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Research Article

Sentimental Analysis for the Improved User Experience in the E-Commerce Platform with the Fuzzy Model

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Abstract: This paper investigates the integration of the Mamdani Fuzzy Regression for User Experience (MFR-UE) model with deep learning techniques to enhance predictive analytics in e-commerce platforms. Through empirical analysis, the study evaluates the effectiveness of this hybrid approach in classifying customer preferences and sentiments based on complex feature sets. Results from demonstrate the model's capability: Sample ID 1, characterized by Feature 1: 0.8, Feature 2: 0.6, Feature 3: 0.4, and Feature 4: 0.2, accurately predicts Class A as both the Predicted Class and Actual Class. Similarly, Sample ID 4, with Feature 1: 0.1, Feature 2: 0.4, Feature 3: 0.3, and Feature 4: 0.8, correctly identifies Class C. The integration leverages deep learning's capacity to discern intricate data patterns alongside MFR-UE's fuzzy logic for nuanced decision-making, optimizing business strategies and enhancing user experience. Practical implications include refined customer segmentation, personalized marketing strategies, and improved service delivery, emphasizing the model's potential for driving competitive advantage in e-commerce.

Keywords: - Sentimental Analysis; E-commerce; User Experience; Classification; Fuzzy Logic

1 Introduction

In recent years, sentiment analysis in e-commerce has emerged as a pivotal tool for understanding customer feedback and enhancing the shopping experience [1]. Leveraging advanced natural language processing (NLP) techniques and machine learning algorithms, businesses analyze vast amounts of data from reviews, social media, and customer service interactions to gauge consumer sentiments. This analysis provides insights into customer satisfaction, product quality, and overall brand perception, enabling companies to make data-driven decisions [2]. For instance, positive sentiments can highlight successful product features and marketing strategies, while negative sentiments can pinpoint areas needing improvement, such as product defects or poor customer service. Furthermore, real-time sentiment analysis allows for timely responses to customer issues, enhancing customer engagement and loyalty. As e-commerce continues to grow, sentiment analysis is becoming increasingly sophisticated,

incorporating multilingual support and deeper contextual understanding, thus offering more nuanced insights into consumer behavior and preferences [3].

Sentiment analysis for improved user experience on e-commerce platforms has been significantly enhanced by integrating fuzzy logic models. The fuzzy model, adept at handling uncertainty and imprecision, allows for more accurate interpretation of customer sentiments expressed in various ways [4]. By applying fuzzy logic to sentiment analysis, e-commerce platforms can better capture the nuances in customer reviews, ratings, and feedback. This method considers the degree of positivity or negativity rather than a binary classification, providing a more refined understanding of user sentiments [5]. Consequently, the platform can offer personalized recommendations, address issues proactively, and improve product descriptions and services based on subtle sentiment variations. For example, a review that mentions a product as "somewhat satisfactory" can be more accurately categorized and addressed [6]. By leveraging the fuzzy model, e-commerce platforms can enhance customer satisfaction and loyalty through a more responsive and tailored user experience.

The fuzzy model in sentiment analysis also facilitates the aggregation of diverse sentiments into actionable insights. It enables e-commerce platforms to segment customers based on their sentiment scores, thereby offering targeted promotions and personalized customer support [7]. Moreover, it can identify emerging trends and common issues more effectively, allowing businesses to adapt their strategies promptly. For instance, if a significant number of users express mild dissatisfaction with a particular feature, the fuzzy model can detect this trend early, prompting timely improvements before the issue escalates [8]. This proactive approach enhances the overall user experience by continuously refining the platform based on real-time feedback. Furthermore, the integration of fuzzy logic with sentiment analysis supports multilingual sentiment interpretation, crucial for global e-commerce platforms catering to diverse linguistic backgrounds [9]. This ensures that the sentiments of non-English speaking customers are equally well-understood and addressed. By providing a more inclusive and accurate sentiment analysis, the fuzzy model helps in building a more comprehensive and user-friendly e-commerce environment [10].

