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Utilizing Multiagent-Based Conceptual Learning in STEM Education for Analytical Learners through a Random Classifier Model

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Abstract: The study illustrates a multiagent-based conceptual learning framework for analytical learners using logical, linguistic, numerical, and abstract reasoning skills. This approach provides tailored and adaptable learning paths based on strengths and weaknesses to improve learning. Multiple agents provide individualized feedback and coaching to enhance analytical skills holistically. Engagement, learning style, and material availability are considered while calculating reasoning scores. This analysis helps the framework offer relevant learning materials and activities by understanding each learner's requirements and preferences. The multiagent-based strategy also encourages peer-to-peer learning and knowledge sharing, improving the learning experience. The proposed methodology uses a reasoning score and a random forest classifier to predict learners' learning styles. The model compares to inductive, deductive, and transductive machine learning models. The random forest classifier model beats other learning methods. The random forest classifier may be able to effectively predict learners' learning styles. In addition, multiagent-based learning improves collaboration and enables customized learning experiences.

Keywords: *conceptual learning, deductive, inductive, multiagent, random classifier, STEM.*

1. Introduction

Educating through STEM Technology is collectively known as STEM/CS which is the combination of science, technology, engineering, and mathematics. STEM education strives to enhance problem-solving and creativity abilities, prepare students for the twenty-first century, integrate real-world applications, foster student collaboration and communication, contribute to scientific discoveries, and solve societal concerns. [1]. The National Science Foundation created STEM in 1996 to apply and strengthen individuals' independent thinking and creativity [2]. STEM education encompasses a variety of learning modalities, including game-based learning [3], project-based learning, and the incorporation of AI technologies in STEM education [4]. STEM education enhances students' careers by teaching them problem-solving abilities, preparing them for knowledge-driven occupations, encouraging hands-on learning, satisfying individual needs, and allowing them to choose their particular demands. Students learn problem-solving abilities, which are essential in today's fast-paced world. They learn to think critically, analyse facts, and solve real-world problems in novel ways. Furthermore, preparing the students through STEM education helps them for knowledge-driven employment such as STEM/CS which comprises of various disciplines such as technology, engineering, and science, where qualified workers are in high demand. Students gain exposure to cutting-edge tools and practices that are defining the future of these industries by incorporating AI technologies into STEM instruction. STEM education encourages creativity, teamwork, technical skills, analytical capabilities, and research abilities [5].

A key strategy that concentrates on creating fundamental theories, concepts, and principles within the subject areas is conceptual learning. Students who study topics conceptually are better able to comprehend them. Compared to other learners, analytical learners have a good understanding of the concepts; they recognise patterns in the material; and they apply their knowledge to novel situations. Analytical learners stimulate teamwork, leadership, and communication [6]. Analytical learners can engage with others in a team environment and successfully articulate their ideas by grasping the underlying theories and principles. Their capacity to adapt their expertise to novel circumstances enables them to assume leadership roles and offer creative solutions. Analytical learners may encounter a number of challenges, including understanding the concepts' outline, making the shift from memorization to understanding the concepts, first having trouble developing critical thinking abilities, making connections to real-world scenarios, and requiring alternative

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assessment tools in order to comprehend the concepts [7]. Nonetheless, analytical learners can overcome these obstacles and succeed in their educational journeys with the right direction and assistance. By utilising their aptitude for pattern recognition and knowledge application, they may lead groups, make valuable contributions, and clearly convey their thoughts. Furthermore, offering students a variety of educational materials and evaluation techniques can improve their comprehension and assist them in making connections between ideas and actual situations.

Multiagent-based learning (MBL) is the process of learning in which agents interacts in a shared environment to achieve common goals. MBL enables agents to communicate with one another depending on information which is obtained from the shared environment. To achieve a common goal, multiagent controls are dispersed and dynamically adapt to a complicated learning-based control system. In general, exchanging of information with one another in order to impart high-level knowledge, facilitate decision-based learning, and provide model-based guidance to better the learning process [8]. Agents can share their experiences and learn from each other's achievements and failures using this collaborative learning approach. Agents can collectively improve their decision-making abilities and overall performance by exchanging information and ideas. Furthermore, MBL promotes the construction of robust and adaptive control systems capable of dealing with complex and dynamic settings.

