A MULTI-AGENT MACHINE LEARNING FRAMEWORK FOR PERSONALIZED LEARNING STYLE CLASSIFICATION IN STEM EDUCATION

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Key words:

Learning Style Classification; Multi-Agent System; Personalized Education; STEM-Based Learning; Machine learning

Abstract:
Background: In educational settings, the diversity of individual learning styles often remains under-addressed, leading to variable comprehension and engagement among students. Traditional teaching approaches may not fully accommodate the distinct needs of each learner, particularly in STEM education where personalized, adaptive instruction can greatly benefit understanding and retention. **Objective**: This study aims to develop an intelligent multi-agent framework that can accurately identify and classify learning styles—Visual, Auditory, and Kinesthetic—through a STEM-focused approach. The objective is to create a system that personalizes educational content by analyzing learners' feedback and engagement, thereby enhancing learning outcomes. **Method**: The proposed framework employs a multi-agent system that includes a Teacher Agent, Concept Mapping Agent, Content Analysis Agent, and Sentiment Analysis Agent. Using feedback from learners, the system classifies each learner's style by employing machine learning (ML) algorithms, including Multinomial Naive Bayes, Support Vector Machine (SVM), Decision Tree (DT), and Random Forest (RF). The performance of each algorithm is measured through Precision, Recall, Accuracy, and F1-score to ensure reliable classification. **Results**: The framework demonstrated high accuracy about 98%, with Multinomial Naive Bayes achieving the best classification results among the algorithms. The inclusion of sentiment analysis provided further insights into learners' engagement levels, supporting a refined understanding of each student's preferred learning style. **Conclusion**: This study presents a successful model for personalized learning that dynamically adapts to individual styles, promoting inclusivity and engagement in STEM education. Future work could enhance this framework by expanding to more learning styles and refining real-time adaptability, paving the way for a fully responsive, student-centered educational experience.

1. INTRODUCTION

Learning styles refer to the different ways individuals prefer to acquire, process, and retain information. Several models categorize these preferences. The VARK model identifies four types: visual learners who favor diagrams and charts, auditory learners who benefit from listening, reading/writing learners who prefer interacting with text, and kinesthetic learners who thrive with hands-on activities. Kolb's experiential learning theory outlines four types as well: diverging learners who reflect on different perspectives, assimilating learners who prefer logical reasoning, converging learners who apply theory to practical problems, and accommodating learners who learn through action and intuition. Gardner's Multiple Intelligences proposes diverse intelligences, such as linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic, each influencing different learning approaches. The Honey and Mumford model aligns closely with Kolb's, categorizing learners as activists, reflectors, theorists, and pragmatists, based on their interaction with experiences. Fleming's model, an extension of VARK, emphasizes sensory preferences for processing information, while left-brain vs. right-brain dominance theory suggests logical, analytical left-brain learners contrast with creative, intuitive right-brain learners. Additionally, social learners thrive in group settings, while solitary learners prefer self-study. Emerging digital learning styles include interactive and mobile learners who adapt to technology-driven environments. These diverse models highlight the importance of understanding and catering to individual learning preferences for more effective education.

Identifying different learning styles presents several challenges, as the concept is complex and influenced by various factors. One of the primary difficulties is the subjectivity involved; individuals may not always be aware of their own preferences or may exhibit mixed learning styles that do not fit neatly into established categories like VARK or Gardner's intelligences. Additionally, overgeneralization can occur when educators or learners assume that people learn best through a single style, whereas research suggests that most benefit from a combination of methods. The lack of empirical evidence supporting the effectiveness of tailoring education strictly to learning styles further complicates identification, with some studies indicating that diverse teaching methods benefit all learners equally. Another challenge lies in the dynamic nature of learning preferences, which can change over time or vary depending on the subject matter, environment, or learning context. Cultural and contextual factors also influence learning styles, as cultural backgrounds, educational experiences, and socioeconomic conditions can shape how individuals process information. Moreover, assessment tools designed to identify learning styles, such as self-report questionnaires, may be unreliable due to biases or misinterpretation of questions. Lastly, the implementation of differentiated teaching based on identified learning styles can be resource-intensive for educators, making it difficult to balance personalized instruction with practical classroom constraints. These challenges make it difficult to consistently and accurately identify and apply learning styles in educational settings.