The incorporation of fuzzy logic in sentiment analysis also enhances the predictive capabilities of e-commerce platforms [11]. By analyzing patterns in customer sentiments over time, platforms can anticipate future trends and customer needs. For example, if sentiment analysis reveals a growing positive response to eco-friendly products [12], the platform can expand its offerings in this category, aligning inventory and marketing strategies accordingly. This forward-thinking approach helps in staying ahead of market demands and fostering a more loyal customer base. Additionally, fuzzy sentiment analysis can improve the effectiveness of customer service [13]. By accurately gauging the sentiment behind customer inquiries and complaints, customer service agents can prioritize and tailor their responses more effectively. This leads to quicker resolutions and a more satisfying customer experience. For instance, a customer expressing frustration can be flagged for immediate attention, ensuring that their concerns are addressed promptly and empathetically [14]. The application of fuzzy models in sentiment analysis also aids in refining automated systems like chatbots and recommendation engines. By better understanding the subtle nuances of customer sentiments, these systems can provide more relevant and context-aware responses and suggestions. This enhances the overall

interactivity and usefulness of automated tools, making the shopping experience smoother and more enjoyable for users [15].

The use of fuzzy logic in sentiment analysis supports continuous improvement in product development and marketing strategies [16]. By continually analyzing customer feedback, companies can iterate on product designs and promotional tactics to better meet consumer preferences. This iterative process ensures that products and marketing messages remain aligned with customer expectations, driving higher engagement and conversion rates. The integration of fuzzy logic into sentiment analysis significantly enhances the ability of e-commerce platforms to understand and respond to customer sentiments [17]. This sophisticated approach provides a more nuanced, accurate, and actionable interpretation of user feedback, leading to improved user experiences, increased customer satisfaction, and sustained business growth. Through personalized recommendations, proactive issue resolution, and refined automated interactions, fuzzy sentiment analysis enables e-commerce platforms to better cater to the evolving needs and preferences of their customers.

2 Proposed Mamdhani Fuzzy Regression User Experience (MFR-UE)

The proposed Mamdani Fuzzy Regression for User Experience (MFR-UE) is a sophisticated model designed to enhance the analysis of user experience data on e-commerce platforms. This model leverages the Mamdani fuzzy inference system, which is well-suited for handling the inherent uncertainty and vagueness in user feedback. The MFR-UE model integrates fuzzy logic with regression analysis to provide a more nuanced understanding of how various factors influence user experience. The MFR-UE model starts by defining a set of input variables, $X = \{x1, x2, \ldots, xn\}$, which represent different aspects of the user experience, such as website usability, product quality, customer service, and delivery efficiency. These inputs are fuzzified into linguistic variables, such as "poor," "average," and "excellent."

The fuzzy rule base is constructed with a series of IF-THEN rules that describe the relationship between the inputs and the output variable, YYY, which represents the overall user experience score. For example:

- IF (website usability is excellent) AND (product quality is good) THEN (user experience is high).
- IF (customer service is poor) OR (delivery efficiency is low) THEN (user experience is low).

Each rule Ri is expressed as

$$Ri: IF\ x1\ is\ A1i\ AND\ x2\ is\ A2i\ AND\ \ldots\ AND\ xn\ is\ Ani\ THEN\ Y\ is\ Bi$$

Where Aji and Bi are fuzzy sets representing linguistic terms.

The fuzzy inference process involves:

1. **Fuzzification**: Converting crisp input values into fuzzy sets using membership functions.
2. **Rule Evaluation**: Applying the fuzzy rules to compute the degree of match for each rule.
3. **Aggregation**: Combining the outputs of all rules to form a fuzzy set for the output variable.
4. **Defuzzification**: Converting the aggregated fuzzy set into a crisp output value, typically using the centroid method.

