (GAN), and generative artificial intelligence (GAI). However, these methods are unable to customize tutorials based on individual preferences, where efficiency and working preferences are involved, as noted by Criollo-C et al. [20]. An effective way to implement instructional techniques such as flipped classrooms and integrated learning is also explored. Multiple Choice Questions (MCQs) are utilized to improve teaching and learning strategies. Based on research on second-order fuzzy multi-agent systems with input saturation limitations, the impulsive control strategy method was developed to address formation challenges, which is discussed in Ren et al. [21]. Traditional methods of communication are used to produce unnecessary details, whereas saturated multi-agent systems are demonstrated via nonlinear contraction analysis. The classification of synthetic aperture radar's (SAR) terrain is crucial, as it is useful for feature representation. The primary focus is on the problem of impulse consensus in multi-agent systems, together with associated time delay and communication limitations, which is discussed in Shi et al. [22].

3. Methodology

An AI-driven strategy for individualized instruction is shown in the block diagram (Figure 1), which makes use of a variety of intelligent agents and their algorithms to improve learning management. A teaching agent collaborates with a concept mapping agent to rewrite the learning experience before providing knowledge through STEM-based learning, which is discussed in Jiang et al.

[23]. Through indications like text, the content analysis agent gathers student input, allowing for real-time insights into a student's understanding framework. These feedbacks are analyzed by the Sentimental Analysis Agent, which accesses the emotional tone, helping in modifications to instructional methods. Additionally, the pupils are divided into three learning styles: kinesthetic, auditory, and visual learners, which is discussed in You et al. [24]. These classifications are carried out using machine learning techniques such as SVM for high-dimensional classification problems, DT models for interpretability, RF for enhanced accuracy through ensemble learning, and multinomial Naive Bayes for text data processing. Lastly, measures are used in statistical analysis to guarantee the efficacy of these algorithms. Learner categorization, statistical validation, and sentiment and feedback analysis all work together to support an adaptive, data-driven teaching strategy.

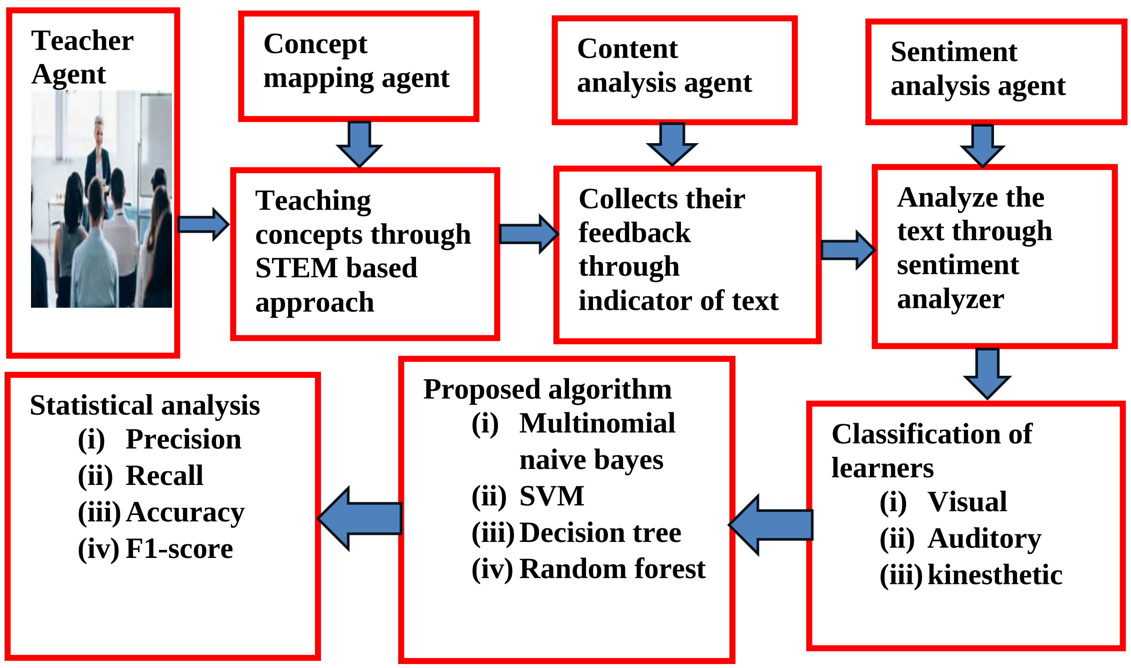

Figure 1.
Block Diagram.

3.1. SVMs, or Support Vector Machines

SVM is a supervised machine learning method that finds the best hyperplane for data categorization by maximizing the margin between data points. It may be used for both binary and multiclass classification problems and performs well with high-dimensional datasets.

3.2. Decision Tree (DT)

To get the best classification at each node, DT, a tree-structured classifier, recursively divides data according to feature values. It works well in a variety of applications, including learning analysis, and is simple to understand.

3.3. RF, or Random Forest

To improve classification accuracy, RF, an ensemble learning technique, generates a large number of DTs and combines their predictions. To reduce overfitting and improve generalization performance, each tree has been trained on an arbitrarily chosen sample of data.