A multi-agent system (MAS) for classifying learning styles involves the collaboration of several intelligent agents to gather data, analyze learning behavior, and adapt educational experiences based on individual preferences. The system typically includes a Data Collection Agent, which gathers information on learner interactions, a Learning Behavior Analysis Agent that uses ML algorithms to identify patterns, and a Learning Style Classification Agent that maps behaviors to models like VARK or Gardner's intelligences. Once classified, the Feedback Agent offers personalized learning resources or adapts the learning environment in real-time. A Collaboration Agent ensures effective communication between agents, integrating their outputs for cohesive decision-making. This multi-agent approach provides numerous advantages, such as scalability, adaptability, real-time decision-making, and improved accuracy by utilizing diverse data sources and processing methods. For instance, an online learning platform could use MAS to track student interactions, identify a dominant learning style, and adjust content delivery accordingly, enhancing the overall educational experience. However, challenges like data privacy, integration complexity, and dynamic learning preferences must be addressed to ensure the system's effectiveness. Despite these challenges, MAS offers a promising approach to creating personalized and adaptive learning environments.

Classifying learning styles using deep learning (DL) models presents several challenges due to the complexity and subjectivity involved in capturing individual preferences. One major issue is the lack of standardized, large-scale datasets, as learning styles are often identified through self-reported questionnaires, which can be biased and inconsistent. Additionally, learning styles are inherently subjective and fluid, making it difficult for models to classify them accurately, especially since many learners exhibit mixed preferences that change over time. Feature selection is another challenge, as representing abstract learning behaviors, such as interaction with content, in a format that DL models can process is not straightforward. Furthermore, models trained in one learning environment may struggle to generalize across different contexts, limiting their applicability across diverse educational settings. The black-box nature of DL models also complicates interpretability, making it hard to understand how the model arrived at a particular classification, which reduces trust and usability in educational settings. Additionally, as learning preferences evolve, these models may not adapt effectively to the dynamic nature of learning, requiring more sophisticated techniques such as reinforcement learning. There are also concerns about data privacy and ethical usage, since collecting detailed behavioral data may infringe on learners' privacy. Moreover, imbalanced data can lead to biased models that misclassify less common learning styles. Customization and real-time personalization further complicate the development of these models, as they need to continuously adapt to changing learner behaviors. Lastly, the computational costs associated with training DL models, particularly for real-time adaptive learning systems, can be prohibitively high, especially in resource-limited educational settings. Addressing these challenges requires advancements in data collection, adaptive modeling, and ethical considerations to effectively integrate DL into personalized learning environments.

Problem Statement

In traditional educational settings, the diversity of individual learning styles often remains unaddressed, leading to suboptimal engagement and varying levels of comprehension among students. There is a growing need for an adaptive, intelligent system that can automatically classify learners into distinct learning styles—Visual, Auditory, and Kinesthetic—and deliver customized content, particularly in STEM education. Existing approaches lack robust multi-agent integration and fail to utilize ML algorithms effectively to identify learning preferences and optimize learning outcomes.

Contributions

1. **Development of a Multi-Agent Framework**: We propose an intelligent, multi-agent framework that includes a teacher agent, concept mapping agent, content analysis agent, and sentiment analysis agent, designed to work in tandem for dynamic learning style classification in STEM education.
2. **Learning Style Classification Using ML**: The framework integrates four ML algorithms—Multinomial Naive Bayes, SVM, DT, and RF—to classify learners' styles based on their feedback with high accuracy, allowing for personalized educational interventions.
3. **Implementation of Sentiment Analysis for Engagement Assessment**: By using sentiment analysis, the framework provides deeper insights into learners' engagement and attitudes, aiding in more nuanced understanding and improved classification of learning styles.
4. **Comprehensive Performance Evaluation**: We evaluate the effectiveness of the classification algorithms using statistical metrics, system's predictions are reliable and adaptable to diverse learning environments.