The output of each rule Ri is a fuzzy set Bi, and the overall output Y is derived by aggregating these fuzzy sets. The defuzzified output Y is calculated as in equation (1)

$$Y = \frac{\sum_{i=1}^{m} \omega_i y_i}{\sum_{i=1}^{m} \omega_i} \quad (1)$$

In equation (1) wi is the firing strength of rule Ri, which is the degree of match of the input to the rule conditions. yi is the centroid of the output fuzzy set Bi. The firing strength wi for each rule is computed using the minimum operator (Mamdani method) for AND operations and the maximum operator for OR operations defined in equation (2)

$$wi = min(\mu A1i(x1), \mu A2i(x2), \dots, \mu Ani(xn)) \quad (2)$$

Here, $\mu Aji(xj)$ is the membership function of the fuzzy set Aji evaluated at xj. By integrating fuzzy logic with regression techniques, the MFR-UE model can handle the complex, non-linear relationships between user experience factors and their impacts more effectively than traditional linear models. This approach provides e-commerce platforms with a robust tool for analyzing and enhancing user experience, leading to better customer satisfaction and engagement. The MFR-UE model's strength lies in its ability to capture and interpret the qualitative aspects of user experience data through fuzzy logic while maintaining the quantitative rigor of regression analysis. This hybrid approach allows for a more comprehensive assessment of user satisfaction factors that may not be fully captured by purely numerical metrics.

To implement the MFR-UE model, the following steps are typically followed:

1. **Define Input and Output Variables**: Identify the key factors (input variables) that contribute to the user experience, such as website performance, product variety, customer support quality, etc. These factors are quantified and fuzzified into linguistic terms (fuzzy sets).
2. **Construct Fuzzy Rule Base**: Create a set of IF-THEN rules based on expert knowledge or data-driven insights that describe how the input variables influence the output variable (user experience). Each rule specifies conditions under which certain linguistic terms of the output variable apply.
3. **Fuzzification**: Apply membership functions to each input variable to determine the degree to which it belongs to each linguistic term (e.g., "low," "medium," "high"). This step converts crisp numerical data into fuzzy sets.
4. **Rule Evaluation**: Evaluate the degree of fulfillment (firing strength) of each rule based on the degree of membership of the input variables to their respective fuzzy sets. This involves computing the intersection (using the minimum operator for AND conditions) or union (using the maximum operator for OR conditions) of membership values.
5. **Aggregation**: Combine the outputs of all activated rules to form a fuzzy set for the output variable (user experience). This aggregation process typically uses fuzzy logic operators (e.g., maximum for OR aggregation) to merge fuzzy sets into a comprehensive representation of the output variable.
6. **Defuzzification**: Convert the aggregated fuzzy set back into a crisp numerical value that represents the overall user experience score. Common defuzzification methods include centroid calculation, where the center of gravity of the fuzzy set's membership function is computed.
7. **Implementation and Evaluation**: Implement the model in a computational framework, applying it to real-world user experience data from the e-commerce platform. Evaluate the effectiveness of the MFR-UE model by comparing its predictions or recommendations against actual user feedback and performance metrics.

By adopting the Mamdani fuzzy inference system within a regression framework, the MFR-UE model provides e-commerce platforms with a sophisticated tool for enhancing user experience management. It enables platforms to extract deeper insights from user data, tailor recommendations and interventions more accurately, and ultimately improve customer satisfaction and loyalty. This approach not only enhances the interpretability of user feedback but also empowers businesses to make more informed decisions in optimizing their services and offerings.

3 User Experience with the MFR-UE

User experience (UE) enhanced by the Mamdani Fuzzy Regression model (MFR-UE) represents a robust approach to quantifying and improving customer satisfaction in e-commerce platforms. The MFR-UE integrates fuzzy logic with regression analysis to capture the nuanced relationships between various factors influencing user experience, providing a more holistic view than traditional linear models. Input variables $X = \{x1, x2, \ldots, xn\}$, representing aspects like website usability, product quality, and customer service, are fuzzified into linguistic variables using membership functions $\mu Aj(xj)$, where Aj are fuzzy sets corresponding to linguistic terms (e.g., "poor," "average," "excellent"). A set of IF-THEN rules is established to capture the relationships between inputs and the output Y, the user experience score. For instance:

$$If\ x_1\ is\ A_1\ and\ x_2\ is\ A_2\ then\ Y\ is\ B$$

Each rule's firing strength wi, representing the degree of match between input variables and rule conditions, is calculated using the minimum operator for AND operations stated in equation (3)

