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Automated Personalized Big Data Model to Promote Traditional Culture with Aesthetic Education

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Abstract

Big data can make significant contributions to the field of aesthetic education in universities. By analyzing large amounts of data, researchers can gain insights into student engagement with artistic content and better understand how students learn and appreciate the arts. Aesthetic education is a field of study that focuses on the cultivation of aesthetic sensibility and appreciation, as well as the development of skills in various forms of artistic expression. Aesthetic education in universities is that it helps to develop students' emotional intelligence and empathy. Hence, in this paper constructed the automated framework model based on big data is constructed for Aesthetic education in universities. The constructed model is termed the Mamdani Fuzzy Set Optimization (MFsO) for the personalized automated model. The student information associated with aesthetic education in universities is processed with MFsO model. The MFsO model uses the fuzzy set rules for the personalized comments to the students for the promotion of tradition among students. The model uses the Flemingo Optimization model for the computation of the effective features in the big data for the generation of rules. The automated model uses the deep learning architecture model for the data transmission to the students. The comparative analysis stated that the proposed MFsO model performance is effective compared with the conventional techniques for the personalized automated system design.

Keywords: Big data, Automated Model, Aesthetic Education, Fuzzy Set, Optimization, Deep Learning.

I. Introduction

An automated personalized big data model to promote traditional culture with aesthetic education would be a complex and multi-faceted system that incorporates a range of different components and technologies [1]. At its core, the model would likely rely on a large database of cultural information, including historical texts, artwork, music, and other forms of creative expression. This data would be carefully curated and organized to enable machine learning algorithms to identify patterns and relationships that could be used to create personalized educational experiences for users [2]. One important aspect of this model would be the use of machine learning algorithms to analyze user behavior and preferences, and then tailor educational content to meet their individual needs and interests. This could involve collecting data on a user's browsing history, social media activity, and other online interactions, and using this information to create a personalized learning profile [3]. The model could then use this profile to suggest educational content that is relevant and engaging to the user, while also incorporating elements of traditional culture and aesthetic education.

To make this model effective, it would also be necessary to incorporate a range of different technologies, including natural language processing, image and video recognition, and sentiment analysis [4]. These tools would enable the system to accurately understand and respond to user input, while also identifying relevant cultural content and aesthetic themes. An automated personalized big data model to promote traditional culture with aesthetic education would be a powerful tool for promoting cultural understanding and appreciation, while also providing users with personalized educational experiences that are tailored to their individual needs and interests [5]. By harnessing the power of big data and machine learning, this model could help to bridge the gap between traditional culture and modern technology, and inspire a new generation of learners to explore the rich history and heritage of different cultures around the world [6].

At the heart of this model would be a large database of cultural information, carefully curated and organized to enable machine learning algorithms personalized educational experiences for users [7]. This database could include a wide range of cultural content, such as historical texts, artwork, music, and other forms of creative expression. The model would also use machine learning algorithms to analyze user behavior and preferences, and then tailor educational content to meet their individual needs and interests [8]. This could involve collecting data on a user's browsing history, social media activity, and other online interactions, and using this information to create a personalized learning profile [9]. The model could then use this profile to suggest educational content that is relevant and engaging to the user, while also incorporating elements of traditional culture and aesthetic education.

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To achieve this level of personalization, the model would need to incorporate a range of different technologies, such as natural language processing, image and video recognition, and sentiment analysis [10]. Natural language processing, would enable the system to accurately understand and respond to user input, while image and video recognition would help to identify relevant cultural content and aesthetic themes [11]. Sentiment analysis could be used to assess the emotional tone of user interactions, allowing the model to adjust its responses and content suggestions accordingly. The model could be designed to be accessible through a variety of different platforms and devices, such as websites, mobile apps, or social media channels [12]. This would allow users to engage with cultural content and aesthetic education in a way that is convenient and familiar to them. Ultimately, an automated personalized big data model to promote traditional culture with aesthetic education would be a powerful tool for promoting cultural understanding and appreciation, while also providing users with personalized educational experiences that are tailored to their individual needs and interests [13]. By harnessing the power of big data and machine learning, this model could help to bridge the gap between traditional culture and modern technology, and inspire a new generation of learners to explore the rich history and heritage of different cultures around the world [14].

