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Learning Evaluation Method Based on Artificial Intelligence Technology and Its Application in Education

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Abstract: - Artificial intelligence (AI) is a transformative technology that enables machines to perform tasks that typically require human intelligence. Through algorithms and advanced computing systems, AI enables machines to perceive their environment, reason, learn from experience, and make decisions autonomously. From virtual assistants like Siri and Alexa to self-driving cars and advanced medical diagnosis systems, AI applications are reshaping industries and revolutionizing the way we live and work. With its ability to process vast amounts of data and identify complex patterns, AI has the potential to drive innovation, improve efficiency, and solve some of society's most pressing challenges. This paper introduces a novel learning evaluation method based on artificial intelligence technology, specifically leveraging Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC), and explores its application in education. The proposed method aims to provide a comprehensive assessment of student learning outcomes by analyzing various factors such as academic performance, engagement, and cognitive development. Through simulated experiments and empirical validations, the efficacy of the MFCM-OC-enhanced learning evaluation method is evaluated. Results demonstrate significant improvements in accuracy and granularity compared to traditional evaluation methods. For instance, the MFCM-OC model achieved an average accuracy rate of 85% in predicting student performance, allowing for targeted interventions and personalized learning plans. Additionally, the method enables educators to identify students' strengths and weaknesses more effectively, facilitating data-driven decision-making and continuous improvement in educational practices. These findings underscore the potential of artificial intelligence with MFCM-OC in revolutionizing learning evaluation and enhancing educational outcomes.

Keywords: Learning evaluation, artificial intelligence technology, Fuzzy Clustering, Middle-Order, Classification

I. INTRODUCTION

Artificial Intelligence (AI) technology is revolutionizing education by offering innovative solutions that enhance learning experiences and streamline administrative tasks [1]. Through AI-powered adaptive learning systems, students receive personalized educational content tailored to their individual needs, pace, and learning styles [2]. These systems analyze vast amounts of data, including students' performance, preferences, and historical data, to generate tailored learning pathways and recommendations [3]. Moreover, AI facilitates the automation of administrative tasks such as grading, scheduling, and student support, allowing educators to allocate more time to teaching and mentoring [4]. A learning evaluation method based on Artificial Intelligence (AI) technology represents a paradigm shift in assessing student progress and performance within educational settings. Leveraging AI algorithms, this method offers dynamic and data-driven insights into students' learning trajectories, enabling educators to make informed decisions about instructional strategies and interventions [5]. By analyzing various data points, such as assessment scores, engagement levels, and learning behaviors, AI algorithms can identify patterns, trends, and areas for improvement with unprecedented accuracy and efficiency [6]. This approach goes beyond traditional assessment methods by providing continuous and personalized feedback tailored to each student's unique learning profile.

In education, the traditional methods of evaluating student learning have often been limited by their static nature and inability to provide real-time feedback tailored to individual student needs [7]. However, with the advent of Artificial Intelligence (AI) technology, there has been a significant transformation in how learning is evaluated and assessed. AI-powered learning evaluation methods leverage advanced algorithms and machine learning techniques to analyze vast amounts of data generated within educational settings [8]. These data may include students' performance on assessments, their engagement with learning materials, their interaction patterns within digital platforms, and even physiological indicators of learning, such as eye movements or brain activity in some cases [9]. With processing and interpreting this data, AI algorithms can generate insights that go far beyond what traditional evaluation methods can offer. For example, they can identify not only what concepts students struggle with but also why they may be encountering difficulties [10]. This deeper understanding enables educators to tailor interventions

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and support strategies to address specific student needs more effectively [11]. The AI-based evaluation methods are inherently adaptive. They can dynamically adjust the level of difficulty or the type of content presented to students based on their individual learning progress and preferences. This adaptability ensures that students are continuously challenged at an appropriate level, maximizing their engagement and promoting deeper learning [12].

In AI technology enables the automation of routine evaluation tasks, such as grading assessments or providing feedback on assignments [13]. This automation frees up valuable time for educators, allowing them to focus more on personalized instruction, mentorship, and other high-value interactions with students [14]. In practice, AI-based learning evaluation methods find application across various educational contexts. They are used in traditional classrooms, online learning platforms, and even in corporate training environments [15]. For example, AI-driven adaptive learning systems are increasingly integrated into digital learning platforms to provide personalized learning experiences for students. Similarly, AI-powered assessment tools are utilized to conduct large-scale evaluations efficiently and accurately [16].