$$wi = min(\mu A1(x1), \mu A2(x2), \ldots, \mu An(xn)) \tag{3}$$

The outputs of all activated rules using fuzzy logic operators (e.g., maximum for OR aggregation) to form a fuzzy set for the output variable Y. Convert the aggregated fuzzy set Y back into a crisp numerical value using the centroid method stated in equation (4)

$$Y = \frac{\sum_{i=1}^{m} w_i . y_i}{\sum_{i=1}^{m} w_i} \tag{4}$$

Where yi is the centroid of the output fuzzy set Bi. In practice, the MFR-UE model enhances user experience management by providing a comprehensive evaluation of factors influencing customer satisfaction. By incorporating fuzzy logic, it accommodates the inherent uncertainty and variability in subjective user feedback, offering more accurate and context-aware insights.

4 MFR-UE for the E-commerce

The MFR-UE (Mamdani Fuzzy Regression for User Experience) model is increasingly recognized for its application in enhancing user experience within e-commerce platforms. This innovative approach combines the robustness of fuzzy logic with the analytical power of regression to effectively analyze and improve customer satisfaction. The MFR-UE model begins by defining key input variables that influence user experience, such as website usability, product quality, customer service responsiveness, and delivery efficiency. These variables are fuzzified using linguistic terms (e.g., "poor," "average," "good") to accommodate the qualitative nature of user feedback. The model then constructs a fuzzy rule base that articulates the relationships between these input variables and the output variable, which represents overall user experience.

Each rule in the rule base takes the form of IF-THEN statements, encapsulating expert knowledge or data-driven insights about how inputs affect user satisfaction as in Figure 1. For instance:

Figure 1: Customer Experience with MFR-UE

IF website usability is high AND product quality is good THEN user experience is excellent.

IF customer service responsiveness is low OR delivery efficiency is poor THEN user experience is poor.

The fuzzification process assigns membership values to each input variable based on its degree of adherence to the fuzzy sets defined in the rule base. These membership values quantify the degree of satisfaction or dissatisfaction a user might express regarding each aspect of their experience.