Models which are used in Machine learning are also used in STEM education to improve learning outcomes, make better decisions, and collaborate with one another. Bradleys University uses eight types of machine learning models for predicting students' academic performance [9]. Another researcher [10] employed IoT-based speech recognition and facial recognition in school education. Predictive modelling which is also known as Machine learning models which is used to give an warning about early student dropouts [11], whereas robotic-based models provide personal learning to develop hands-on experiences for students by [12]. The benefit of random-classifier-based multiagent STEM learning is that it minimizes dropout rates by identifying dull students early and providing individualized guidance to individual students to increase their learning aptitude, hence enhancing retention through STEM education [13]. It eventually leads to improved academic achievement and professional opportunities for these students. Furthermore, the application of machine learning models in education can aid in the identification of patterns and trends in student performance, allowing educators to make data-driven decisions and interventions. Furthermore, incorporating robots into the classroom not only increases student engagement but also improves critical thinking and problem-solving skills, preparing kids for future STEM employment.

Problem Statement

The objectives of STEM education include interdisciplinary learning, critical thinking, and problem-solving strategies; however, it can be challenging to meet the different learning styles of pupils, especially analytical learners. Environments that stress data analysis and logical reasoning tend to be ideal for analytical learners. Making STEM classes that particularly address individual tastes while simultaneously encouraging interdisciplinary learning, critical thinking, and problem-solving abilities can be difficult, though. Therefore, teachers need to come up with innovative ways to include opportunities for in-depth analysis and reflection, practical experiments, and real-world applications in order to engage analytical learners. These students usually struggle to connect abstract concepts to real-world applications, which have a detrimental impact on their educational experience and restrict their capacity to assume leadership roles and make original contributions to STEM fields. Customized solutions are also required for improving the learning experience of analytical learners in STEM education, since standard educational approaches are not adequate to meet their specific needs.

Contribution

To target analytical learners, the proposed approach seeks to connect abstract concepts with real-world examples.

To improve STEM education by using multiagent-based learning approaches to support knowledge sharing, decision-making, and model-based guidance.

Random Classifier Model—allows for the early detection of learners for those who have difficulty and offers individualized support and data-driven interventions.

Section 2 describes the conceptual learning strategies that analytical learners currently employ. Information on the suggested machine learning model for integrating conceptual learning into STEM education for analytical learners is given in Section 3. The outcomes and discussions are covered in Section 4. The usefulness of the suggested machine learning methodology for integrating conceptual learning in STEM education for analytical learners is concluded in Section 5.

1.1. Literature Survey

The survey outlines analytical learners' conceptual learning processes. These students typically perform exceptionally well in courses that require analytical and problem-solving abilities. Before putting a notion to use in real-world scenarios, they frequently prefer to comprehend the underlying theories and principles behind it. For Combining the STEM-based conceptual learning, the researchers have proposed various models in machine learning for examining the programming learning technique among B.Tech. Information technology students [14]. Using text and rule mining techniques, the author [15] mapped conceptual learning and machine learning models in healthcare applications. The author [16] proposed using changes in higher education in the country of England to predict economic growth using a machine learning model. By combining Chat GPT with a ubiquitous learning model, the author [17] offered a stress managing acceptance model through technology so that Pakistan University students experience from their academic pursuits. In order to generate adaptability and customization for individualized developers, the author [18] employed clustering algorithms to design learning environments, competency matrices, educational programs, and methodologies in the smart learning environment.

In order to teach STEM education, the author [19] suggested using a human-machine system to build a virtual home environment in the classroom. Students can participate in practical exercises and experiments in the virtual house setting, which helps them better, comprehend STEM subjects. The author's human machine system improves student learning and motivates active engagement in STEM education by incorporating technology into the classroom. With learning behaviour analysis, the author [20] developed predictive modelling to examine learner behaviour. The author's analysis revealed patterns and trends in the learning behaviours of the students, paving the way for tailored feedback and intervention to improve their comprehension and proficiency in STEM subjects. This predictive modelling technique can guide future STEM education instructional design by offering insightful information about the efficacy of various teaching pedagogies.