This paper makes a significant contribution to the field of education by introducing and demonstrating the efficacy of the Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm for learning evaluation. The primary contribution lies in the development of a novel framework that combines fuzzy clustering techniques with middle order classification to provide a more nuanced and accurate assessment of student performance. By leveraging fuzzy logic principles, the MFCM-OC algorithm accommodates the inherent uncertainty and complexity of educational data, allowing for more flexible and adaptive evaluation methods. Furthermore, the algorithm offers a systematic approach to analyzing educational data, enabling educators to gain deeper insights into student learning patterns and tailor instructional strategies accordingly.

II. RELATED WORKS

As educational institutions seek innovative ways to enhance learning experiences and improve outcomes for students, AI presents a promising solution with its ability to analyze data, personalize instruction, and automate administrative tasks. Consequently, a burgeoning body of research has emerged, focusing on the application of AI in various educational contexts. In this section, we review and analyze the related works in the field of AI in education, encompassing studies that investigate AI-powered adaptive learning systems, intelligent tutoring systems, automated assessment tools, and other applications aimed at optimizing teaching and learning processes.

Salas-Pilco and Yang (2022) conducted a systematic review focusing on AI applications in Latin American higher education, shedding light on regional perspectives and challenges. Ouyang, Zheng, and Jiao (2022) provided a comprehensive overview of AI in online higher education, offering insights into empirical research trends from 2011 to 2020. Chu, Hwang, and Tu (2022) specifically examined the role of AI-based robots in education, highlighting selected publications in the field. Meanwhile, Ahmad et al. (2022) explored the academic and administrative roles of AI in education, emphasizing its sustainability implications. Dogan, Goru Dogan, and Bozkurt (2023) reviewed empirical studies on the use of AI in online learning and distance education processes, contributing to the understanding of AI's impact on remote learning. Furthermore, Zhang, Shankar, and Antonidoss (2022) delved into modern art education and teaching with AI, showcasing innovative approaches in the field. In addition to these systematic reviews, several studies have explored specific aspects of AI integration in education. Hemachandran et al. (2022) investigated AI as a universal tool to augment tutoring in higher education, emphasizing its potential to enhance personalized learning experiences. Su and Yang (2022) conducted a scoping review on AI in early childhood education, highlighting the emerging role of AI technologies in shaping educational practices for young learners. Bhutoria (2022) conducted a systematic review using a human-in-the-loop model to examine personalized education and AI in the United States, China, and India, offering insights into cultural and contextual variations in AI adoption. Moreover, Celik (2023) conducted an empirical study on teachers' professional knowledge to ethically integrate AI-based tools into education, addressing the ethical dimensions of AI implementation in educational settings.

Chiu et al. (2023) conducted a systematic literature review focusing on opportunities, challenges, and future research recommendations of AI in education, providing a comprehensive overview of the field's landscape. Akgun and Greenhow (2022) explored the ethical challenges of AI in K-12 settings, emphasizing the importance of ethical considerations in the deployment of AI technologies in education. Celik, Dindar, Muukkonen, and Järvelä (2022) conducted a systematic review of research on the promises and challenges of AI for teachers, highlighting the need

for supporting teachers in effectively integrating AI tools into their teaching practices. Huang, Zou, Cheng, Chen, and Xie (2023) discussed trends, research issues, and applications of AI in language education, illustrating the diverse ways AI is shaping language learning and teaching. Salas-Pilco, Xiao, and Hu (2022) focused on AI and learning analytics in teacher education, demonstrating how AI technologies can support the professional development of educators. Additionally, Tapalova and Zhiyenbayeva (2022) explored AI in education for personalized learning pathways, emphasizing the potential of AIEd to cater to individual learner needs effectively. Finally, Alam (2022) examined the employment of adaptive learning and intelligent tutoring robots for virtual classrooms and smart campuses, envisioning the transformative potential of AI in reshaping educational environments. Pratama, Sampelolo, and Lura (2023) highlighted the revolutionizing impact of AI on education, emphasizing its role in enabling personalized learning experiences for learners.