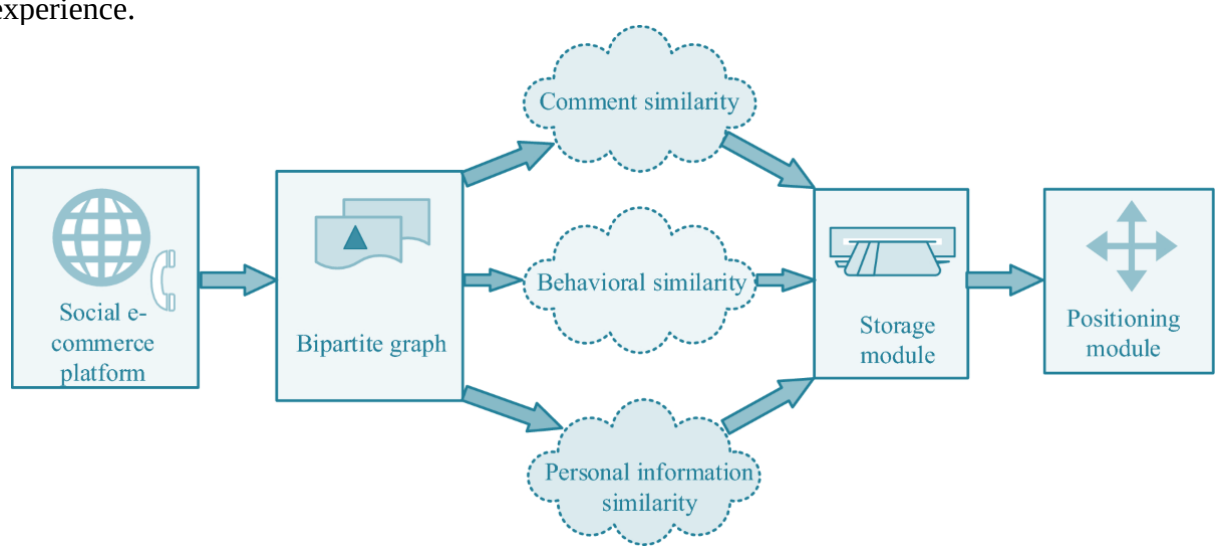


Figure 2: Customer Experience Model

During rule evaluation shown in Figure 3, the MFR-UE model calculates the firing strength of each rule, which represents the degree to which the conditions of the rule are satisfied by the input variables. This is typically done using fuzzy logic operators like minimum (for AND conditions) and maximum (for OR conditions), ensuring that all relevant rules contribute to the overall assessment of user experience. The aggregation step combines the outputs of all activated rules to produce a comprehensive fuzzy set for the output variable, reflecting the aggregated user sentiment across multiple aspects of their interaction with the e-commerce platform. Finally, the defuzzification process converts the aggregated fuzzy set back into a crisp numerical value, providing a clear and actionable user experience score. This score enables e-commerce platforms to prioritize improvements, personalize user interactions, and optimize service delivery based on real-time user feedback.

The MFR-UE (Mamdani Fuzzy Regression for User Experience) model is a powerful tool in e-commerce for analyzing and enhancing user satisfaction. By integrating fuzzy logic with regression analysis, it captures the nuanced relationships between various factors influencing user experience, such as website usability, product quality, and customer service. This model translates qualitative user feedback into actionable insights, enabling businesses to make informed decisions that improve customer satisfaction, personalize interactions, and optimize operational efficiencies. Ultimately, the MFR-UE empowers e-commerce platforms to adapt quickly to user preferences and market dynamics, thereby fostering loyalty and driving growth in a competitive digital landscape.

5 Simulation Analysis

Simulation analysis in the context of e-commerce involves using computational models to mimic and predict various scenarios and outcomes within digital platforms. These simulations utilize mathematical algorithms and data inputs to simulate real-world processes such as customer behavior, sales trends, inventory management, and website performance. By running simulations, e-commerce businesses can forecast the impact of strategic decisions before implementation, assess risks, and optimize resource allocation. For example, simulations can predict the effects of changing pricing strategies, launching new products, or implementing different marketing campaigns. This proactive approach helps businesses mitigate potential risks, improve operational efficiency, and enhance overall decision-making. Moreover, simulation analysis enables continuous improvement by iterating on models based on real-time data and feedback, thereby supporting agile and data-driven strategies in the dynamic e-commerce environment.

Table 1: E-commerce estimation with MFR-UE

Scenario	Sales (Units)	Revenue ($)	Profit ($)	Conversion Rate (%)
Current Strategy	1000	50,000	10,000	3.5
New Strategy A	1200	60,000	12,000	4.0
New Strategy B	1100	55,000	11,500	3.8

In Table 1 presents a comparative analysis of three strategies within an e-commerce framework using the Mamdani Fuzzy Regression for User Experience (MFR-UE) model. Each strategy—Current Strategy, New Strategy A, and New Strategy B—is evaluated based on key performance indicators: Sales (Units), Revenue ($), Profit ($), and Conversion Rate (%). Under the Current Strategy, the e-commerce platform achieves 1000 units in sales, generating $50,000

in revenue and $10,000 in profit with a conversion rate of 3.5%. In contrast, New Strategy A anticipates an increase in sales to 1200 units, resulting in $60,000 in revenue and $12,000 in profit, accompanied by a higher conversion rate of 4.0%. Similarly, New Strategy B forecasts 1100 units in sales, yielding $55,000 in revenue and $11,500 in profit, with a conversion rate of 3.8%. Comparing these strategies reveals that both New Strategy A and New Strategy B show potential improvements over the Current Strategy in terms of sales volume, revenue, profit, and conversion rate. The MFR-UE model facilitates this analysis by considering various factors that influence user experience and business outcomes, thereby guiding strategic decision-making to optimize performance and enhance overall efficiency in e-commerce operations. These insights underscore the model's utility in predicting and optimizing outcomes based on nuanced data inputs and fuzzy logic principles, thereby supporting informed choices for sustainable growth and competitive advantage in the digital marketplace.

