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Usage of XG Booster Classifier in Implementation of STEM Education Among Different Types of Learners for Multiagent System.

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Abstract: This study uses the Honey and Mumford Learning Styles Questionnaire to investigate how a multiagent system (MAS) can be integrated into STEM (Science, Technology, Engineering, and Mathematics) curricula to accommodate a variety of learner profiles. To improve individualized learning, the MAS uses an XGBoost classifier to identify several learning styles, including active, reflective, theoretical, and pragmatic. The system modifies its resource allocation, collaborative activities, and teaching tactics to accommodate individual preferences and cognitive processes. Student, teacher/tuition, collaborative learning, assessment and evaluation, adaptation and recommendation, resource management, and system coordination agents are the agents that make up the MAS. The goal of the study is to determine how well MAS supports engagement, comprehension, and skill across a variety of learning styles, therefore catering to the needs of diverse students in STEM education. It accomplishes this by fusing instructional strategies with technology.

Keywords: *Multiagent system, STEM, XGBoost, Honey and Mumford Learning styles*

1. Introduction

STEM education faces several challenges, including a lack of resources, such as curricular resources, laboratory facilities, and school support. These obstacles can limit students' ability to participate in hands-on learning experiences and expose them to real-world applications of STEM concepts. Furthermore, a lack of resources may have an impact on professional development opportunities for teachers, making it difficult for them to keep up with the latest advancements in STEM fields. Following that is a lack of teacher training in STEM concepts and pedagogy teaching methods. Teachers face additional challenges as a result of interdisciplinary STEM education and a lack of resources. Furthermore, a lack of STEM teacher training and teaching methods can impede teachers' ability to effectively deliver STEM education to students. This can lead to a disconnect between what is taught in the classroom and real-world STEM applications, limiting students' understanding and engagement with these subjects. Furthermore, the interdisciplinary nature of STEM education necessitates teachers having a thorough understanding of multiple subjects, which can be difficult without adequate training and resources. Student participation is also lower as a result of Smartphone and gadget use, as well as a lack of knowledge about STEM education.

In education, there are various learning styles, and everyone has a unique learning style. The standard classroom teaching and learning approach does not cater to all kids' demands. As a result, various methods of learning, such as engaging students, are more effective than traditional learning since traditional learning is rigid, lacks drive, and lacks interest in the subject matter. Different learning styles help students enhance their critical thinking and problem-solving skills while also allowing them to make their own choices and fresh ideas. In a classroom, there are various types of learners, including visual, auditory, kinaesthetic, read/write, logical, social, and solitary learners. Educators can adapt to the varying requirements of students and create a more inclusive and dynamic learning environment by incorporating various learning styles. Visual aids and images help visual learners, whereas discussions and lectures help auditory learners. Kinaesthetic learners prefer hands-on tasks, whereas readers/writers excel at written projects. Logical learners enjoy assignments that require logical reasoning and problem solving; sociable learners flourish in group activities; and solitary learners prefer individual study. Recognising and adapting these various learning styles can boost student engagement and academic success.

A multiagent system provides an adaptive and personalized learning environment, and instructors may readily identify the learning behavioural pattern and evaluate STEM education success. This technology analyzes student data and provides individualized recommendations for improvement using artificial intelligence and machine learning techniques. Furthermore, it provides real-time

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feedback to both students and teachers, thereby improving the overall learning experience in STEM education. A virtual learning environment is included in a multiagent system to assist learners acquire topics fast by assigning different tasks to different types of learners. The multi-agent system learning method is student-centered, self-paced, and highly interactive, allowing for a more personalized learning experience. This method encourages collaborative learning by allowing students to participate in group activities and conversations within the virtual learning environment. Furthermore, the multi-agent system is capable of adapting to each student's unique learning style and preferences, ensuring that they receive targeted help and resources that are matched to their specific needs.

A multiagent system (MAS) is a collection of independent agents that collaborate to achieve a shared goal. Adaptive learning, intelligent tutoring systems, collaborative learning, automated assessment and feedback, and conceptual learning are all examples of MAS used in STEM learning settings. Personalisation and adaptation, customized learning paths, collaborative learning paths, resource allocation and recommendation, constant monitoring and feedback, greater engagement and motivation are all advantages of integrating a multiagent system. Furthermore, multiagent systems in STEM learning environments encourage students' critical thinking and problem-solving abilities. They also facilitate peer-to-peer learning and knowledge sharing, promoting a collaborative and dynamic learning environment.