The author [21] found that students, who took part in group problem-solving exercises which engage in greater levels and a game-based learning environment, are used for the retention of STEM ideas. The improvement in student learning implies that outcomes can be achieved by introducing interactive and cooperative components into STEM education. According to the author's examination of intragroup interactions in the project-based learning environment [22], students who actively participated in group discussions and offered their views showed enhanced problem-solving abilities and a deeper comprehension of STEM subjects. These results emphasize how crucial it is to create cooperative learning settings in order to advance successful STEM education.

Using a random classifier model can further enhance conceptual learning in STEM education for analytical learners. By incorporating this type of model into an environment that is specifically designed which meets the need of the analytical learners, it may be possible to provide individualized support, early detection of difficulties, and interventions that improve understanding and performance. STEM education provides a promising strategy for analytical learners, which are the combination of conceptual learning strategies with machine learning models, interactive technologies, and cooperative learning environments.

2. Proposed Methodology

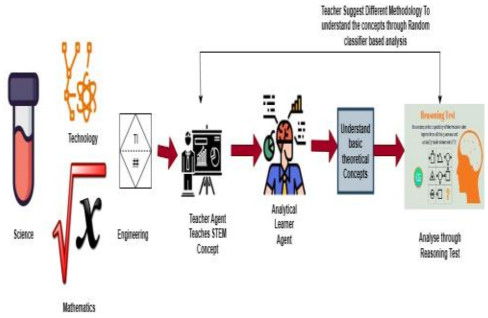


Fig 1. Proposed architecture of applying conceptual learning through analytical learners

The recommended multiagent system for conceptual learning among analytical learners is shown in Figure 1. It accomplishes this by assessing their reasoning abilities in a variety of domains, including logical, abstract, numerical, and verbal reasoning, depending on their degree of happiness, engagement, and preferred learning method. Every reasoning talent has three performance levels: poor, middle, and high. Initially, many types of conceptual learning techniques have been used by the educators for knowledge sharing through STEM education. The student uses the fundamental theoretical understanding in practical applications. Based on the concepts, the teacher assesses the students' competence to employ various types of reasoning evaluation tools. By using random machine learning classifier, the assessment agent assesses the students' comprehension of fundamental ideas by assigning them to one of four learning styles: visual, auditory, kinaesthetic, or read-write. Each learner is then given a reasoning skill level by the evaluation agent based on how well they apply the theoretical knowledge to practical situations. This makes it easier for the teacher to determine the advantages and disadvantages of each student's reasoning skills and adjust their teaching strategies accordingly. Furthermore, the assessment agent offers insightful feedback to the student and the teacher, allowing them to monitor development and make the required modifications for the best possible learning results.

2.1 Reasoning Domains

Analytical learners are evaluated using a variety of reasoning skills, including verbal, abstract, logical, and numerical reasoning. Logical reasoning skills: the capacity to evaluate the ideas on an aptitude test by seeing patterns, analyzing relationships, and drawing conclusions. The ability to think creatively, make connections across areas, and comprehend the novelty of important concepts is known as abstract reasoning. Applying quantitative abilities and mathematical knowledge to comprehend concepts is known as numerical reasoning. The goal of verbal reasoning is to efficiently extract key ideas, texts, and concepts from scientific study and analysis in STEM fields. These critical thinking abilities required are essential for success in a variety of professional and academic contexts. They help people to think critically, work through challenging issues, and come to reasoned, well-informed conclusions. These kind of skills are highly valued by companies as well, since they demonstrate a person's capacity for rational thought, information analysis, and effective communication.