2. LITERATURE SURVEY

In order to achieve the objective of education and learning for all, e-learning has emerged as a fresh substitute for traditional learning methods. Because an instructor must manage multiple students at once in a typical classroom setting, the classroom learning style is based on a "one size fits all" approach. Initially, a multilabel fusion-based learning style labelling framework (LSDFA) is presented, which can mine potential information of two sets of inventories to obtain learning style labels. Additionally, to identify learners' learning styles, a two-layer ensemble model (SRGSML) is proposed, which uses data from online learning behaviours and resampling technology to address unreliable prediction issue brought on by class imbalance. Although learning management systems encourage teachers' creativity and productivity, they usually give all students in a course the same material, disregarding their individual learning preferences. We suggest a semisupervised ML method that uses data mining to identify students' learning preferences in order to solve this problem. These difficulties are frequently made worse by traditional rule-based instruction, underscoring the need for more efficient teaching strategies. We suggest a Visual Prompt-Based Mobile Learning Strategy (VPML) to close this gap**[1-5]**.Current educational landscape necessitates constant adaptation towards methodologies enhance individualised learning because of inherent diversity in learning styles and rhythms. This study examines how well ML models work for learning personalisation, which adjusts instructional materials to suit different learning preferences. According to research, gamified learning experiences can help students with persistent problems in online learning, like burnout and a lack of motivation, which will increase the efficacy of online learning. However, there is still more research to be done on how to improve the gamified learning experience in online learning and how the gamified learning experience affects the efficacy of online learning. Using emotion tags, the multi-task learning framework improves the model's capacity to produce emotionally complex music**[6-9]**.We use convolutional neural network (CNN) to precisely distinguish between style categories during style recognition phase. The potential of artificial intelligence (AI) for content creation, individualised learning, and engaging educational support is enormous. With a focus on generative adversarial networks (GANs), this paper explores generative artificial intelligence (GAI) and its possible uses within GAI. In order to increase learning efficiency, current methods for creating learning resources suggest personalised courses based on interests and learning styles. These approaches, however, are unable to create customised tutorials based on learners' preferences or modify the content of tutorials in response to shifting moods or knowledge levels. The need for effective and efficient multiple-choice question (MCQ) generation has been brought to light by the development of teaching strategies like blended learning and flipped classrooms in the ever-changing world of modern education. In response, we present MCQGen, a brand-new generative AI framework for automatically producing multiple-choice questions**[10-15]**. In this brief, event-triggered control is used to study nonlinear multiagent prescribed-time cooperative fault-tolerant output regulation. The degree of freedom of the ETC is increased by designing the system-related dynamic coefficient for the control signal, in contrast to the current dynamic event-triggered mechanisms (DETMs), where the coefficients of the control signal of event-triggered conditions (ETCs) are constants. This paper uses an impulsive control strategy to study leader-following formation problems for second-order fuzzy multiagent systems (MASs) with input saturation constraints. Conventional communication techniques waste resources by producing a lot of extraneous information. Nonlinear contraction analysis is used to demonstrate that, for both saturated multiagent systems, standard distributed protocols are adequate for reaching consensus under uniformly jointly strongly connected topology conditions, without the need for persistent connectivity. The consensus of a class of nonlinear multiagent systems with switching topologies and random packet loss is attained in this article using a dynamic event-triggered control scheme**[16-20]**.The key to classifying the terrain in synthetic aperture radar (SAR) images is effective feature representation. The performance is hampered by the abstract appearance and lack of high-quality labelled data in this field, which limit the directivity and applicability of the features learnt by current methods, particularly DL models. In order to accomplish directional feature learning and acquire generalised features using a limited amount of patch-level labelled data, this article suggests multi-image factor self-supervised learning (MFSSL). The impulse consensus issue in multiagent systems with communication limitations and time delays is the primary focus of this article. Both global and partial saturation constraints are taken into account, given the agent's constrained communication bandwidth. Additionally, a novel control protocol that combines the general impulse control protocol with the event-triggered strategy is proposed **[21-25]**.

Inferences from literature survey

The literature survey highlights the evolving role of e-learning as an alternative to traditional classroom settings, which typically follow a "one size fits all" approach. This inadequacy has led to development of personalized learning models, such as the multilabel fusion-based learning style labelling framework (LSDFA) and the two-layer ensemble model (SRGSML). These models seek to accommodate diverse learning styles by utilizing online learning behavior data and resampling techniques to improve prediction accuracy, particularly in imbalanced classes.While learning management systems have increased educators' productivity, they often fail to cater to individual student preferences. To address this, a semisupervised ML model is proposed to mine student preferences and enhance the learning experience, contrasting with traditional rule-based approaches. A VPML is also suggested to bridge existing gaps in personalizing education.Moreover, the study emphasizes the importance of gamification in online learning to counter burnout and motivation loss, although further research is needed to enhance this experience. The literature also explores advanced AI applications, such as CNNs for learning style classification and GANs for content creation. Personalization in education is bolstered by frameworks like MCQGen for automatically generating multiple-choice questions.In the broader context, control strategies in MASs are discussed, showing their relevance in areas like event-triggered control mechanisms and nonlinear consensus problems. Techniques like self-supervised learning (MFSSL) are proposed to overcome limitations in domains like SAR imaging, further illustrating the potential of ML for efficient feature representation and communication in constrained environments.The survey underscores the need for continuous innovation in personalized learning, particularly through ML and AI technologies, to improve both instructional methods and learner engagement in diverse educational settings.