Multiple agents, such as students, tutors, instructional software, or robots, collaborate to achieve learning objectives in STEM education. When integrated with machine learning techniques such as neural networks, decision trees, and XGBoost classifiers, MAS becomes flexible and sophisticated in dealing with different sorts of learners. To detect behavioural patterns, preferences, and learning styles, the computers analyze vast amounts of data. MAS additionally tailors the learning environment to the needs of each individual learner. MAS improves overall efficacy in STEM education by optimizing instructional approaches, automating routine tasks, and automating routine tasks. Using machine learning algorithms, MAS can efficiently identify each student's strengths and shortcomings, allowing for tailored training and targeted interventions. Furthermore, MAS can give real-time feedback and progress tracking, allowing instructors to make data-driven decisions and improve the learning experience for STEM students.

1.1 Problem Statement

Handling multiple types of learners in a single classroom is a significant task in traditional STEM education. There is a need for a consistent approach to teaching that takes into account individual student needs, cultural differences, and learning preferences. As a result, creative techniques that can suit the needs of many types of learners are required. Combining a multiagent system (MAS) with advanced machine learning algorithms, such as the XGBoost classifier, appears to be a potential answer to this problem. The successful implementation of such a system, however, raises various significant issues, such as the precise identification and classification of different types of learners based on their distinct traits and learning styles. Furthermore, ensuring that all of the agents in the MAS framework can communicate and collaborate without issues while using the predictive capabilities of the XGBoost Classifier necessitates careful planning and strong system architecture. Furthermore, ethical concerns about data privacy, algorithmic biases, and equal access to personalized learning experiences necessitate careful consideration throughout the deployment process. Solving these issues is critical for developing a complicated MAS with an XGBoost Classifier that can satisfy the demands of a diverse variety of students and improve STEM education by providing customized, flexible, and engaging lessons.

1.2 Contribution

1. We created agents such as students, teachers, resource management agents, collaborative learning agents, evaluation and assessment agents, adaption recommendation agents, and system coordination agents.

2. We used the Honey and Mumford Learning Styles Questionnaire to analyze learner styles.

3. Based on dubious values the learners are classified as active, reflective, theoretical, or pragmatic using the XGBoost classifier.

4. Resource management assigns resources based on the different sorts of learners.

The work is structured as follows: Section 2 presents innovative approaches, Section 3 addresses proposed methodology, and Section 4 summarizes results and discussions. Section 5 contains a conclusion.

2. State of the Art Techniques

The following topics are covered in the discussion of machine learning models in STEM education: the development and use of MAS systems among various types of learners.Alessio Gaspar (2019) [1] created a puzzle system to assess the relationship between co evolutionary and educational processes among pupils. Muhammad Zahid Iqbal (2023) [2] created AGILEST to help kinaesthetic learners in STEM education through touchless interaction in chemistry. Gerardo Ibarra-Vazque (2023) [3] used open data to estimate student competency levels using a random forest and decision tree model. Gerardo Ibarra-Vazquez (2023) [4] used random forest, C5.0, CART, and an artificial neural network model to analyse the adaptability level of students in entrepreneurship education in order to determine the abilities required to build a marketable and successful environment. As a result, the model is used to determine the student's adaptation to online entrepreneurship education. Muhammad Zahid Iqbal (2023) [5] created learning agents to allow interactive kinaesthetic learning in science and engineering education through real-time hand engagement in the virtual world.

Hasnain Ali Poonja (2023) [6] created a computer vision model to improve the learning environment by monitoring facial expressions, position estimation, and head rotation. Using the partial least squares method, David Mutambara (2021) [7] established the Technology Acceptance Model (TAM) to develop STEM education through mobile learning in rural areas. Bilge Gencoglu (2023) [8] employed latent drichlet topic modelling to analyse students' behaviour in a higher education learning setting using open-ended questions. J. Ramadevi (2023) [9] employed the artificial intelligence model to promote collaborative learning among students in order to introduce a new technology called blended learning through the mix of digital gadgets with contemporary learning techniques. RaliaThoma (2023) [10] employed a universal design learning framework to offer a link between pedagogy and STEM education. Chih-Pu Dai (2022) [11] learned mathematical ideas using a computerised game-based math learning setting. Yaser M. Banadaki (2020) [12] used a machine learning model in STEM education to improve the research experience of undergraduate students in a project learning setting. These studies show how incorporating technology into STEM education can improve students' learning experiences.