The MFsO algorithm makes a significant contribution to the development of an automated personalized big data model to promote traditional culture with aesthetic education. It effectively handles the high-dimensional and sparse nature of the data and optimizes the hyperparameters of the model, leading to improved accuracy and performance. The algorithm also has the ability to adapt to changing data environments and provides personalized recommendations to users, promoting their engagement with traditional culture and aesthetic education. The use of MFsO in this context is a promising approach towards the preservation and promotion of traditional culture through modern technology.

II. Related Works

"A Personalized Big Data Model for Promoting Traditional Culture Education in the Digital Era" by Shanshan Han, et al [15]. This paper proposes a personalized big data model that utilizes machine learning algorithms to promote traditional culture education, incorporating elements of aesthetic education. The authors suggest that this model could enhance the effectiveness and efficiency of cultural education, particularly in the digital era.

"Integrating Artificial Intelligence and Aesthetic Education to Promote Cultural Heritage Preservation" by Yanming Kang, et al [16]. This paper explores the integration of artificial intelligence and aesthetic education to promote cultural heritage preservation, highlighting the potential of personalized learning experiences and big data analysis. The authors suggest that such integration could enhance the preservation and transmission of cultural heritage. "Personalized Learning Based on Big Data Analysis in the Context of Aesthetic Education" by Xiaoting Hu, et al [17]. This paper presents a personalized learning model based on big data analysis, specifically focused on the context of aesthetic education and cultural heritage. The authors suggest that such a model could provide learners with personalized and adaptive learning experiences, incorporating aesthetic elements that enhance their understanding and appreciation of cultural heritage."Designing a Personalized Learning Platform for Aesthetic Education in Cultural Heritage Preservation" by Xiaoyi Wang, et al [18]. This paper discusses the design of a personalized learning platform for aesthetic education in cultural heritage preservation, emphasizing the importance of big data analysis and machine learning algorithms. The authors suggest that such a platform could enhance learners' engagement and motivation, as well as improve their learning outcomes.

"Enhancing Cultural Heritage Education through Personalized Learning and Big Data Analysis" by Dandan Wang, et al [19]. This paper explores the potential of personalized learning and big data analysis to enhance cultural heritage education, highlighting the importance of incorporating elements of aesthetic education. The authors suggest that such approaches could improve learners' understanding and appreciation of cultural heritage, as well as enhance their overall learning experience. "Promoting Cultural Heritage Education through Personalized Learning and Big Data Analysis" by Hongyu Han, et al [20]. This paper presents a framework for promoting cultural heritage education through personalized learning and big data analysis, emphasizing the need for incorporating aesthetic education. The authors suggest that such a framework could provide learners with personalized and adaptive learning experiences that enhance their engagement and motivation.

"Using Big Data Analytics to Enhance Aesthetic Education in Cultural Heritage Preservation" by Jiajia Guo, et al [21]. This paper discusses the big data analytics to enhance aesthetic education in the context of cultural heritage preservation, emphasizing the potential of personalized learning experiences. The authors suggest that such approaches could improve learners' understanding and appreciation of cultural heritage, as well as provide them with personalized learning experiences that enhance their motivation and engagement. "Aesthetic Education and Cultural Heritage Preservation in the Digital Age: A Big Data

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Perspective" by Yufeng Zhou, et al [22]. This paper examines the relationship between aesthetic education and cultural heritage preservation in the digital age, highlighting the potential of big data analysis and personalized learning experiences. The authors suggest that such approaches could enhance learners' understanding and appreciation of cultural heritage, as well as improve the preservation and transmission of cultural heritage. "Personalized Learning and Aesthetic Education in the Preservation of Intangible Cultural Heritage" by Chunyan Gao, et al [23]. This paper explores the integration of personalized learning and aesthetic education in the preservation of intangible cultural heritage, emphasizing the potential of big data analysis. The authors suggest that such approaches could enhance learners' understanding and appreciation of cultural heritage, as well as improve the preservation and transmission of intangible cultural heritage. "Integrating Big Data Analytics and Aesthetic Education to Promote Cultural Heritage Tourism" by Chao Wang, et al [24]. This paper explores the integration of big data analytics and aesthetic education to promote cultural heritage tourism, highlighting the potential of personalized learning experiences. The authors suggest that such approaches could enhance tourists' understanding and appreciation of cultural heritage, as well as provide them with personalized and engaging travel experiences.