2.2Assessment Process

The preferred learning method, level of engagement, and level of enjoyment all affect evaluations. Happiness and involvement are quantified on a scale of 0 to 1. Numerical values are filled in for preferred learning styles. By evaluating students according to their level of satisfaction, engagement, and preferred learning style, teachers can develop a comprehensive picture of their entire educational experience. Educators can assess the emotional and motivational factors that affect the efficacy of the learning process by using a 0–1 scale to measure engagement and happiness. Furthermore, by giving numerical values to preferred learning styles, modification of lesson plans done by teachers are best suited for the unique preferences of each student and enhance their academic performance.

Equation (1) represents the assessment process' mathematical equation.

$$\text{Assesment Score} = \text{f}((\text{degree of happines, engagement level, @Preferred Learning Style@})) \quad (1)$$

(1)

2.3Concept Learning in STEM education

In STEM education, there are various forms of conceptual learning, including inquiry-based learning (IBL), project-based learning (PrBL), and problem-based learning (PBL).

2.3.1 Learning via Projects (PBL)

Encourage students to work together to solve problems from the real world. The PBL is shown in equation (2). PBL is an instructional strategy that promotes students' active participation in using critical thinking and teamwork to solve real-world problems. It encourages students to apply their knowledge and abilities in real-world situations, which help them, get a deeper comprehension of the material. Furthermore, PBL is frequently applied through group projects or practical exercises, helps students to develop their communication and cooperation abilities.

$$PBL = \frac{1}{Problem\ Complexity} \quad (2)$$

A lower value denotes greater complexity and is associated with higher levels of learning depth and engagement.

2.3.2Project Based Learning (PrBL)

PrBL education encourages cooperation and useful application techniques. Equation (3) represents PrBL. Equation (3) shows how collaborative problem-solving and real-world scenarios are included in PrBL. With the help of this method, students can actively participate in practical experiences that deepen their grasp of the material.

$$PrBL = \frac{1}{Time\ spent\ to\ the\ project} \quad (3)$$

Spending more time on the project indicates a deeper understanding of it. Throughout the course of the project, this greater understanding may result in more effective problem-solving and decision-making. It also makes it possible to pay closer attention to details and produce a better final product.

2.3.3 Inquiry Based Learning (IBL)

Students research the subjects on their own. Students are urged to carry out independent study and evaluate the data they collect. This method encourages pupils to learn independently and self-directedly, giving them the opportunity to form own viewpoints on the material. IBL is represented mathematically in equation (4).

$$IBL = \frac{1}{Level\ of\ inquiry\ based\ learning} \quad (4)$$

Increased engagement with inquiry-based learning is a sign of improved analytical abilities. Through active exploration and investigation of subjects, inquiry-based learning develops students' critical thinking skills. By using this method, learners can become more autonomous learners and strengthen their problem-solving abilities.

2.3.4Random Forest Classifier (RF)

An ensemble learning classifier is the Random Forest (RF) classifier. It creates forecasts by combining several decision trees. The decision tree trained by Random Forest classifier is using by a different subset of the training set. Combining the predictions from all of the individual decision trees yields the final prediction. This method aids in lowering over fitting and raising the classifier's overall accuracy.

3. Decision Tree

A decision tree is a tree-structured classifier in which each internal node reflects a feature-based decision. The decision tree grows from the root node to the leaf nodes, which indicate the ultimate categorization or outcome. Each internal node divides the data based on a certain characteristic, providing for a hierarchical and intuitive representation of decision-making. Each branch represents a choice, and each node is a class label. Because of their simplicity and interpretability, decision trees are commonly employed in machine learning and data mining. They can handle category and numerical data, making them adaptable to a wide range of applications. Furthermore, decision trees may manage missing values by determining the optimal feature to split the data using different splitting criteria, such as the Gini index or information gain. Decision tree is constructed using equation (5).

$$Decision\ Tree = Feature \leq threshold\ then\ Class\ A\ else\ Class\ B \qquad (5)$$

Ensemble of decision tree is represented in equation (6)

$$Random\ Forest\ Prediction = 1/(Number\ of\ decision\ Tree) \sum\_(i = 1)\hat{}(Number\ of\ decision\ tree)(Decision\ Tree(feature)) \qquad (6)$$

A random forest user's impurity is measured using the Gini index, which is represented by equation (7), and feature randomness to create different trees.