These studies show that incorporating technology into STEM education has the potential to improve student learning experiences. Educators can develop engaging and dynamic learning settings that enhance deeper understanding of complicated subjects by using digital devices and contemporary learning approaches such as universal design learning frameworks and game-based environments. Educators can develop engaging and dynamic learning settings that enhance deeper understanding of complicated concepts by incorporating digital devices and contemporary learning approaches, such as universal design learning frameworks and game-based environments. Furthermore, the use of machine learning models in project-based learning environments can provide undergraduate students with significant research experiences, preparing them for future employment in STEM domains. Chih-Pu Dai (2022) [11] employed a digital game-based math learning environment to grasp mathematical ideas. Furthermore, the use of machine learning models in project-based learning environments can provide useful research experiences for undergraduate students, preparing them for future jobs in STEM domains.

3. Proposed Methodology

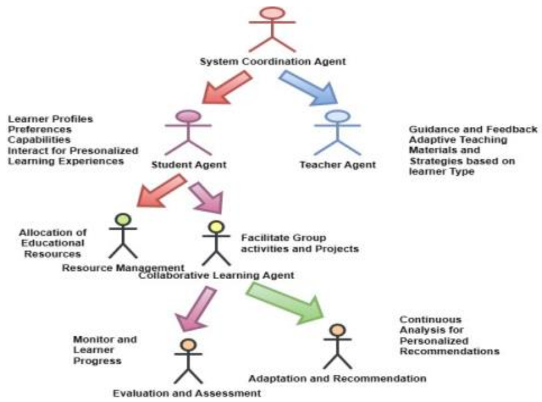


Fig 1: Overall Architecture of MAS-STEM

Figure 1 illustrates a Multiagent System (MAS) architecture built for individualized and adaptive STEM learning experiences. The system coordination agent serves as a central agent, communicating with other agents. Individual learners with diverse profiles, interests, and talents are represented by student agents. Based on predictions made by the XGBoost Classifier, these agents interact with the system to obtain individualized learning materials, recommendations, and adaptive support. Concurrently, teacher and tutor agents serve as virtual instructors or facilitators, providing students with guidance, feedback, and personalized assistance based on their identified learning types and adapting teaching strategies and materials as needed by administering psychometric tests to students. Resource Management Agents control instructional resource allocation, such as textbooks, simulations, or videos, depending on the XGBoost Classifier's prediction of the needs of various learner groups. Collaborative learning agents facilitate group activities, discussions, and projects while encouraging teamwork, communication, and problem-solving skills in learners of various profiles. Individual learners' progress is monitored and assessed by evaluation and assessment agents, who provide individualized feedback based on the XGBoost Classifier's identification of their distinct learning styles and talents. Finally, adaptation and recommendation agents continuously assess learner data using machine learning techniques like XGBoost, providing individualized recommendations for content, exercises, or interventions to match the requirements of varied students.

3.1 Honey and Mumford Learning styles

The Honey and Mumford Learning Styles Questionnaire(Swailes.S,1999)[13] is an assessment tool used to identify an individual's preferred learning style based on a model developed by Peter Honey and Alan

Mumford. This model categorizes learners into four distinct learning styles:

Activist: Activists prefer to learn through engaging in new experiences, hands-on activities, and group discussions. They are enthusiastic about trying new things but may sometimes be impulsive in their approach to learning.

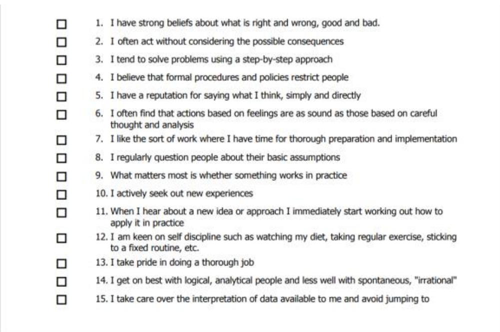
Reflector: Reflectors prefer to observe and reflect on information before making conclusions. They take time to consider different perspectives, analyze experiences, and think deeply before taking action.

Theorist: Theorists prefer to learn through structured approaches, theories, and systematic understanding. They like to analyze and conceptualize information, creating logical frameworks to understand concepts.

Pragmatist: Pragmatists prefer to apply what they have learned in practical, real-world situations. They focus on the relevance of learning and seek immediate application of knowledge.