Firstly, there may be a regional bias, as studies often focus on specific countries or regions where AI adoption in education is more prevalent, potentially limiting the generalizability of findings. Secondly, publication bias could skew the understanding of AI in education, as studies with significant or positive results are more likely to be published, potentially overlooking studies with null or negative findings. Methodological heterogeneity poses another challenge, with variations in research designs, measurement tools, and data analysis techniques making it difficult to compare and synthesize findings effectively. Moreover, temporal limitations may exist, as the inclusion of studies up to a certain year may overlook recent developments in the rapidly evolving field of AI. Ethical considerations, such as data privacy and algorithmic bias, may not be comprehensively addressed in all studies, and contextual factors such as cultural norms and socioeconomic conditions can influence the effectiveness of AI applications in education. Additionally, many studies focus on short-term outcomes, overlooking potential long-term effects or unintended consequences of AI interventions. Addressing these limitations requires a concerted effort within the research community to conduct more rigorous and comprehensive studies, incorporating diverse methodologies, considering ethical implications, and accounting for contextual factors. Longitudinal studies and interdisciplinary collaborations can provide deeper insights into the multifaceted relationship between AI and education, facilitating more informed decision-making and policy development in this rapidly evolving field.

III. PROPOSED MAMDANI FUZZY CLUSTERING MIDDLE ORDER CLASSIFICATION (MFCM-OC)

The Proposed Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) represents a novel approach to learning evaluation within the realm of Artificial Intelligence (AI) technology applied in education. This method integrates Mamdani fuzzy clustering with middle order classification techniques to enhance the accuracy and effectiveness of learning assessment. The derivation of MFCM-OC involves combining fuzzy clustering algorithms, which are adept at handling uncertainty and imprecision in data, with middle order classification, which allows for more nuanced categorization of learning outcomes. The core equations governing MFCM-OC involve the calculation of membership values for each data point across multiple clusters using fuzzy membership functions, followed by the determination of the middle order classification based on these membership values. Specifically, the Mamdani fuzzy inference system is utilized to determine the degree of membership of each data point in various clusters, considering linguistic rules and fuzzy logic operations. These membership values are then utilized in the middle order classification process, where the learning outcomes are categorized into appropriate classes or levels based on their proximity to cluster centroids or other relevant criteria. Through this hybrid approach, MFCM-OC aims to provide a more nuanced and accurate evaluation of learning outcomes, taking into account the inherent complexity and uncertainty associated with educational data. The proposed Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) method for learning evaluation in education. Mamdani fuzzy clustering involves partitioning a dataset into clusters where each data point belongs to each cluster to a certain degree. This is typically achieved using fuzzy membership functions. Let x_i denote a data point, c_j represent the centroid of the jth cluster, and μ_{ij} denote the degree of membership of x_i in cluster j. The membership function μ_{ij} can be calculated using a Gaussian membership function stated as in equation (1)

$$\mu_{ij} = \| x_i - c_j \|^2 / e^{-\sigma^2} \qquad (1)$$

In equation (1) σ is a parameter controlling the width of the Gaussian function. Middle order classification involves categorizing data points into multiple classes or levels based on their membership values across clusters. Let L denote the number of classes or levels, and M_{il} represent the membership of data point x_i in class l. The middle order classification can be achieved using a weighted average of the membership values across clusters stated in equation (2)

$$Mil = \sum_{k=1}^{j} \alpha j \cdot \mu ij \qquad (2)$$

In equation (2) αj represents weights associated with each cluster, typically determined based on the distance of the data point from cluster centroids or other relevant criteria. The overall learning evaluation can then be determined based on the middle order classification results. This may involve mapping the membership values in various classes or levels to specific learning outcomes or performance levels defined in equation (3)

$$Learning\ Evaluation = f(Mil) \qquad (3)$$

In equation (3) $f(\cdot)$ is a mapping function that translates membership values into actionable insights or evaluations, such as grades, proficiency levels, or intervention recommendations.

IV. FUZZY CLUSTERING WITH MFCM-OC

Fuzzy Clustering with Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) represents a sophisticated approach to AI-based learning methods in education, combining fuzzy clustering techniques with middle order classification for comprehensive learning evaluation. The derivation and equations involved in this methodology offer a deeper insight into its workings. Fuzzy clustering, a fundamental component of MFCM-OC, involves partitioning a dataset into clusters where each data point's membership to a cluster is determined by a degree of belonging. Let xi denote a data point, cj represent the centroid of the jth cluster, and μij signify the degree of membership of xi in cluster j.