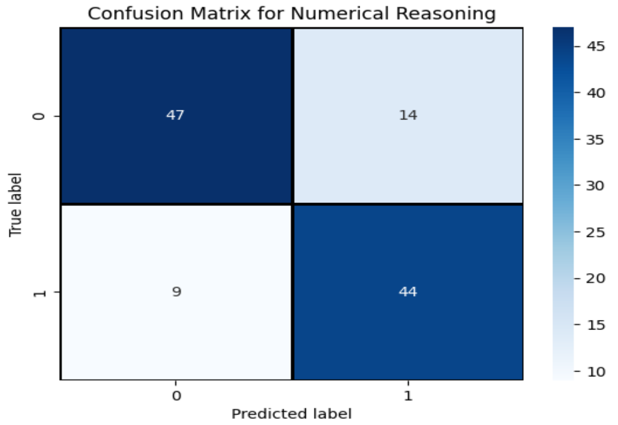
$$Gini(p) = 1 - \sum_{i=1}^{classes} probabilty_i^{\,2} \qquad (7)$$

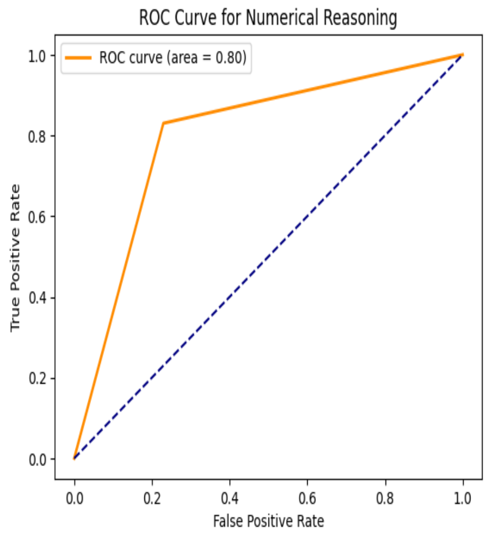
4. Results and Discussions

Based on the engagement levels and preferred learning styles of 1000 analytical learners, the dataset provides multiple reasoning scores such as numerical, verbal, abstract, and logical reasoning scores. To establish a representative sample, these analytical learners were chosen from a variety of educational backgrounds and age groupings. Demographic characteristics such as gender, ethnicity, and socioeconomic position are also included in the dataset to further investigate the impact of these factors on reasoning scores. Figure 2shows the learning style's clustered structure.

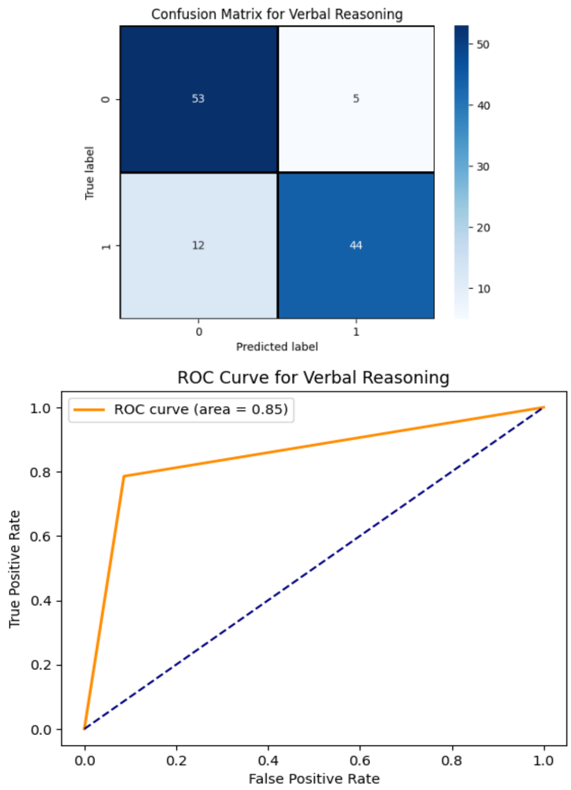
Fig 2. Visualization of analytical reasoning scores