The Honey and Mumford Learning Styles Questionnaire typically consists of a series of questions or scenarios that participants respond to, indicating their preferences or behaviors in various learning situations. Based on their responses, individuals are categorized into one or more of the four learning styles mentioned above.

This questionnaire helps individuals and educators understand their preferred learning styles, allowing them to tailor teaching methods and learning experiences to suit these preferences. It emphasizes the importance of accommodating diverse learning styles to enhance the effectiveness of education and training programs. **Figure 2** shows the sample questionaries of Honey and Mumford Learning Styles



☐ 1. I have strong beliefs about what is right and wrong, good and bad.
☐ 2. I often act without considering the possible consequences
☐ 3. I tend to solve problems using a step-by-step approach
☐ 4. I believe that formal procedures and policies restrict people
☐ 5. I have a reputation for saying what I think, simply and directly
☐ 6. I often find that actions based on feelings are as sound as those based on careful thought and analysis
☐ 7. I like the sort of work where I have time for thorough preparation and implementation
☐ 8. I regularly question people about their basic assumptions
☐ 9. What matters most is whether something works in practice
☐ 10. I actively seek out new experiences
☐ 11. When I hear about a new idea or approach I immediately start working out how to apply it in practice
☐ 12. I am keen on self discipline such as watching my diet, taking regular exercise, sticking to a fixed routine, etc.
☐ 13. I take pride in doing a thorough job
☐ 14. I get on best with logical, analytical people and less well with spontaneous, "irrational"
☐ 15. I take care over the interpretation of data available to me and avoid jumping to

Fig 2: Honey and Mumford Learning Questionnaires

3.2 XGBoost Classifier

The XGBoost algorithm is a gradient-boosting technique. To address missing values, the XGBoost method is employed in a scalable machine learning model to integrate predictions from numerous weak models to build a stronger prediction, and the model performs classification and regression quickly. Regularization techniques are used in the process to prevent over fitting and increase generalization. It also enables parallel processing, allowing it to handle huge datasets and save training time.

D is a set of data that can be represented as in equation (1),

$$D = \{x_i, y_i\} \qquad (1)$$

In equation (1), x_i *indicates set of features and* y_i *represents the corresponding labels.*

The output of XGBoost classifier is represented in equation (2).

$$Final\ Prediction\ of\ ensemble\ Weak\ Learner = \sum_{i=1}^{total\ number\ of\ Weak\ Learners} Individual\ Weak\ Learner$$

Weak Learner to correct the error is represented in equation (3)

$$Individual\ Weak\ Learner = Prediction\ made\ by\ ensemble\ weak\ learner + learning\ rate * new\ weak\ learner\ addded\ to\ the\ residual \qquad (3)$$

To minimize loss function and prevent over fitting, the objective function is defined in equation (4).

$$Objective_k = \sum_{i=1}^{n} L(y_i, F_{k-1}(x_i) + h_k(x_i) + \Omega f_k) \qquad (4)$$

In equation (4), y_i is a true label, F_{k-1} is the prediction of previous iteration, Ωf_k is a regularization term.

4. Results and Discussions

The precision, recall, f1score, and accuracy metrics that are displayed in equations (5), (6), (7), and (8) are the metrics that the suggested model measures using.

$$Precision = True\ Positive / True\ Positives + False\ Positives \qquad (5)$$

$$Recall = True\ Positive / True\ Positive + False\ Negative \qquad (6)$$

$$F1socre = 2 \times Precision \times Recall / (Precision + Recall) \qquad (7)$$

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ number\ of\ Predictions} \qquad (8)$$

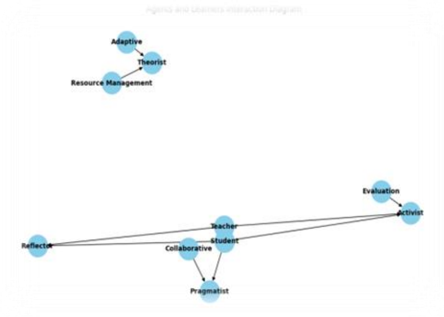


Fig 3: Agents and Learners interaction diagram

Figure 3 displays the interaction between the agent and the learner system. A directed graph depicting agents (Student, Teacher, etc.) and learner types (Activist, Reflector, etc.), with edges representing interactions between different entities inside a simulated system or learning environment. For instructional or system modeling purposes, this form aids in visualizing the relationships and interactions between various components.