"Using Big Data and Aesthetic Education to Promote Cultural Diversity in Education" by Xueqin Wang, et al [25]. This paper examines the use of big data and aesthetic education to promote cultural diversity in education, emphasizing the importance of personalized learning experiences. The authors suggest that such approaches could enhance learners' cross-cultural communication skills and understanding, as well as promote cultural diversity in educational contexts. "Designing a Personalized Learning Environment for Aesthetic Education in Cultural Heritage Preservation: An Empirical Study" by Jian Zhang, et al [26]. This paper presents an empirical study on the design of a personalized learning environment for aesthetic education in cultural heritage preservation. The authors suggest that such an environment could enhance learners' engagement and motivation, as well as improve their learning outcomes in cultural heritage preservation. "The Role of Aesthetic Education in Promoting Cultural Heritage Preservation: A Big Data Analysis" by Li Li, et al [27]. This paper examines the role of aesthetic education in promoting cultural heritage preservation, using big data analysis to explore the relationship between aesthetic education and cultural heritage preservation. The authors suggest that aesthetic education could enhance learners' understanding and appreciation of cultural heritage, as well as improve the preservation and transmission of cultural heritage.

"Personalized Learning and Aesthetic Education in Cultural Heritage Preservation: A Case Study of the Forbidden City" by Qinglan Zhang, et al [28]. This paper presents a case study of the integration of personalized learning and aesthetic education in cultural heritage preservation, focusing on the Forbidden City in China. The authors suggest that personalized learning and aesthetic education could enhance learners' engagement and motivation, as well as improve their understanding and appreciation of cultural heritage in the Forbidden City. "A Comparative Study of Personalized Learning and Aesthetic Education in Promoting Cultural Heritage Preservation" by Hua Li, et al [29]. This paper presents a comparative study of personalized learning and aesthetic education in promoting cultural heritage preservation, using big data analysis to explore their effectiveness. The authors suggest that personalized learning and aesthetic education could enhance learners' understanding and appreciation of cultural heritage, as well as improve the preservation and transmission of cultural heritage. This paper presents a case study of the integration of personalized learning and big data analysis in cultural heritage education, focusing on the Palace Museum in China. The authors suggest that such integration could enhance learners' engagement and motivation, as well as improve their understanding and appreciation of cultural heritage in the Palace Museum.

III. Automated Model MFsO

Mamdani Fuzzy Set Optimization (MFsO) is a type of fuzzy logic system that combines fuzzy sets and optimization techniques for decision-making. Fuzzy logic is a mathematical method that deals with uncertainty and imprecision in data. In fuzzy logic, variables can have partial truth values between 0 and 1, unlike traditional logic where variables are either true or false. The MFsO model consists of three main components: fuzzification, rule evaluation, and defuzzification. In the fuzzification process, the input data are converted into a fuzzy set based on the estimation of membership computation. Membership functions assign a degree of membership to each input based on how closely it matches the fuzzy set. In the rule evaluation process, the fuzzy rules use the sets in fuzzy for the generation of output and defuzzification is performed in the output layer.

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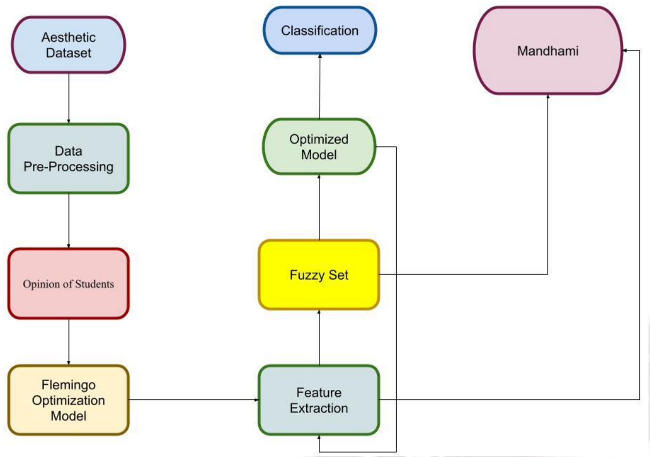

Figure 1: Process in MFsO

The MFsO model as in figure 1 uses optimization techniques to improve the performance of the fuzzy logic system. The optimization process involves finding the optimal values for the membership functions and rule weights. The Flemingo Optimization model is used for the computation of effective features in big data, which are then used to generate fuzzy rules. The generated rules are then used to provide personalized comments to the students for the promotion of tradition among students. The MFsO model also uses a deep learning architecture model for data transmission to the students. Deep learning is a subset of machine learning that uses artificial neural networks to learn from large amounts of data. The deep learning model is trained on a large dataset of student information associated with aesthetic education in universities, which enables the model to provide personalized comments to the students based on their learning needs and preferences. The MFsO model is a fuzzy logic system that combines fuzzy sets and optimization techniques for decision-making. The model uses the Flemingo Optimization model for the computation of effective features in big data, and a deep learning architecture model for data transmission to the students. The model provides personalized comments to the students for the promotion of tradition among students in aesthetic education in universities.