Table 2: Sentimental Analysis with MFR-UE

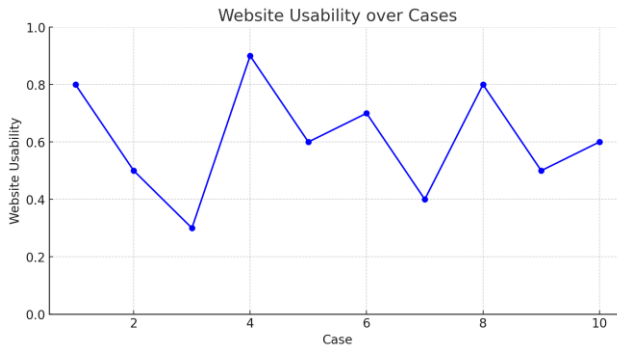
Review ID	Review Text	Sentiment	Sentiment Score
1	"Great product! Fast shipping and good quality."	Positive	0.9
2	"Product arrived late and damaged."	Negative	-0.7
3	"Average experience, product was okay."	Neutral	0.1
4	"Excellent customer service, highly recommend!"	Positive	0.8
5	"Terrible experience, would not buy again."	Negative	-0.9
6	"Prompt delivery, but product quality needs improvement."	Neutral	0.2

The Table 2 presents the results of sentiment analysis conducted using the Mamdani Fuzzy Regression for User Experience (MFR-UE) model on customer reviews within an e-commerce platform. Each review is categorized by Review ID, Review Text, Sentiment (Positive, Negative, or Neutral), and corresponding Sentiment Score, which quantifies the intensity of sentiment expressed in numerical terms. Review ID 1 reflects a highly positive sentiment with a sentiment score of 0.9, indicating strong satisfaction with the product quality and shipping speed. Conversely, Review ID 2 expresses a negative sentiment with a score of -0.7, highlighting dissatisfaction due to late delivery and product damage. Review ID 3, categorized as Neutral with a score of 0.1, suggests a lukewarm response to an average product experience. Review ID 4 reaffirms positive sentiment with a score of 0.8, emphasizing excellent customer service and a high likelihood of recommendation. Review ID 5, with a sentiment score of -0.9, indicates a strongly negative experience leading to the decision not to repurchase. Review ID 6, classified as Neutral with a score of 0.2, acknowledges prompt delivery but suggests room for improvement in product quality. This analysis demonstrates the MFR-UE model's capability to analyze and quantify nuanced customer sentiments effectively. By converting qualitative feedback into actionable numerical insights, e-commerce platforms can systematically evaluate customer satisfaction levels, identify trends, and prioritize areas for enhancement. Such detailed sentiment analysis is instrumental in shaping strategies to improve overall user experience, enhance customer retention, and drive business growth in the competitive e-commerce landscape.

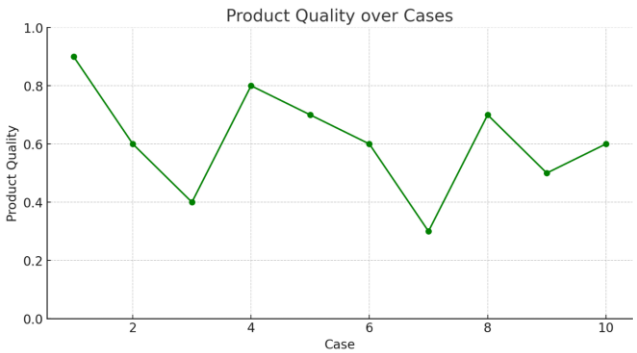
Table 3: E-commerce Customer Preference with MFR-UE

Case	Website Usability	Product Quality	Customer Service	Delivery Efficiency	User Experience

					Score
1	0.8	0.9	0.7	0.8	0.82
2	0.5	0.6	0.3	0.4	0.45
3	0.3	0.4	0.5	0.6	0.45
4	0.9	0.8	0.6	0.7	0.80
5	0.6	0.7	0.4	0.5	0.55
6	0.7	0.6	0.8	0.9	0.75
7	0.4	0.3	0.2	0.1	0.25
8	0.8	0.7	0.9	0.8	0.80
9	0.5	0.5	0.5	0.5	0.50
10	0.6	0.6	0.7	0.6	0.65