Based on the different reasoning scores, engagement levels, and satisfied by the content of the analytical learners, the KMeans cluster analysis is produced by three distinct clusters (designated 0, 1, and 2). The cluster centers represent the mean values of each feature inside the clusters. For each cluster, they display the average scores for the various reasoning areas, as well as the engagement and material satisfaction levels. Group 0: This cluster has lower scores in abstract reasoning but relatively high scores in verbal, logical, and numerical reasoning. Out of the three clusters, it exhibits the lowest level of involvement and satisfaction with the subject. Cluster 0 may benefit from more engaging teaching methods to increase participation. Cluster 1 could improve verbal thinking with targeted help. A more balanced method that maintains Cluster 2's enthusiasm and develops their thinking skills may be needed.





(a)



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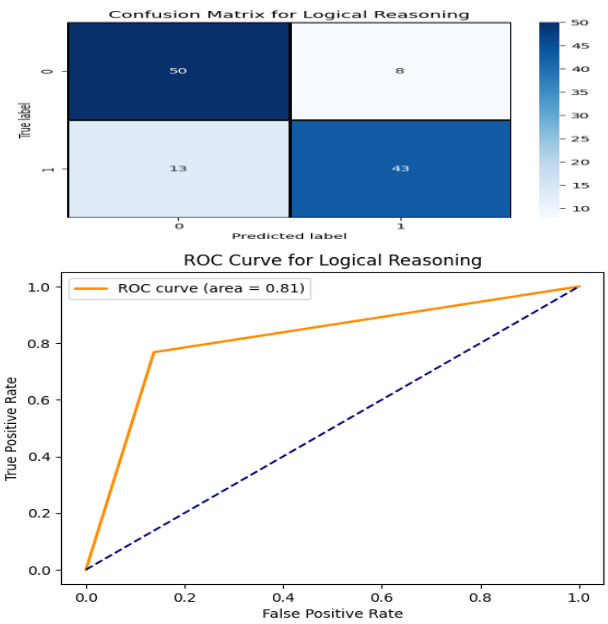

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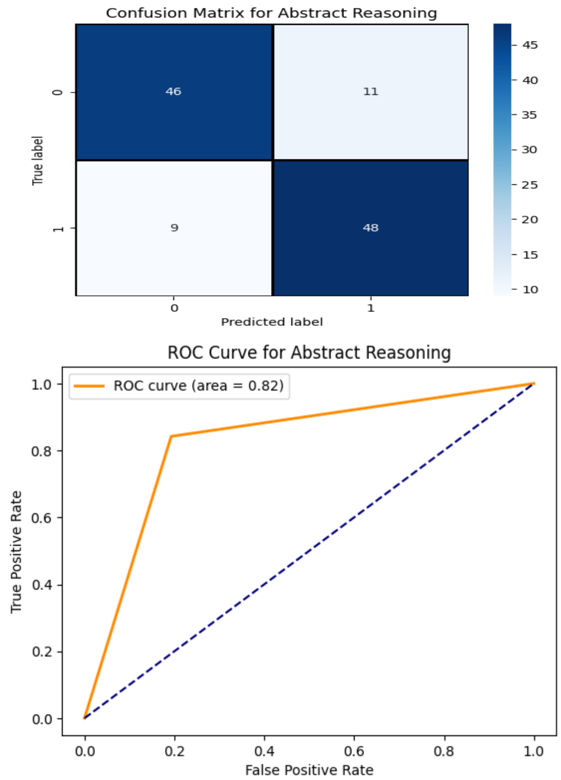

(d)

Fig 3: Performance of Random Forest Classifier (RF) with various Reasoning Skills

Figure 3 indicates the performance of various reasoning skills of random forest classifier. The classifier performs well across reasoning capabilities, with accuracies of 0.80–0.85. This shows the model can predict reasoning skill classes well. Precision and recall, which evaluate positive prediction precision and positive instance coverage, show trade-offs among reasoning skills and performance levels within each skill area. The F1 score, which balances precision and recall, ranges from 0.80 to 0.86 across reasoning skills. The classifier's AUC values, around 0.80-0.85, indicate its ability to differentiate classes across reasoning skills. Though verbal reasoning is most precise and accurate, logical reasoning has a lower AUC and recall for class 1. However, all reasoning skills have F1 scores between 0.80-0.86, suggesting good competence.