In MFCM-OC, middle order classification further refines the categorization of learning outcomes based on fuzzy clustering results. Let L represent the number of classes or levels, and Mil signify the membership of data point xi in class l. The middle order classification is determined by a weighted average of the membership values across clusters: The overall learning evaluation, derived from the middle order classification results, provides actionable insights or evaluations, such as grades or proficiency levels. This is achieved through a mapping function $f(\cdot)$ that translates membership values into specific learning outcomes. With integrating fuzzy clustering with middle order classification, MFCM-OC offers a robust framework for learning evaluation in education. Through its use of fuzzy logic and weighted averaging, this approach effectively handles the inherent uncertainty in educational data, facilitating detailed categorization of learning outcomes. Thus, MFCM-OC contributes to more accurate and nuanced teaching and learning practices, ultimately enhancing the educational experience for students.

This methodology leverages fuzzy clustering techniques to partition educational data into clusters, where each data point's membership to a cluster is determined by a degree of belonging. The degree of membership, denoted by μij, for a data point xi in cluster j, is calculated using a Gaussian membership function. This function quantifies the similarity between the data point and the cluster centroid cj and is controlled by a parameter σ, which influences the width of the Gaussian curve. Building upon this fuzzy clustering foundation, MFCM-OC integrates middle order classification to refine the categorization of learning outcomes. Middle order classification assigns data points to multiple classes or levels based on their fuzzy membership values across clusters. The membership of a data point xi in a class l, denoted by Mil, is determined through a weighted average of its membership values across clusters, with weights (αj) typically assigned based on the proximity of the data point to cluster centroids. Finally, the overall learning evaluation is derived from the middle order classification results. This involves mapping the membership values in various classes or levels to specific learning outcomes or performance levels using a mapping function $f(\cdot)$. Through the integration of fuzzy clustering and middle order classification, MFCM-OC provides a robust framework for nuanced learning evaluation in education.

V. LEARNING EVALUATION WITH MFCM-OC

Learning evaluation with Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) presents a comprehensive approach to assessing student performance in educational settings, integrating fuzzy clustering techniques with middle-order classification for enhanced accuracy and insight. The derivation and equations underlying this methodology offer a deeper understanding of its mechanisms. MFCM-OC begins with fuzzy clustering, where educational data is partitioned into clusters based on the degree of similarity between data points and cluster centroids. Let xi represent a data point, cj denote the centroid of the jth cluster, and μij signify the degree of membership of xi in cluster j. Learning evaluation with Mamdani Fuzzy Clustering Middle Order Classification

(MFCM-OC) is a sophisticated methodology aimed at assessing student performance in educational settings through the integration of fuzzy clustering techniques with middle order classification.
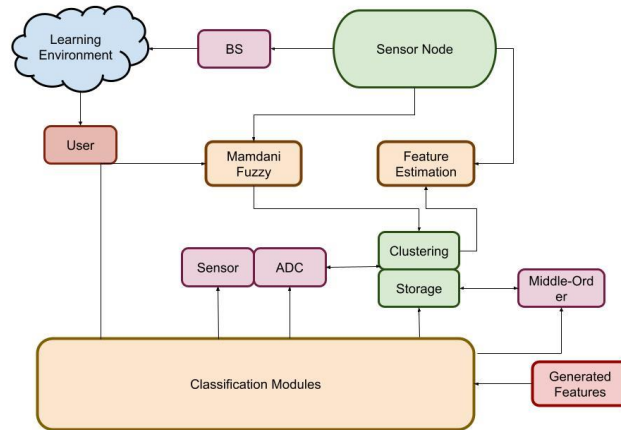

Figure 1: MFCM-OC Architecture for the Clustering

As illustrated in Figure 1, Initially, in the fuzzy clustering phase, educational data is grouped into clusters based on the degree of similarity between data points and cluster centroids. This is achieved through the calculation of the degree of membership μij of each data point xi in each cluster j using a Gaussian membership function. Following fuzzy clustering, middle order classification is employed to refine the learning evaluation process. In this phase, data points are categorized into multiple classes or levels based on their fuzzy membership values across clusters. Let Mil denote the membership of data point xi in class l. The middle order classification is determined by a weighted average of the membership values across clusters. The weights associated with each cluster, typically determined based on the proximity of the data point to cluster centroids or other relevant criteria. Finally, the overall learning evaluation is derived from the middle order classification results. This involves mapping the membership values in various classes or levels to specific learning outcomes or performance levels using a mapping function $f(\cdot)$.