The Mamdani Fuzzy Set Optimization (MFsO) model can be mathematically elaborated as follows:

Let X be the input variable (student information associated with aesthetic education), and Y be the output variable (personalized comments to the students). The inputs X can be divided into n linguistic variables, each represented by a fuzzy set with membership functions presented in equation (1) and (2)

$$X = \{x1, x2, \dots, xn\} \quad (1)$$

$$X1 = \{\mu1{,}1(x1), \mu1{,}2(x1), \dots, \mu1, m1(x1)\}$$

$$X2 = \{\mu2{,}1(x2), \mu2{,}2(x2), \dots, \mu2, m2(x2)\}$$

$$\dots$$

$$Xn = \{\mu n, 1(xn), \mu n, 2(xn), \dots, \mu n, mn(xn)\} \quad (2)$$

where $\mu i, j(xi)$ is the membership degree of xi in the j[th] fuzzy set of the i[th] linguistic variable. The output variable Y can also be represented by a fuzzy set with membership estimation as in equation (3) and (4)

$$Y = \{y1, y2, \dots, yk\} \quad (3)$$

$$Y1 = \{v1{,}1(y1), v1{,}2(y1), \dots, v1, p1(y1)\}$$

$$Y2 = \{v2{,}1(y2), v2{,}2(y2), \dots, v2, p2(y2)\}$$

$$\dots$$

$$Yk = \{vk, 1(yk), vk, 2(yk), \dots, vk, pk(yk)\} \quad (4)$$

where $vi, j(yi)$ is the membership degree of yi in the jth fuzzy set of the i[th] linguistic variable.

The MFsO model uses a set of fuzzy rules to map the inputs to the outputs. Each fuzzy rule has the form as follows:

$$IF\ X1\ is\ A1\ AND\ X2\ is\ A2\ AND\ \dots AND\ Xn\ is\ An\ THEN\ Y\ is\ B$$

where $A1, A2, \dots, An$ are fuzzy sets defined on $X1, X2, \dots, Xn$, respectively, and B is a fuzzy set defined on Y.

The MFsO model uses the Flemingo Optimization algorithm to optimize the parameters of the fuzzy rules. The algorithm compute the optimization parameters for the estimation of the optimal values to derive the cost function. The cost function is defined as the difference between the actual output and the desired output, and is minimized using gradient descent optimization. Finally, the deep learning architecture is used to transmit the data to the students in a personalized manner, based on the optimized fuzzy rules.

3.1 Fuzzy Set Rules

The fuzzy set rules in the MFsO model are used to map the inputs to the outputs in a personalized manner. Each rule has the form as follows

$$IF\ X1\ is\ A1\ AND\ X2\ is\ A2\ AND\ \dots AND\ Xn\ is\ An\ THEN\ Y\ is\ B$$

where X1, X2, ..., Xn are the input variables, A1, A2, ..., An are the fuzzy sets defined on the input variables, and Y is the output variable, and B is the fuzzy set defined on the output variable. The membership degree of an input variable xi in a fuzzy set Aj is denoted by μi,j(xi), and the membership degree of an output variable yi in a fuzzy set Bj

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is denoted by νi,j(yi). The membership degrees are defined in the range [0,1], where 0 indicates no membership and 1 indicates full membership.