3.4. Multinomial Naive Bayes

A popular probabilistic approach for text classification applications, such as learning analysis, is multinomial Naive Bayes. When working with categorical data, such as document word counts, it performs very well. Assuming that features are conditionally independent, Multinomial Naive Bayes is a rapid and scalable method. Classifying pupils' learning is done in learning analysis. Given input data (student feedback), the Multinomial Naive Bayes technique determines the likelihood of learning a type based on patterns or preferences found in text data (such as feedback).

$$P(C|X) = \frac{P(X|C) \times P(C)}{P(X)} \tag{1}$$

$$P(X|C) = \prod_{i=1}^{n} P(x_i|C)^{x_i} \tag{2}$$

4. Results and Discussion

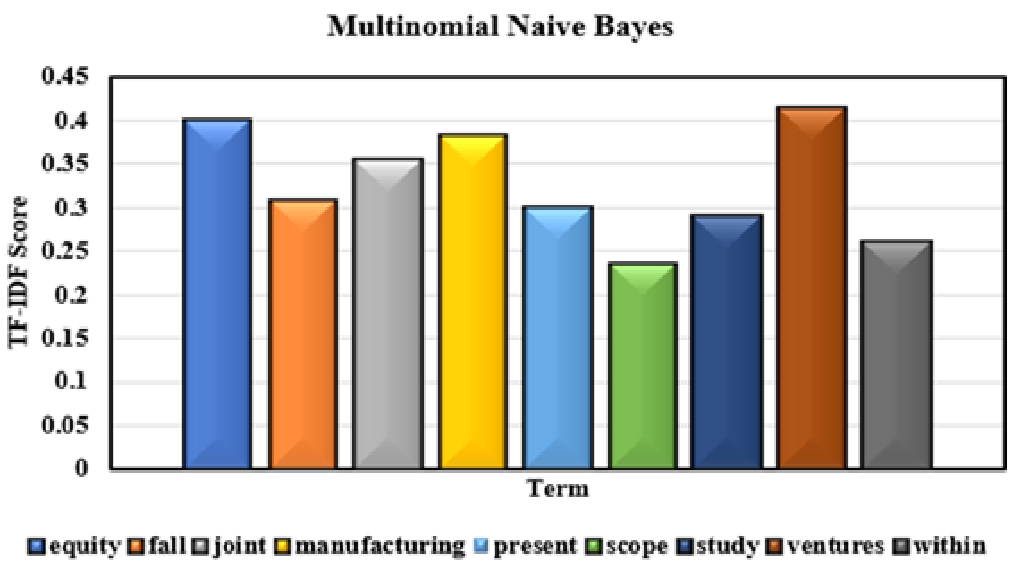

Figure 2.
Multinomial naïve Bayes TF-IDF scores.

A Multinomial Naive Bayes model can be used to thoroughly assess a model's performance on a classification task. One of the primary metrics that indicate how well the model predicts the target classes is precision, which determines the percentage of true positive predictions among all positive predictions and displays the accuracy of positive class identification; recall, also known as sensitivity, indicates the model's capacity to recognize all pertinent events. An extremely helpful metric for unbalanced datasets is the F1-score, which is the harmonic mean of precision and recall. Displaying the class distribution, support, and the number of actual instances of each class in the dataset helps put accuracy and recall into context. The overall proportion of correct forecasts to all predictions is known as accuracy. Macro-averaged metrics ignore class imbalance by calculating the average accuracy, F1-score, and recall for every class independently. Micro-averaged metrics, on the other hand, average true positives, false negatives, and false positives over all classes to provide a complete overall statistic, then compute accuracy, recall, and F1-score.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Table 1.
Report on the Multinomial Naïve Bayes algorithm's classification.

Class	Precision	Recall	F1-score	Support
Auditory	0.92	0.84	0.88	951
Kinesthetic	0.94	0.81	0.87	938
Visual	0.82	0.97	0.89	1201
Accuracy	—	—	0.98	3090
Macro avg.	0.89	0.87	0.98	3090
Weighted avg.	0.89	0.88	0.98	3090

With an accuracy of 98%, the model performs well overall; it has a somewhat harder time recognizing "Auditory" instances, but it excels at predicting "Visual" with good recall (0.97) and "Kinesthetic" with great precision (0.94). The methodology works well with various learning styles, as seen by weighted averages that indicate balanced performance across courses and F1-scores that are almost 0.88 for all measurements. The classification report is shown in Figure 3 alongside other algorithms.