3. METHODOLOGY

Block diagram (**Figure 1**) presents an AI-driven approach to personalized teaching, utilizing several intelligent agents and classification algorithms to enhance learner engagement. The process begins with a Teacher Agent that rewrites the learning experience, collaborating with a Concept Mapping Agent to deliver content through a STEM-based approach, where concepts are visually organized for easier comprehension. Feedback from students is then gathered by the Content Analysis Agent through indicators in text, enabling the framework to capture real-time insights into student understanding. This feedback is further analyzed by a Sentiment Analysis Agent that assesses the emotional tone—positive, neutral, or negative—allowing for adaptive adjustments in teaching strategies. Following this, students are classified into one of three learning styles: Visual Learners, who benefit from diagrams and visual aids; Auditory Learners, who prefer information presented through discussions or lectures; and Kinesthetic Learners, who thrive with hands-on activities. This classification is achieved using ML algorithms, including Multinomial Naive Bayes for text data processing, SVM for handling high-dimensional classification tasks, DT models for interpretability, and RF for enhanced accuracy through ensemble learning. Finally, to ensure the effectiveness of these algorithms, Statistical Analysis is conducted using metrics. This combination of sentiment and feedback analysis, learner classification, and statistical validation promotes a responsive, data-driven educational approach.

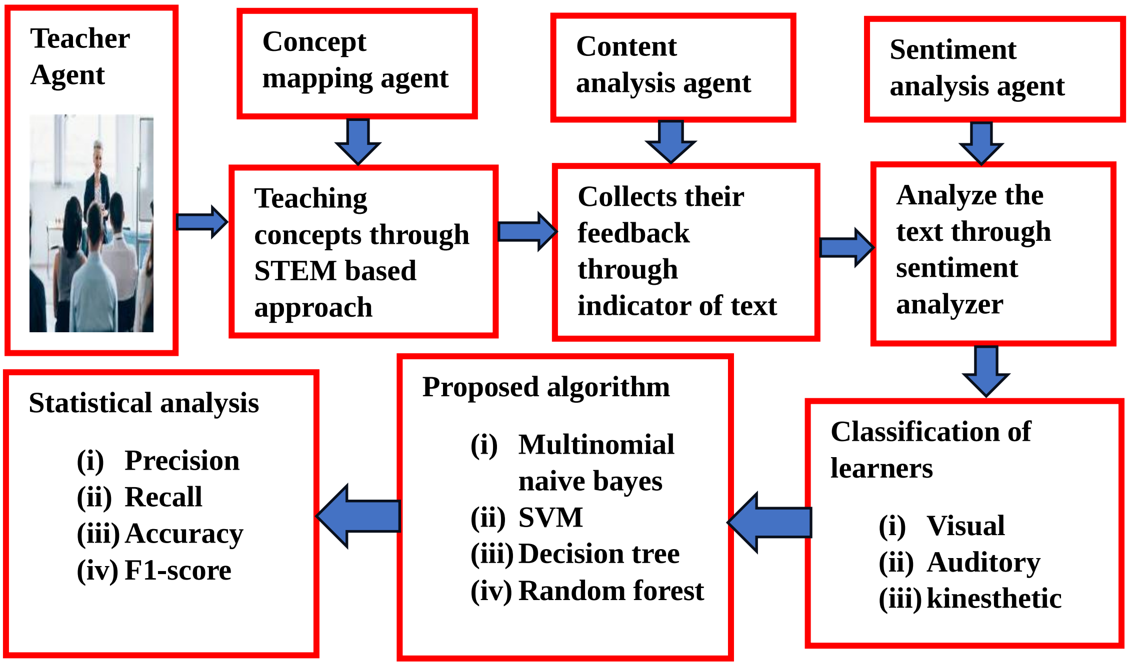

Fig 1 Block diagram

3.1. Support Vector Machine (SVM)

SVM is a supervised ML algorithm designed to find the best hyperplane that separates data points into distinct classes by maximizing margin between them. It is highly effective for handling high-dimensional datasets and can be applied to both binary and multiclass classification tasks.