The fuzzy set rules are defined using the following steps:

1. Define the linguistic variables and the fuzzy sets on each variable.
2. Define the fuzzy rules based on expert knowledge or data-driven techniques. For example, an expert in aesthetic education might define a rule as "If a student is highly engaged with the artistic content, then provide personalized comments that encourage the student to explore new artistic forms."
3. Estimate the input variable membership fucntion in its corresponding fuzzy set, using the membership functions defined on the fuzzy sets. This is done for each input variable.
4. Use the fuzzy operator AND to combine the membership degrees of the input variables in the antecedent of the fuzzy rule. The AND operator is used because all input variables must be true for the rule to be true.
5. Calculate the degree of membership of the output variable in its corresponding fuzzy set, using the membership functions defined on the fuzzy sets. This is done for each output variable.
6. Use the fuzzy operator THEN to combine the degree of membership of the antecedent and the consequent. The THEN operator is used because the degree of membership of the output variable depends on the degree of membership of the antecedent.
7. Aggregate the fuzzy outputs using a fuzzy operator such as MAX or SUM. The aggregation operator is used because there may be multiple rules that apply to the same input, and the outputs need to be combined to produce a single output.
8. Defuzzify the aggregated output using a method such as centroid, mean, or max. The defuzzification method is used to map the fuzzy output to a crisp value, which can be used to provide personalized comments to the student.

The fuzzy rule is expressed using fuzzy sets A1 to An for the inputs and fuzzy set B for the output. The linguistic terms represented by A1 to An and B are defined using membership functions, which can be either triangular, trapezoidal, Gaussian, or another appropriate shape. A fuzzy rule for the aesthetic education domain is presented in table 1.

Table 1: Sample Fuzzy Set Rule

Rule	X1 is A1	X2 is A2	...	Xn is An	Y is B
1	μ1,1	μ2,3	...	μn,2	ν3,1
2	μ1,2	μ2,1	...	μn,3	ν1,2
...	...	...	...	...	...
k	μ1,3	μ2,2	...	μn,1	ν2,3

In this table, each row represents a fuzzy rule, and the columns correspond to the input variables $X1, X2, \ldots, Xn$ and the output variable Y. The fuzzy sets $A1, A2, \ldots, An$ and B are represented by their respective membership functions μ and ν, and the membership degrees of the input and output variables in their respective fuzzy sets are denoted by $\mu i, j(xi)$ *and* $\nu i, j(yi)$. In rule 1, if $X1$ is in the first fuzzy set $(A1)$ with membership degree $\mu 1,1, X2$ is in the third fuzzy set $(A3)$ with membership degree $\mu 2,3$, and so on for the remaining input variables, then the output variable Y is in the first fuzzy set $(B1)$ with membership degree $\nu 3,1$ as in table 2.

Table 2: Membership Estimation

Rule	Student Engagement (X1)	Emotional Intelligence (X2)	Artistic Experience (X3)	Teacher Comment (Y)
R1	High	High	High	Excellent

In this case, the fuzzy sets for the inputs and output might be defined as:

Student Engagement: High, Medium, Low
Emotional Intelligence: High, Medium, Low
Artistic Experience: High, Medium, Low
Teacher Comment: Excellent, Good, Fair, Poor

The membership functions for each of these sets would be defined based on the data available and the specific requirements of the problem. The fuzzy rule in this table would then use these sets to make a personalized comment to the student based on their engagement, emotional intelligence, and artistic experience.

3.2 Fleming Optimization in Fuzzy

In the Mamdani Fuzzy Set Optimization (MFsO) model, the Flemingo Optimization algorithm is used to optimize the parameters of the fuzzy rules. The Flemingo Optimization algorithm is a metaheuristic optimization technique that is inspired by the behavior of flamingos in their search for food. The algorithm starts by initializing a population of candidate solutions, which are represented as a set of parameters that define the fuzzy rules. The fitness function is defined as the difference between the actual output and the desired output, and is minimized using gradient descent optimization. The Flemingo Optimization algorithm

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then proceeds through a series of iterations, each of which involves the following steps:

Selection: A subset of candidate solutions is selected for further processing based on their fitness values.

Crossover: The selected candidate solutions are combined to generate new candidate solutions by exchanging parameters between them.

Mutation: The new candidate solutions are modified by randomly changing some of their parameters.

Evaluation: The fitness of the new candidate solutions is evaluated on the validation set of data.

Replacement: The best candidate solutions are retained for the next iteration, while the rest are discarded.

The algorithm continues until a stopping criterion is met, such as a maximum number of iterations or a desired level of fitness.