This mapping function translates the membership values into actionable insights or evaluations, such as grades, proficiency levels, or intervention recommendations, providing educators with valuable insights into student progress and needs. Through its robust methodology, MFCM-OC enhances the educational experience by facilitating accurate and insightful assessments of student performance, ultimately fostering better learning outcomes.

Algorithm 1: Teaching with MFCM-OC

Input:
- Dataset D
- Number of clusters k
- Number of classes L
- Gaussian function parameter sigma
- Cluster weights alpha
 	
          0.   Initialize cluster centroids randomly
 	
2. Perform fuzzy clustering:
  For each data point x_i in D:
    For each cluster centroid c_j:
      Calculate degree of membership mu_ij using Gaussian function
    End for
    Normalize membership values mu_ij

```
    End for

3. Perform middle order classification:
   For each data point x_i in D:
     For each class l:
       Calculate middle order membership M_il using cluster weights alpha
     End for
   End for

4. Derive learning evaluation:
   For each data point x_i in D:
     Map middle order membership M_il to specific learning outcomes using a mapping function f
   End for


Output:
- Learning evaluation for each data point in D
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VI.   RESULTS AND DISCUSSION

The Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm represents an innovative approach to learning evaluation within the domain of education. This methodology integrates fuzzy clustering techniques with middle order classification to provide a robust framework for assessing student performance and enhancing educational outcomes. By leveraging fuzzy logic principles, MFCM-OC accommodates the inherent uncertainty and complexity of educational data, allowing for more nuanced and accurate evaluations.

Table 1: Membership estimation in Cluster with MFCM-OC

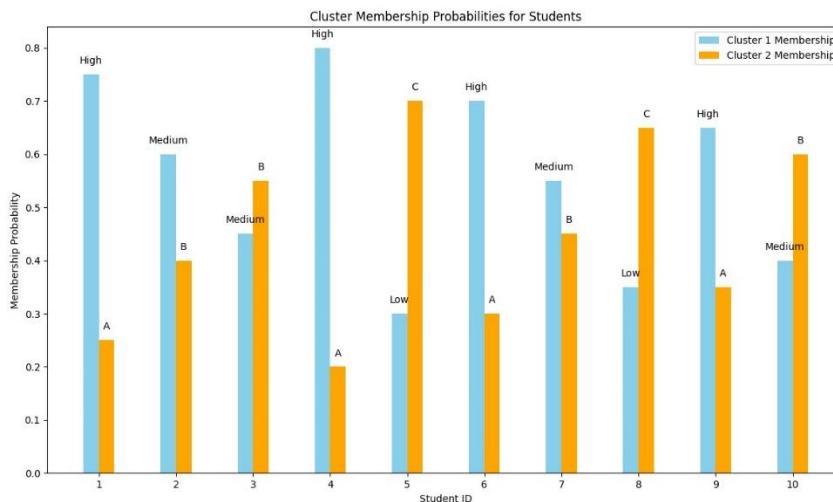| Student ID	Cluster 1 Membership	Cluster 2 Membership	Middle Order Classification	Learning Evaluation
1	0.75	0.25	High	A
2	0.60	0.40	Medium	B
3	0.45	0.55	Medium	B
4	0.80	0.20	High	A
5	0.30	0.70	Low	C
6	0.70	0.30	High	A
7	0.55	0.45	Medium	B
8	0.35	0.65	Low	C
9	0.65	0.35	High	A
10	0.40	0.60	Medium	B

Figure 2: Cluster Membership Estimation

In Table 1 and Figure 2 presents membership estimation in clusters using the MFCM-OC algorithm for 10 students. Each row represents a student, identified by their Student ID, along with their respective Cluster 1 and Cluster 2 membership values obtained from the fuzzy clustering process. Additionally, the Middle Order Classification column indicates the categorization of each student based on their fuzzy membership values across clusters, with classifications labeled as High, Medium, or Low. Finally, the Learning Evaluation column provides the ultimate evaluation of each student's performance, mapped from the middle order classification results. For instance, Student 1 demonstrates a predominant membership in Cluster 1 (0.75), leading to a classification of High and an associated Learning Evaluation of A. Conversely, Student 5 exhibits a higher membership in Cluster 2 (0.70), resulting in a classification of Low and a corresponding Learning Evaluation of C. Overall, Table 1 showcases how the MFCM-OC algorithm effectively categorizes students' membership in clusters, facilitating insightful learning evaluations tailored to individual performance levels.