Pseudocode for SVM

Input: Training data with features and classes

Output: SVM model for classification

1. Choose a kernel function (e.g., linear, polynomial, RBF) for the data.

2. Initialize hyperparameters (e.g., regularization parameter C).

3. Use optimization to find weights (w) and bias (b) by maximizing the margin:

 - Minimize: ||w||^2 / 2

 - Subject to: $y_i (w \cdot x_i + b) \geq 1$ for each sample i

4. For new data point x, calculate decision function:

 - If $w \cdot x + b > 0$, classify as positive class.

 - Otherwise, classify as negative class.

Return: Model with optimal hyperplane for classification.

3.2. Decision Tree (DT)

DT is tree-structured classifier that recursively splits data based on feature values to achieve the best classification at each node. It's easy to interpret and effective in many applications, including learning analysis.

Pseudocode for DT

Input: Training data with features and classes

Output: DT model

1. Calculate Gini impurity for the root node.

2. For each feature:

   - Split the data based on each possible value.

   - Calculate Gini impurity for each split.

   - Choose the split that reduces Gini impurity the most (highest information gain).

3. Recursively repeat steps 1-2 for each child node until a stopping criterion is met (e.g., max depth, minimum samples).

4. Assign class labels based on majority class at each leaf node.

Return: DT model for classification.

3.3. Random Forest (RF)

RF is an ensemble learning technique that constructs multiple DTs and aggregates their predictions to enhance classification accuracy. Each tree is trained on a randomly selected subset of data, which helps to minimize overfitting and boost generalization performance.

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Pseudocode for RF

Input: Training data with features and classes, number of trees (N)

Output: RF model

1. For each tree i (1 to N):

   a. Draw a random bootstrap sample from the training data.

   b. Grow a DT from the bootstrap sample:

      - At each node, randomly select a subset of features.

      - Find the best split based on the selected features.

      - Repeat until the stopping criterion is met.

2. For a new data point:

   a. Each tree makes a prediction (class label).

   b. Aggregate predictions from all trees by majority vote.

Return: RF model for classification.

3.4. Multinomial Naive Bayes

Multinomial Naive Bayesis probabilistic ML algorithm commonly used in text classification tasks, including learning analysis. It's particularly effective when dealing with categorical data, such as word counts in documents. Multinomial Naive Bayes assumes features are conditionally independent, and makes algorithm fast and scalable. In learning analysis, where we classify students' learning patterns or preferences based on text data (e.g., feedback), Multinomial Naive Bayes algorithm computes probability of learning type given input data (student feedback).

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

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

Pseudocode for implementing Multinomial Naive Bayes

Input: Training data (texts and their classes)

Output: Model that can predict the class of new texts

1. Initialize:

- Vocabulary = Set of all unique words in the training data

- For each class C in training data:

- Calculate P(C) = (Number of documents in class C) / (Total number of documents)

- Initialize total_word_count[C] = 0 (Total count of words in class C)

- For each word w in Vocabulary:

- Count word_freq[C][w] = Number of occurrences of word w in class C

- total_word_count[C] += word_freq[C][w]

2. Calculate Likelihood:

For each class C:

For each word w in Vocabulary:

P(w|C) = (word_freq[C][w] + 1) / (total_word_count[C] + |Vocabulary|)

Using Laplace Smoothing by adding 1 to numerator and Vocabulary size to denominator

3. Prediction:

Input: New text X (array of word counts for words in Vocabulary)

For each class C:

score[C] = log P(C)

For each word w in Vocabulary:

score[C] += X[w] * log P(w|C)

Return class with highest score

4. RESULTS and DISCUSSION

Stopwords and the Punkt Tokenizer are tools often used in NLP to preprocess and simplify text data, making it easier to analyze.

Preprocessing- stopwords removal:

Original: Ali, who was two at the time, loved the story about the little girl who lived in a teeny, weeny house and played with itty, bitty toys.

Cleaned: ali two time loved story little girl lived teeny weeny house played itty bitty toys

Original: Look at my dad, spiffed up in jodhpurs, ready to ride that bay mare he loved.