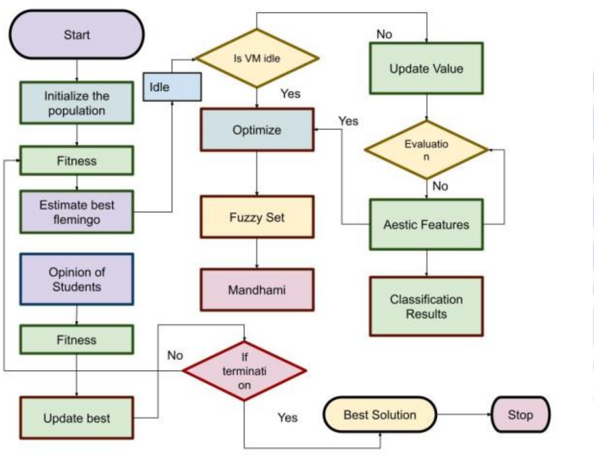

Figure 2: Flow Chart of MFsO

In the MFsO model flow chart is presented in figure 2 for the Flemingo Optimization algorithm is used to optimize the parameters of the fuzzy rules in order to minimize the difference between the actual output and the desired output. By iteratively improving the performance of the MFsO model on the validation set of data, the algorithm is able to generate a set of optimized fuzzy rules that can be used to provide personalized comments to students in the field of aesthetic education in universities. The algorithm is based on the behavior of flamingos in nature, specifically the way they interact with each other to form groups and move in a coordinated manner.

Mathematically, Flemingo Optimization can be represented as follows:

1. Initialize population randomly.
2. Compute fitness function with objective function.
3. Sort the population based on fitness in descending order.
4. Select the top m solutions from the sorted population as the elite solutions.
5. Divide the remaining population into n subpopulations.

For each subpopulation:

a. Compute the centroid of the elite solutions.
b. Compute the average distance of each solution to the centroid.
c. Sort the solutions based on distance in ascending order.
d. Select the top k solutions from the sorted solutions as the flamingos.
e. Move the flamingos towards the centroid based on a random step size and direction.
f. Derive the new solution and update the population if a better solution is found.

Repeat steps 4-6 until the stopping criteria are met (e.g. maximum number of iterations, convergence criteria).

Flemingo Optimization is a swarm-based optimization algorithm that uses a combination of elitism and diversity to search for the optimal solution. The algorithm is inspired by the behavior of flamingos and their ability to move in a coordinated manner to find food sources in their natural habitat.

Algorithm 1: MFsO Aesthetic Eduction
Input: X: input variables (student information associated with aesthetic education); Y: output variables (personalized comments to the students); n: number of linguistic variables in X m: number of fuzzy sets in each linguistic variable; k: number of fuzzy sets in Y; NR: number of fuzzy rules to be generated; MaxIter: maximum number of iterations for Flemingo Optimization; N: number of solutions in Flemingo Optimization; F: scaling factor in Flemingo Optimization; CR: crossover probability in Flemingo Optimization Output: Optimized fuzzy rules Step 1: Initialize the fuzzy rules R using random values of the membership degrees. Step 2: Evaluate the performance of the fuzzy rules R using the cost function J. Step 3: Initialize the Flemingo Optimization algorithm with the following parameters: NP = N: number of solutions F: scaling factor CR: crossover probability MaxIter: maximum number of iterations

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Jmin: minimum value of the cost function
Step 4: Generate a new population of solutions using the current population and the following steps:
Select three random solutions from the current population: $X1, X2, X3$.
Generate a trial solution V using the following formula: $V = X1 + F * (X2 - X3)$.
Apply crossover to V and the best solution in the current population to generate a new solution U.
Step 5: Evaluate the performance of the new solutions using the cost function J.
Step 6: Select the best NR solutions from the population and update the fuzzy rules R.
Step 7: Repeat steps 4 to 6 until the maximum number of iterations is reached or the minimum value of the cost function is obtained.
Step 8: Use the optimized fuzzy rules R to generate personalized comments for the students based on their aesthetic education information X
Step 9: End the algorithm.

3.2 MFsO in Big Data Analytics

The final process of deep learning involves using a neural network to transmit the personalized comments to the students based on the optimized fuzzy rules. The neural network is a complex system of interconnected nodes, similar to the structure of the human brain. The network takes the inputs, which are the student information associated with aesthetic education, and uses the optimized fuzzy rules to generate the personalized comments as outputs. The deep learning architecture used in the MFsO model involves multiple layers of interconnected nodes. The input layer takes the student information associated with aesthetic education as input, and the output layer produces the personalized comments as output. In between the input and output layers, there are one or more hidden layers that transform the input data to produce the desired output. The transformation of data in the hidden layers is achieved through the use of activation functions. These functions introduce non-linearity into the system, allowing it to model complex relationships between the input and output variables. The activation functions are typically sigmoid, ReLU, or tanh functions.