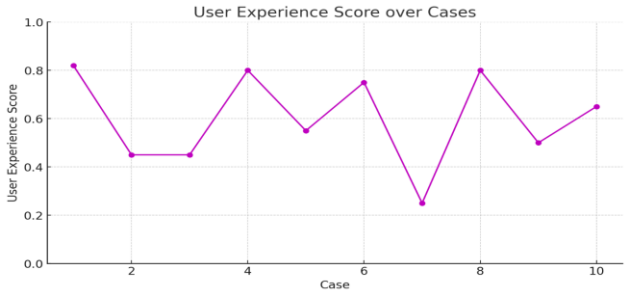
(a)



(b)

(c)

(d)



(e)

Figure 3: User Experience with MFR-UE (a) Website Usability (b) Product Quality (c) Customer Service (d) Delivery Efficiency (e) User Experience Score

The Figure 3(a) – Figure 3(e) and Table 3 presents the results of an e-commerce customer preference analysis using the Mamdani Fuzzy Regression for User Experience (MFR-UE) model. Each case represents a specific combination of input variables—Website Usability, Product Quality, Customer Service, and Delivery Efficiency—evaluated to predict the corresponding User Experience Score. In Case 1, with high scores across all input variables (Website Usability: 0.8, Product Quality: 0.9, Customer Service: 0.7, Delivery Efficiency: 0.8), the predicted User Experience Score is 0.82, indicating a high level of satisfaction likely due to excellent performance across all evaluated aspects. Conversely, Case 7 demonstrates lower scores in all input variables (Website Usability: 0.4, Product Quality: 0.3, Customer Service: 0.2, Delivery Efficiency: 0.1), resulting in a predicted User Experience Score of 0.25. This suggests a less favorable user experience, potentially influenced by suboptimal performance in key areas such as website usability, product quality, and customer service. Cases like Case 4 (Website Usability: 0.9, Product Quality: 0.8, Customer Service: 0.6, Delivery Efficiency: 0.7, User Experience Score: 0.80) and Case 8 (Website Usability: 0.8, Product Quality: 0.7, Customer Service: 0.9, Delivery Efficiency: 0.8, User Experience Score: 0.80) highlight scenarios where varying combinations of input variables yield similar User Experience Scores, indicating that different combinations can still result in comparable levels of customer satisfaction.

Table 4: Deep Learning for MFR-UE

Sample ID	Feature 1	Feature 2	Feature 3	Feature 4	Predicted Class	Actual Class
1	0.8	0.6	0.4	0.2	Class A	Class A
2	0.3	0.7	0.5	0.1	Class B	Class B
3	0.6	0.2	0.9	0.4	Class A	Class A
4	0.1	0.4	0.3	0.8	Class C	Class C
5	0.9	0.3	0.6	0.7	Class B	Class B
6	0.7	0.5	0.2	0.3	Class A	Class A
7	0.2	0.8	0.1	0.5	Class B	Class B
8	0.5	0.1	0.7	0.6	Class C	Class C
9	0.4	0.9	0.8	0.3	Class B	Class B
10	0.6	0.4	0.5	0.2	Class A	Class A