Cleaned: look dad spiffed jodhpurs ready ride bay mare loved

Original: Believe me it's far more difficult to know what to say to an unconscious loved one than the movies make out.

Cleaned: believe far difficult know say unconscious loved one movies make

Original: The Surrealists loved bad movies, seeing them as subversive attacks on the tyranny of narrative form.

Cleaned: surrealists loved bad movies seeing subversive attacks tyranny narrative form

Original: He idolised prize-fighters, regarded racketeers as his friends and loved money though he had difficulty holding on to it.

Cleaned: idolised prizefighters regarded racketeers friends loved money though difficulty holding

Stopwords are commonly used words in a language (e.g., *"the," "and," "in," "of,"* etc.) that usually don't add much meaning or information to text analysis.These words are often removed from the text as they are considered to have low importance in distinguishing content and don't contribute significantly to understanding or predicting sentiment, topics, or other features.In NLP libraries like NLTK (Natural Language Toolkit) or SpaCy, pre-built lists of stopwords are available for many languages, though they can be customized based on the application needs.The Punkt tokenizer is a pre-trained, unsupervised tokenizer that segments text into sentences and words based on punctuation.Developed by Martin Choen and featured in NLTK, this tokenizer uses ML models trained to identify sentence boundaries, including handling abbreviations, periods, and other punctuation marks. The Punkt tokenizer is particularly useful for processing text that includes complex sentence structures, as it can handle ambiguities in punctuation without needing labeled data for training. In NLP, removing stopwords and tokenizing text with Punkt or similar tools helps streamline data for further processing, such as sentiment analysis, topic modeling, or text classification.

TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical metric used in NLP to evaluate the importance of a word in a document relative to a collection of documents. It helps in identifying words that are more informative by balancing frequency within a document with uniqueness across documents, which makes it especially valuable in information retrieval and text mining.**TF** calculates how often termappears in a document. More frequently a word appears, the higher its TF value. However, TF alone may prioritize common words across all documents (like "the" or "is"), which may not carry important meaning.**IDF** measures how unique or rare a term is across all documents in the corpus. If a word appears in many documents, its IDF score will be low, indicating it's common and perhaps less informative. Words that appear in fewer documents get a higher IDF, making them more unique and thus more valuable.

$$\text{TF-IDF}(t,d)=\text{TF}(t,d)\times\text{IDF}(t) \quad (3)$$

Words with high TF-IDF scores are usually more relevant to the specific document they appear in, making TF-IDF a popular tool for identifying key terms and weighting them for ML models, information retrieval systems, and search engines. Table 1 and Figure 2 shows the TF-IDF scores for multinomial naïve bayes.

Tab 1 TF-IDF Scores

Term	TF-IDF Scores
equity	0.4013135367177564 4
fall	0.3075932577166779
joint	0.3563856025807313
manufacturing	0.3833057339749538
present	0.30017393372594076
scope	0.23557866515773024
study	0.29095210761120144
ventures	0.41409027609620463
within	0.26205775314343166

Higher TF-IDF scores suggest both frequently mentioned in the document and less common across entire corpus, making it particularly meaningful within this document. **Terms like "ventures" (0.4141)** and **"equity" (0.4013)** have high TF-IDF scores, meaning these words appear relatively frequently in the document but are unique or infrequent in other documents in the corpus. This suggests they are central to the document's subject matter.**"Scope" (0.2356)** and **"within" (0.2621)** have lower TF-IDF scores, indicating they are either common across documents or infrequently used within this particular document. These terms may be less significant for identifying the document's unique content.