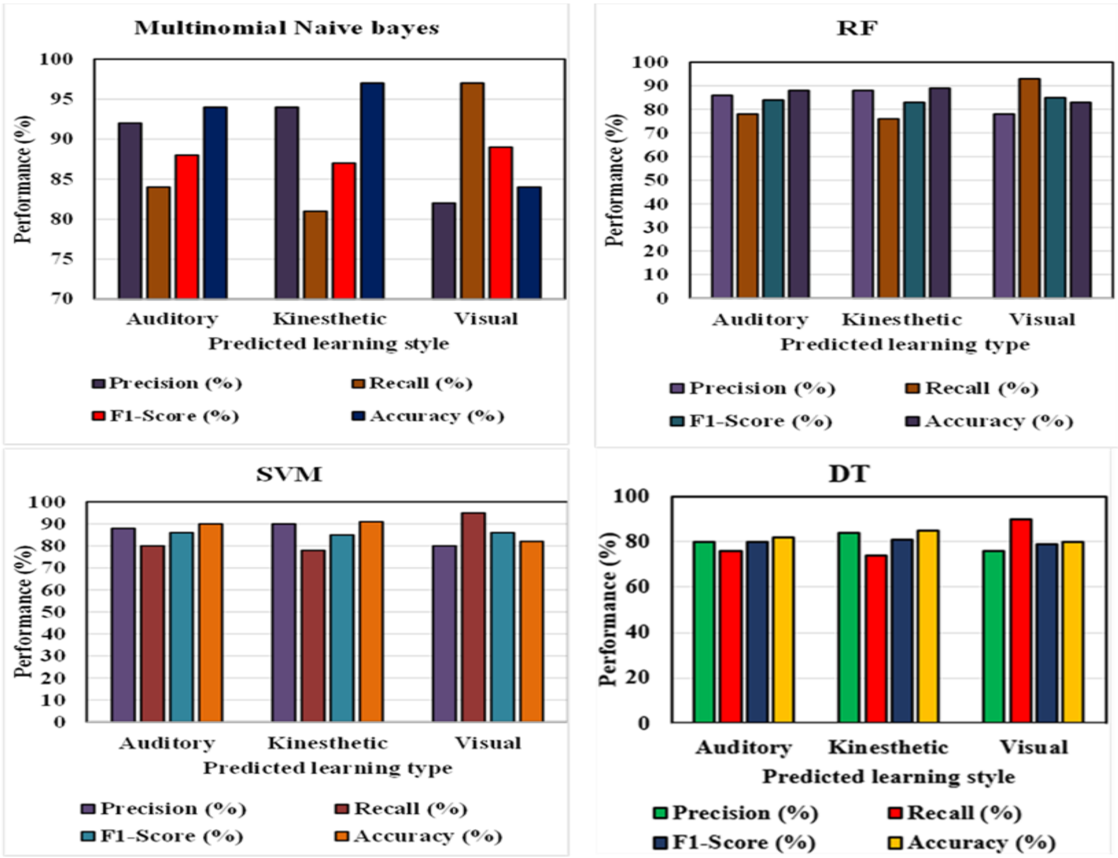

Figure 3.
Report on the suggested algorithm's classification.

The advantages and disadvantages of the Multinomial Naive Bayes model are outlined in this paper, which also guides future enhancements such as adjusting hyperparameters or utilizing additional features to improve prediction performance, as discussed in Li et al. [25]. Multinomial naïve Bayes is used to predict learning style, as seen in Table 2.

Table 2.
Estimated learning preferences.

Text	Predicted Learning Style
I enjoy watching videos to learn new concepts.	Visual
I prefer listening to lectures over reading textbooks.	Auditory
I love doing experiments and hands-on projects.	Visual
I enjoy building models and conducting experiments to learn new concepts.	Kinesthetic

- Examples of particular text claims are presented in this table, combined with their related predicted learning type. According to their assertions, each person's chosen mode of learning is indicated by their learning style, which might be visual, aural, or kinesthetic.
- According to the projected learning style for the sentence "I enjoy watching videos to learn new concepts," the individual learns best when knowledge is presented visually, such as through diagrams, movies, or pictures.
- The learning style of the person who says, "I prefer listening to lectures over reading textbooks," is auditory, meaning that they learn best when they listen, such as during lectures or

conversations.
The statement "I love doing experiments and hands-on projects" is also categorized as visual here, though it might typically be associated with a kinesthetic style, which emphasizes experiential learning. However, because of differences in interpretation or the way the learning styles are defined for this study, the model has classified it as visual.

- One example of a kinesthetic learner's statement is "I like building models and doing experiments to learn new concepts." It displays a predilection for experiential learning and hands-on activities, two essential elements of kinesthetic learning styles. In order to better grasp concepts, kinesthetic learners like working with materials and physically handling items.

5. Conclusion

By employing a data-driven and customized approach to categorize the students into distinct learning styles, the suggested multi-agent architecture effectively facilitates adaptive learning. The system produces dependable and contextually aware classifications using a variety of machine-learning techniques, including Multinomial Naive Bayes, SVM, DT, and RF. Multinomial Naive Bayes has a particularly high accuracy of roughly 98% in learning style prediction. Sentiment analysis is used to analyze and enable the delivery of knowledge in a way that is both resonant and customized according to the preferences of the learners in STEM education. More advanced adaptive learning tools are made possible by this system. In order to improve performance in a variety of educational contexts, future research will benefit from expanding the models that are now in use to include other learning styles and cognitive indicators. Learning experiences could be further improved by incorporating adaptable curricular pathways and real-time feedback loops, which would result in an even more student-centered and responsive approach. Furthermore, the system may be able to identify minute shifts in learning preferences over time thanks to developments in machine learning and natural language processing, facilitating lifetime personalized education.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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