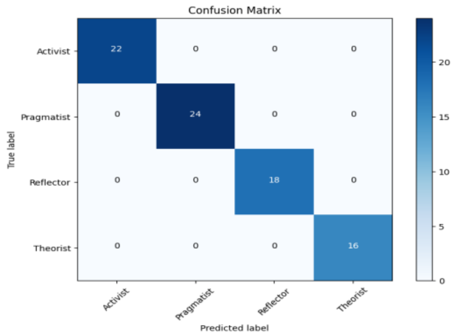


Fig 4: Confusion matrix for different types of learners

The confusion matrix for various learner types, including activists, pragmatics, reflectors, and theorists, is displayed in Figure 4. A thorough summary of each learner type's performance in terms of correctly categorized occurrences and misclassified cases can be found in Figure 4's confusion matrix. It makes it possible to compare and comprehend the advantages and disadvantages that activists, pragmatics, reflectors, and theorists have in relation to their learning processes. Our algorithm uses Honey and Mumford learning styles to accurately forecast the learners. Our approach classifies learners into their respective categories with accuracy by applying the Honey and Mumford learning styles. The receiver operating characteristic curve for various learners is displayed in Figure 5. Using a psychometric exam, the suggested machine learning classifier model accurately predicts the learners from **Figure 5.**

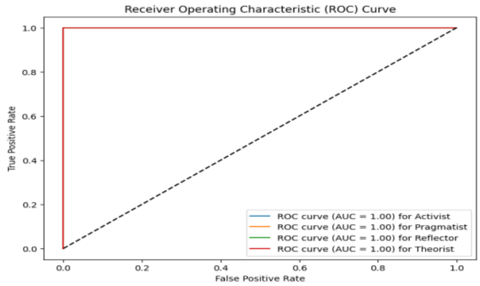


Fig 5: Receiver Operating Curve

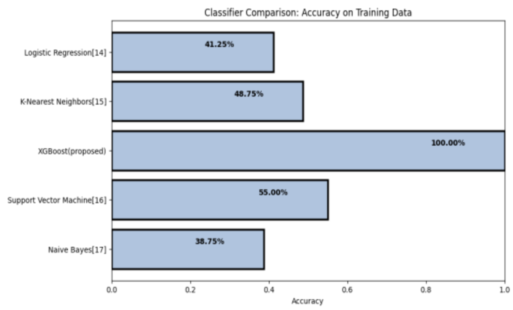


Fig 6: Classification Comparison of Prediction of different learners

A comparison of various machine learning classifiers, including support vector machines [16], logistic regression [14], K-nearest neighbor [15], XGBoost, and Navie Bayesian classifiers [17], is shown in **Figure 6**. According to our observations, the XGboost classifiers' capacity to combine the performance of individual weak learners through boosting allows them to accurately predict the various categories of learners. XGboost classifiers can handle complex datasets and increase prediction accuracy thanks to their boosting capacity. Furthermore, **Figure 6's** comparison illustrates the advantages and disadvantages of each classifier, assisting scholars and professionals in choosing the best algorithm for their particular needs.

5. Conclusion

The Honey and Mumford Learning Styles Questionnaire suggests that incorporating a multiagent system (MAS) into STEM education can provide individualized learning. MAS can cater to learners with different cognitive preferences, such as active, reflective, theoretical, and pragmatic. The study found MAS's adaptability in teaching approaches, resource allocation, and collaborative learning activities. The MAS model's ability to dynamically change and accommodate individual learning preferences is promising for inclusive and effective educational experiences. Continuous research and development of MAS are crucial for maximizing STEM learning results and serving diverse learner needs.

References

1. Gaspar, D.A. (2019). Board 59: Co evolutionary-Aided Teaching: Leveraging the Links Between Co evolutionary and Educational Dynamics.