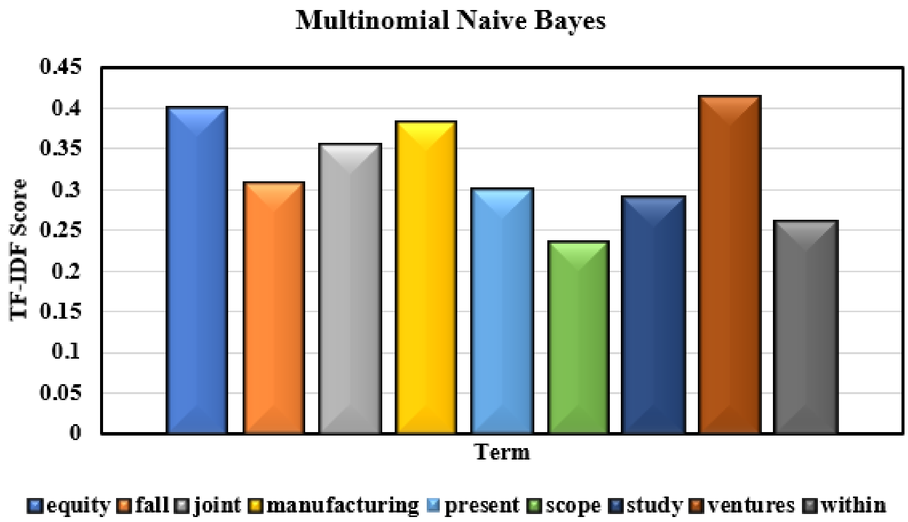

Fig 2 TF-IDF scores for multinomial naïve bayes

A **classification report (Table 2)** for a Multinomial Naive Bayes model provides detailed evaluation of model's performance on classification task. It summarizes key metrics that reflect how well the model predicts the target classes. **Precision** measures the proportion of true positive predictions out of all positive predictions, reflecting the accuracy of positive class identification. **Recall** (or Sensitivity) captures the proportion of true positives among all actual positives, indicating the model's ability to detect all relevant instances. The **F1-score** is the harmonic mean of precision and recall, offering a balanced measure that is especially useful for imbalanced datasets. **Support** refers to the count of actual occurrences of each class in the dataset, helping contextualize precision and recall by showing the class distribution. **Accuracy** represents the overall ratio of correct predictions to the total predictions. **Macro-Averaged Metrics** calculate precision, recall, and F1-score independently for each class and then average these values, disregarding class imbalance. **Micro-Averaged Metrics**, in contrast, aggregate true positives, false negatives, and false positives across all classes before computing precision, recall, and F1-score, giving a comprehensive overall measure.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

Tab 2 Classification report of multinomial naïve bayes algorithm

	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

The model performs well overall, with accuracy of 98%. It is especially accurate in predicting "Kinesthetic" with high precision (0.94) and "Visual" with high recall (0.97), though it struggles slightly more in identifying "Auditory" instances. The weighted averages show model's balanced performance across classes, with F1-scores close to 0.88 for all metrics, indicating that the model performs well across all learning styles. **Figure 3**shows classification report compared to other algorithms.