Different reasoning skill classifiers showed unique trends in precision. For numerical reasoning, the inductive learning (SVM) model had modest precision (63.93%), whereas the deductive inference (gradient boosting) approach had robust precision (79.37%). With 73.85% precision, Transductive Learning (KNN) performed well. Inductive learning (SVM) has 60.61% precision in verbal reasoning. However, the Deductive Inference (Gradient Boosting) model outperformed it with 77.61% precision. The Transductive Learning (KNN) model performed moderately with 70.77% precision. The inductive learning (SVM) model had 59.09% precision for logical reasoning. The Deductive Inference (Gradient Boosting) model classified better with 73.44% precision. The Transductive Learning (KNN) method performed moderately, with 64.41% precision. The Inductive Learning (SVM) model had 71.88% precision in Abstract Reasoning. The Deductive Inference (Gradient Boosting) model had 83.67% precision, indicating good classification capabilities. The Transductive Learning (KNN) model performed moderately well with 77.55% precision. The proposed techniques for all reasoning capabilities outperformed previous models in precision. These proposed techniques showed improved precision in numerical, verbal, logical, and abstract thinking, potentially improving categorization accuracy for these skills sets. Figure 4 illustrates the analysis done in comparative model of different machine learning techniques.

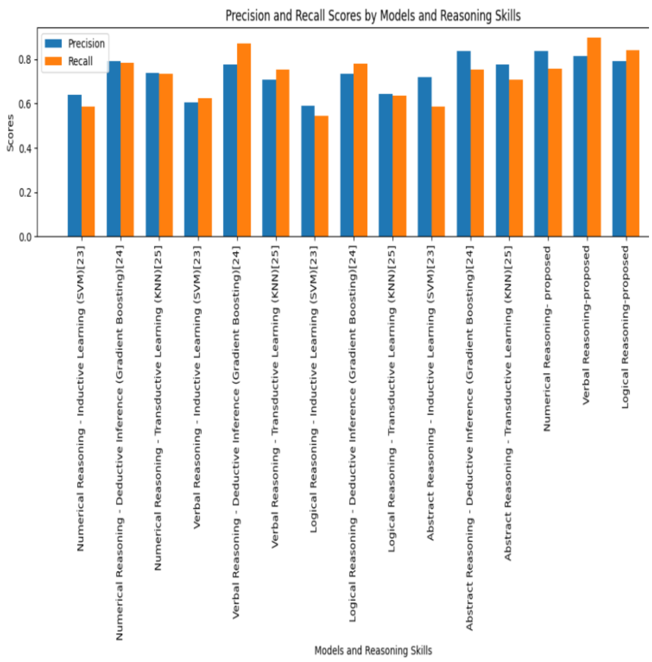

Fig 4. Comparative Analysis of different machine learning models

5. Conclusion

The study introduces a conceptual learning framework for analytical learners that improve logic, language, numbers, and abstraction. This unique approach leverages strengths and weaknesses to generate flexible learning paths that improve performance. The system delivers customized feedback and coaching to develop analytical skills using many agents. Importantly, this method determines reasoning scores utilizing student involvement, preferred learning styles, and topic accessibility. This careful analysis lets the framework choose learning materials and activities that suit each learner. The multiagent-based method encourages peer-to-peer information exchange and personalized learning, producing a collaborative learning environment. The recommended method predicts learning styles using a reasoning score and a robust random forest classifier. Random forest classifiers outperform inductive, deductive, and transductive machine learning models. Predicting learners' learning habits may change tailored education. Finally, our multiagent-based learning system enhances collaboration and personalized learning for analytical learners. To increase educational efficacy, expand collaborative learning, study machine learning models, and refine this framework.

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