2. Muhammad Zahid Iqbal, Abraham G. Campbell, AGILEST approach: Using machine learning agents to facilitate kinesthetic learning in STEM education through real-time touchless hand interaction, Telematics and Informatics Reports, Volume 9, 2023, 100034, ISSN 2772-5030,https://doi.org/10.1016/j.teler.2022.100034.
3. Gerardo Ibarra-Vazquez, María Soledad Ramirez-Montoya, Mariana Buenestado-Fernández, Gustavo Olague, Predicting open education competency level: A machine learning approach, Heliyon, Volume 9, Issue 11, 2023, e20597, ISSN 2405-8440,https://doi.org/10.1016/j.heliyon.2023.e20597.
4. Amit Malik, Edeh Michael Onyema, SurjeetDalal, Umesh Kumar Lilhore, DarpanAnand, Ashish Sharma, SaritaSimaiya,Forecasting students' adaptability in online entrepreneurship education using modified ensemble machine learning model,Array,Volume 19,2023,100303,ISSN 2590-0056,https://doi.org/10.1016/j.array.2023.100303.
5. Muhammad Zahid Iqbal, Abraham G. Campbell, Real-time hand interaction and self-directed machine learning agents in immersive learning environments, Computers& Education: X Reality, Volume 3, 2023, 100038, ISSN 2949-6780,https://doi.org/10.1016/j.cexr.2023.100038.
6. Hasnain Ali Poonja, Muhammad Ayaz Shirazi, Muhammad Jawad Khan, KashifJaved,Engagement detection and enhancement for STEM education through computer vision, augmented reality, and haptics,Image and Vision Computing, Volume 136,2023,104720,ISSN 0262-8856,https://doi.org/10.1016/j.imavis.2023.104720.
7. David Mutambara, AnassBayaga, Determinants of mobile learning acceptance for STEM education in rural areas, Computers&Education, Volume 160, 2021, 104010, ISSN 0360-1315,https://doi.org/10.1016/j.compedu.2020.104010.
8. Bilge Gencoglu, Michelle Helms-Lorenz, Ridwan Maulana, Ellen P.W.A. Jansen, OguzhanGencoglu, Machine and expert judgments of student perceptions of teaching behavior in secondary education: Added value of topic modeling with big data, Computers&Education, Volume 193, 2023, 104682, ISSN 0360-1315,https://doi.org/10.1016/j.compedu.2022.104682.
9. J. Ramadevi, C. Sushama, K. Balaji, VamsidharTalasila, NidhiSindhwani, Mukti,AI enabled value-oriented collaborative learning: Centre for innovative education, The Journal of High Technology Management Research, Volume 34, Issue 2,2023,100478,ISSN 1047-8310,https://doi.org/10.1016/j.hitech.2023.100478.
10. RaliaThoma, NektariosFarassopoulos, Christina Lousta,Teaching STEAM through universal design for learning in early years of primary education: Plugged-in and unplugged activities with emphasis on connectivism learning theory., Teaching and Teacher Education, Volume 132,2023,104210,ISSN 0742-051X,https://doi.org/10.1016/j.tate.2023.104210.
11. Chih-Pu Dai, FengfengKe, Yanjun Pan, YaningLiu, Exploring students' learning support use in digital game-based math learning: A mixed-methods approach using machine learning and multi-cases study, Computers&Education, Volume 194, 2023, 104698, ISSN 0360-1315,https://doi.org/10.1016/j.compedu.2022.104698.
12. Yaser M. Banadaki, Enhancing the Role of Machine Learning in STEM Disciplines through Supervised Undergraduate Research Experiences, Literacy Information and Computer Education Journal (LICEJ),Volume 11, Issue 2, 2020.
13. Swailes, S. and Senior, B. (1999), The Dimensionality of Honey and Mumford's Learning Styles Questionnaire. International Journal of Selection and Assessment, 7: 1-11,https://doi.org/10.1111/1468-2389.00099.
14. Niranjan Kumar, Bhagyashri R. Hanji,Aspect-based sentiment score and star rating prediction for travel destination using Multinomial Logistic Regression with fuzzy domain ontology algorithm, Expert Systems with Applications, Volume 240,2024,122493,ISSN 0957-4174,https://doi.org/10.1016/j.eswa.2023.122493.
15. Lalu M. RizaRizky, SuyantoSuyanto, Adversarial training and deep k-nearest neighbors improves adversarial defense of glaucoma severity detection, Heliyon, Volume 8, Issue 12, 2022, e12275, ISSN 2405-8440,https://doi.org/10.1016/j.heliyon.2022.e12275.
16. TanvirIbnaKaisar, Kais Zaman, Mohammad T. Khasawneh,A new approach to probabilistic classification based on Gaussian process and support vector machine, Computers& Industrial Engineering, Volume 186,2023,109719,ISSN 0360-8352,https://doi.org/10.1016/j.cie.2023.109719.
17. Tzu-Tsung Wong, Hsing-Chen Tsai, Multinomial naïve Bayesian classifier with generalized Dirichlet priors for high-dimensional imbalanced data, Knowledge-Based Systems, Volume 228, 2021,107288, ISSN 0950-7051,https://doi.org/10.1016/j.knosys.2021.107288.