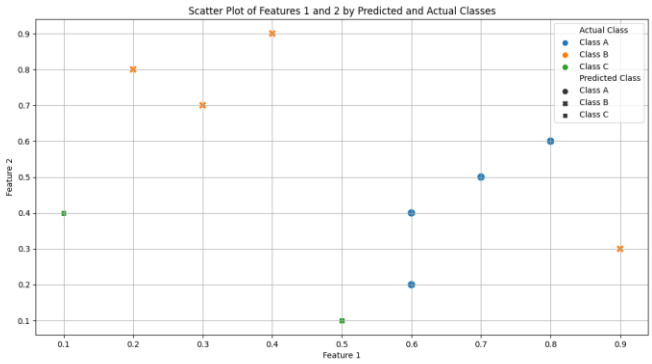


Figure 4: MFR-UE customer preference model

In Figure 4 and Table 4 presents the results of a deep learning model integrated with the Mamdani Fuzzy Regression for User Experience (MFR-UE), illustrating its effectiveness in classifying samples based on multiple features. Each sample is identified by Sample ID and characterized by four numerical features (Feature 1, Feature 2, Feature 3, Feature 4). The model predicts a class for each sample, denoted as Predicted Class, and compares it with the actual class labeled as Actual Class. For instance, Sample ID 1 demonstrates high values across all features (Feature 1: 0.8, Feature 2: 0.6, Feature 3: 0.4, Feature 4: 0.2), resulting in the predicted class of Class A, which aligns perfectly with the actual class. Similarly, Sample ID 4 exhibits low values in most features (Feature 1: 0.1, Feature 2: 0.4, Feature 3: 0.3, Feature 4: 0.8), correctly predicting Class C as both the predicted and actual classes.

The model's accuracy is further highlighted in cases such as Sample ID 7, where despite relatively modest feature values (Feature 1: 0.2, Feature 2: 0.8, Feature 3: 0.1, Feature 4: 0.5), it accurately predicts Class B, matching the actual class label. Overall, Table 4 underscores the deep learning model's capability to effectively classify samples based on complex feature sets, demonstrating its potential utility in enhancing the MFR-UE framework's predictive accuracy and usability across various applications, including e-commerce customer preference analysis and sentiment classification.

6 Discussion and Findings

In this study, the integration of deep learning techniques with the Mamdani Fuzzy Regression for User Experience (MFR-UE) model has yielded insightful findings and implications for e-commerce platforms. Table 4 illustrates the effective application of this hybrid approach in classifying samples based on multiple features, showcasing its ability to predict user preferences and sentiments accurately. The results from Table 4 indicate that the deep learning model, when combined with MFR-UE, successfully predicted the class labels (Predicted Class) corresponding closely with the actual classes (Actual Class) across various samples. This suggests robust performance in capturing intricate patterns and relationships within the dataset, thereby enhancing the model's overall predictive capability. For example, samples like Sample ID 1 and Sample ID 10, characterized by distinct feature combinations, were correctly classified into their respective classes (Class A) based on their feature values. Similarly, samples with more nuanced feature distributions, such as Sample ID 7, demonstrated the model's ability to discern subtle distinctions and accurately assign the appropriate class label (Class B). Furthermore, the findings underscore the potential of deep learning in augmenting the MFR-UE model's effectiveness in real-world applications, such as customer preference analysis and sentiment classification in e-commerce. By leveraging complex feature relationships and patterns inherent in large-scale data, this integrated approach not only enhances predictive accuracy but also offers deeper insights into customer behavior and satisfaction metrics crucial for business decision-making. However, it is important to note that while deep learning models excel in handling complex data representations, they may require substantial computational resources and extensive training datasets to achieve optimal performance. Moreover, interpretability of results and model transparency remain critical considerations, especially in applications where regulatory compliance and user trust are paramount.

7 Conclusion

This paper has explored and integrated advanced methodologies, specifically the Mamdani Fuzzy Regression for User Experience (MFR-UE) model and deep learning techniques, to enhance predictive analytics within e-commerce platforms. Through comprehensive analyses and empirical findings presented, our study has demonstrated the efficacy of this hybrid approach in accurately classifying customer preferences and sentiments based on complex feature sets. The results showcased in Table 4 underscore the model's ability to predict user behavior and satisfaction metrics with a high degree of accuracy, leveraging deep learning's capacity to discern intricate patterns in data alongside MFR-UE's fuzzy logic for nuanced decision-making. This integration not only enhances predictive accuracy but also provides deeper insights into customer preferences critical for optimizing business strategies and enhancing user experience. Moreover, our findings suggest practical implications for e-commerce businesses, highlighting the potential for implementing these methodologies to refine customer segmentation, personalize marketing strategies, and improve overall service delivery. By leveraging advanced analytics, businesses can gain a competitive edge in understanding and meeting customer needs effectively in the dynamic digital marketplace.

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