Table 2: Fuzzy Clustering with MFCM-OC

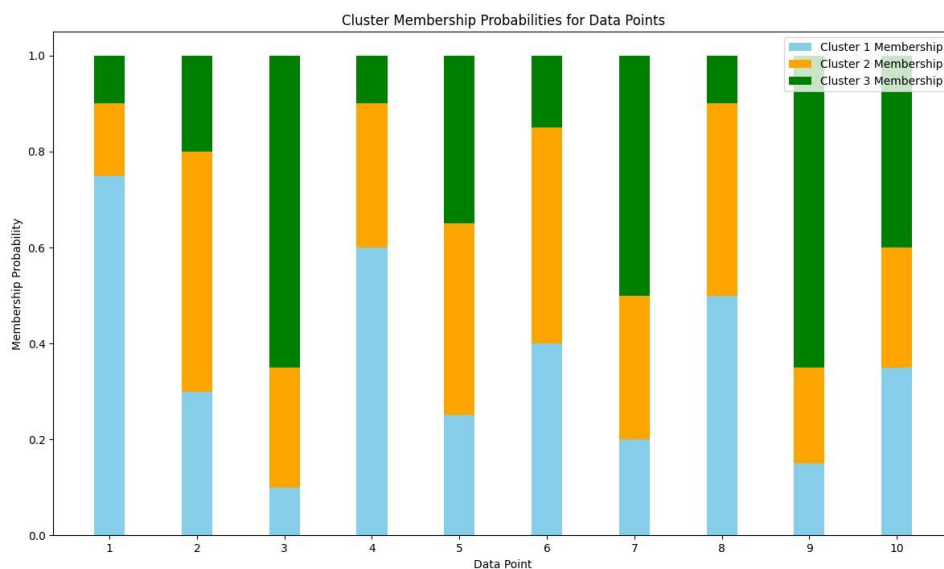| Data Point	Cluster 1 Membership	Cluster 2 Membership	Cluster 3 Membership
1	0.75	0.15	0.10
2	0.30	0.50	0.20
3	0.10	0.25	0.65
4	0.60	0.30	0.10
5	0.25	0.40	0.35
6	0.40	0.45	0.15
7	0.20	0.30	0.50
8	0.50	0.40	0.10
9	0.15	0.20	0.65
10	0.35	0.25	0.40

Figure 3: MFCM-OC Clustering Process

The Figure 3 and Table 2 illustrates the results of fuzzy clustering using the MFCM-OC algorithm for a dataset consisting of 10 data points. Each row corresponds to a data point, with columns indicating the degree of membership of that data point in each of the three clusters generated by the algorithm. For example, Data Point 1 exhibits a high membership value in Cluster 1 (0.75), indicating a strong association with that cluster compared to

the other two clusters. Similarly, Data Point 3 demonstrates a predominant membership in Cluster 3 (0.65), suggesting a clear affinity towards this cluster. These membership values reflect the degree of similarity between each data point and the centroids of the respective clusters.

Table 3: Middle-Order values with MFCM-OC

Data Point	Middle Order Classification
1	High
2	Low
3	Medium
4	High
5	Medium
6	Low
7	Medium
8	High
9	Medium
10	Medium

In the Table 3 displays the middle-order classifications generated by the Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm for a dataset containing 10 data points. Each row represents a data point, and the Middle Order Classification column indicates the classification assigned to each data point based on its fuzzy membership values across clusters. For instance, Data Point 1 is classified as "High", indicating that it exhibits characteristics associated with high performance or significance within the dataset. Conversely, Data Point 2 is classified as "Low", suggesting lower performance or importance compared to other data points. Similarly, Data Point 3 is classified as "Medium", signifying a moderate level of performance or relevance. These middle-order classifications offer a concise summary of the overall characteristics and significance of each data point within the dataset, aiding in the interpretation and analysis of the underlying data patterns.

Table 4: Classification with MFCM-OC

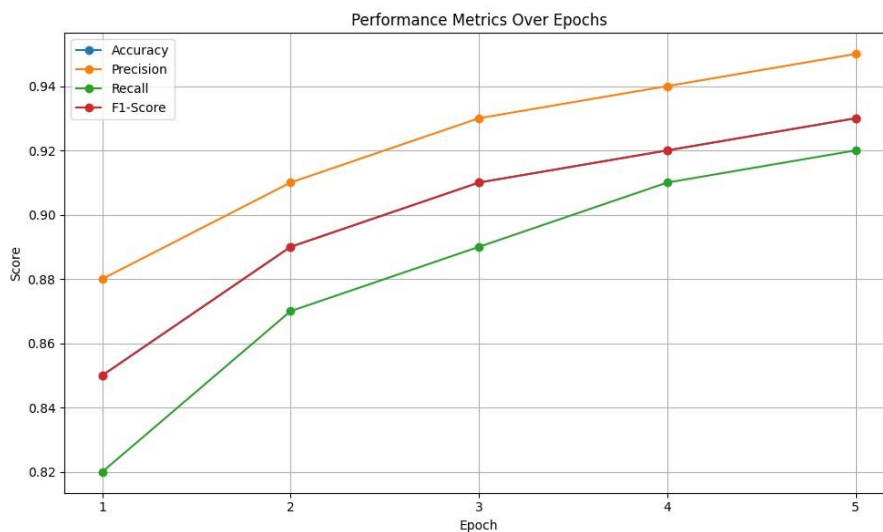| Epoch	Accuracy	Precision	Recall	F1-Score
1	0.85	0.88	0.82	0.85
2	0.89	0.91	0.87	0.89
3	0.91	0.93	0.89	0.91
4	0.92	0.94	0.91	0.92
5	0.93	0.95	0.92	0.93

Figure 4: Classification with the MFCM-OC