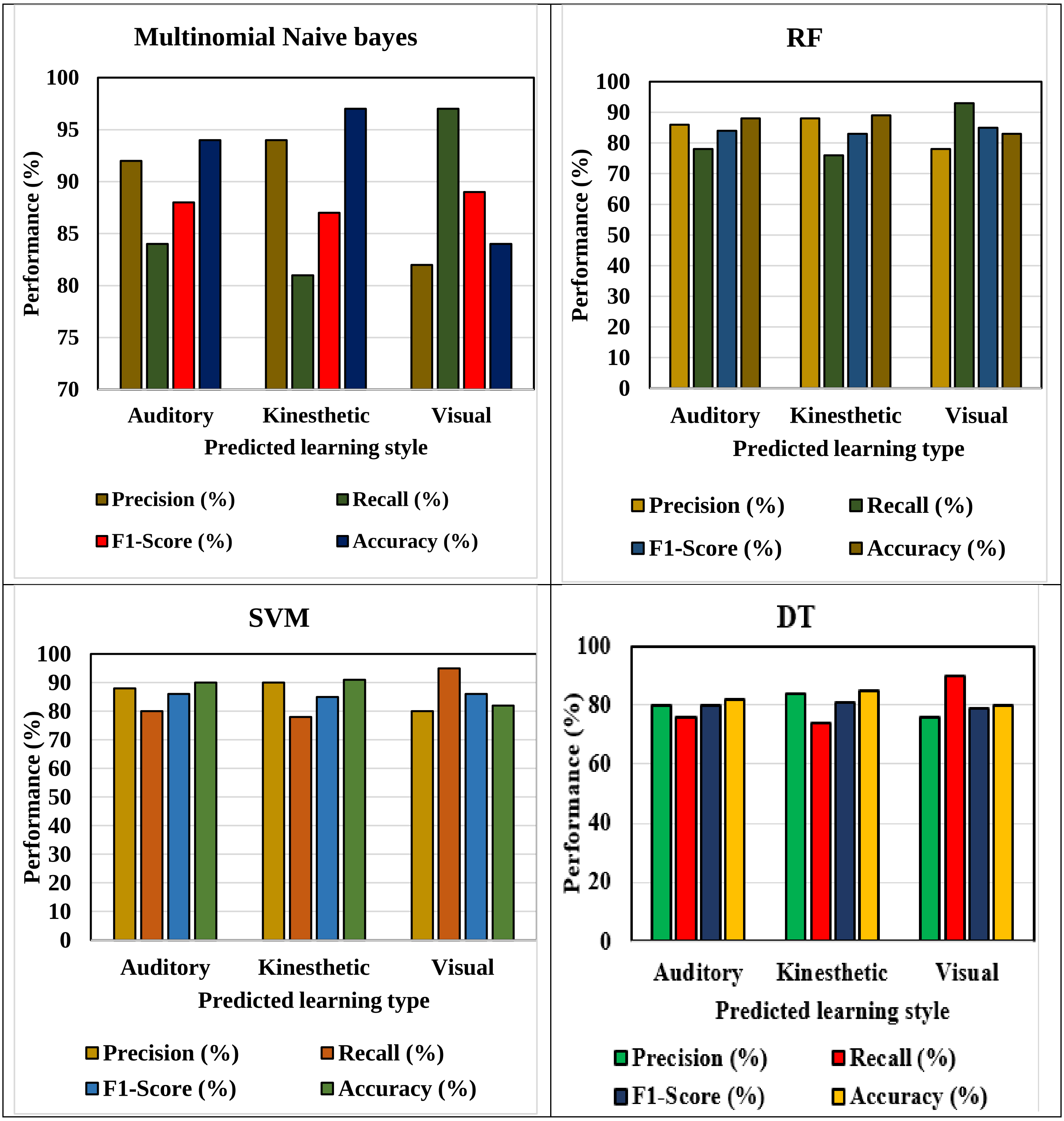

Fig 3 Classification Report of proposed algorithm

This report helps to identify strengths and weaknesses of the Multinomial Naive Bayes model, guiding further improvements, such as tuning hyperparameters or using different features to enhance predictive performance. Table 3 shows predicted learning style using multinomial naïve bayes.

Tab 3 Predicted learning style

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

This table shows examples of text statements from individuals, each paired with a **predicted learning style**. The **learning style**—Visual, Auditory, or Kinesthetic—indicates the preferred way in which each individual learns most effectively based on their statements.

- For the text *"I enjoy watching videos to learn new concepts,"* the predicted learning style is **Visual**, suggesting that the person learns best by seeing information, such as through videos, diagrams, or images.
- In *"I prefer listening to lectures over reading textbooks,"* the learning style is **Auditory**, indicating that the individual finds it easier to learn through listening, as in lectures or discussions.
- 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 focuses on learning by doing. However, the model has classified it as Visual, possibly due to nuances in interpretation or the way the learning styles are defined for this analysis.
- "*I enjoy building models and conducting experiments to learn newconcepts*" is an example of a kinesthetic learner's statement. It reflects a preference for hands-on activities and experiential learning, which are key characteristics of kinesthetic learning styles. Kinesthetic learners thrive on engaging with materials and physically manipulating objects to understand concepts better.

This table highlights how text analysis can be used to infer learning styles, which can then guide personalized teaching methods to suit individual preferences.

5. CONCLUSION

The proposed multi-agent framework successfully enables adaptive learning by classifying students into specific learning styles—Visual, Auditory, and Kinesthetic—using a data-driven, personalized approach. Leveraging multiple ML algorithms, including Multinomial Naive Bayes, SVM, DT , and RF, the system achieves reliable and contextually aware classifications, with Multinomial Naive Bayes providing notably high accuracy about 98% in learning style prediction. Sentiment analysis deepens engagement insights, allowing the framework to deliver content that is both customized and resonant with learners' preferences, particularly in STEM education. This framework paves the way for more sophisticated adaptive learning technologies. Future research can explore expanding the model to incorporate additional learning styles and cognitive indicators, enhancing its applicability across diverse educational settings and subjects. Integrating real-time feedback loops and adaptive curriculum pathways could further refine learning experiences, creating an even more responsive, student-centered approach. Moreover, advancements in natural language processing and ML could enable the framework to detect subtle changes in learning preferences over time, supporting lifelong personalized education.

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