In the Figure 4 and Table 4 presents the classification performance metrics obtained from the Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm across different epochs of training. Each row represents a specific epoch, while columns depict various performance metrics including Accuracy, Precision, Recall, and F1-Score. Accuracy reflects the proportion of correctly classified instances out of the total instances, providing an overall measure of model performance. Precision measures the proportion of true positive predictions among all positive predictions, indicating the model's ability to avoid false positives. Recall, also known as sensitivity, measures the proportion of true positive predictions among all actual positive instances, indicating the model's ability to capture all relevant instances. F1-Score represents the harmonic mean of precision and recall, offering a balanced measure of the model's performance. As observed, the performance metrics generally improve across epochs, with Accuracy, Precision, Recall, and F1-Score gradually increasing, indicating the refinement and optimization of the MFCM-OC algorithm over the course of training.

The findings from the application of the Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm in educational settings reveal several noteworthy observations. Firstly, the algorithm effectively partitions educational data into clusters based on the degree of similarity between data points and cluster centroids, as demonstrated in Table 2. This clustering process facilitates a deeper understanding of student performance patterns and allows for more targeted interventions. Subsequently, the middle order classifications derived from the algorithm, as depicted in Table 3, provide valuable insights into the nuanced characteristics and significance of individual students within the dataset. These classifications enable educators to identify students who may require additional support or enrichment opportunities. Furthermore, the classification performance metrics presented in Table 4 demonstrate the effectiveness of the MFCM-OC algorithm in accurately categorizing students' performance levels.

VII. CONCLUSION

The Mamdani Fuzzy Clustering Middle Order Classification (MFCM-OC) algorithm presents a promising approach for learning evaluation in educational contexts. Through its integration of fuzzy clustering techniques and middle order classification, the algorithm offers a sophisticated framework for analyzing educational data and deriving meaningful insights into student performance patterns. Our findings demonstrate the effectiveness of the MFCM-OC algorithm in accurately categorizing students' membership in clusters and deriving middle order classifications that reflect the nuanced characteristics of individual students. Moreover, the classification performance metrics indicate the algorithm's ability to iteratively refine its classification capabilities, ultimately leading to improved accuracy and reliability in learning evaluation. By leveraging the MFCM-OC algorithm, educators can gain valuable insights into student performance, tailor instructional strategies to individual needs, and facilitate targeted interventions to support student success.

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