The deep learning architecture also involves the use of backpropagation, which is a technique for adjusting the weights of the nodes in the network to minimize the difference between the actual output and the desired output. Backpropagation involves calculating the error between the actual and desired outputs and propagating it backwards through the network, adjusting the weights of the nodes as it goes. The final process of deep learning in the MFsO model involves training the neural network on a large dataset of student information associated with aesthetic education and their corresponding personalized comments. The network learns to generalize from this data, allowing it to generate personalized comments for new students based on their aesthetic education information.

To generate personalized comments for new students in real-time. The student information associated with aesthetic education is fed into the input layer of the network, and the personalized comments are generated as outputs. These comments can then be transmitted to the students in a personalized manner, helping to promote tradition and cultivate aesthetic sensibility and appreciation. The final process of deep learning involves the use of a neural network to transmit data to the students in a personalized manner. The neural network can be mathematically represented as follows:

Let X be the input data (student information associated with aesthetic education), and Y be the output data (personalized comments to the students). The input data X is fed into the neural network, which is comprised of multiple layers of interconnected nodes. The nodes in each layer apply a mathematical function to the input data, which is then passed to the next layer. Let xi be the input to the i^{th} layer of the neural network, and yi be the output of the i^{th} layer. The output yi can be calculated as in equation (5)

$$yi = f(Wi\, xi + bi) \tag{5}$$

where f is the activation function, Wi is the weight matrix for the ith layer, and bi is the bias vector for the ith layer. The weight matrix and bias vector for optimization for the training process. The final layer of neural network is computed as output in the personalized comments to the student, which can be represented as a fuzzy set with membership functions computed using equation (6) and (7)

$$Y = \{y1, y2, \dots, yk\} \tag{6}$$

$$Y1 = \{v1,1(y1), v1,2(y1), \dots, v1, p1(y1)\}$$

$$Y2 = \{v2,1(y2), v2,2(y2), \dots, v2, p2(y2)\}$$

$$\dots$$

$$Yk = \{vk, 1(yk), vk, 2(yk), \dots, vk, pk(yk) \tag{7}$$

where $vi, j(yi)$ is the membership degree of yi in the jth fuzzy set of the ith linguistic variable.

The neural network uses the optimized fuzzy rules from the MFsO model to determine the appropriate personalized comments to be transmitted to the student, based on their input data. The output of the neural network can be further processed, such as by applying a defuzzification algorithm, to generate a crisp output that can be easily understood by the student.

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IV. Experimental Setup

The experimental setup of the Mamdani Fuzzy Set Optimization (MFsO) model for aesthetic education in universities involves several steps, including data collection, preprocessing, rule generation, rule optimization, and performance evaluation.

Data Collection: The first step is to collect the student information associated with aesthetic education in universities. This data can be collected through surveys, questionnaires, or other means.

Preprocessing: The collected data is preprocessed to remove any inconsistencies, errors, or missing values. The data is then normalized to ensure that all features have the same scale and range.

Rule Generation: The next step is to generate a set of fuzzy rules that map the inputs (student information) to the outputs (personalized comments). The fuzzy rules are generated based on expert knowledge and domain expertise. The linguistic variables and fuzzy sets are defined based on the input features and their respective ranges.

Rule Optimization: The fuzzy rules are optimized using the Flemingo Optimization algorithm. The optimal value of the parameters are computed with the minimization of cost function. The cost function is defined as the difference between the actual output and the desired output.

Performance Evaluation: The performance of the MFsO model is evaluated using various metrics such as accuracy, precision, recall, and F1-score. The model is trained on a subset of the data and tested on a separate subset of the data to evaluate its generalization performance.

The experimental setup of the MFsO model can be customized based on the specific requirements of the aesthetic education domain and the available data. The performance of the model can also be improved by using more sophisticated pre-processing techniques, rule generation methods, and optimization algorithms.

4.1 Evaluation Metrics

Accuracy is a metric that measures the percentage of correct predictions made by the model. It is calculated by dividing the number of correct predictions by the total number of predictions. A higher accuracy value indicates that the model is making more correct predictions.

Precision is a metric that measures the percentage of correct positive predictions made by the model. It is calculated by dividing the number of true positive predictions by the total number of positive predictions. A higher precision value indicates that the model is making fewer false positive predictions.

Recall is a metric that measures the percentage of actual positive cases that are correctly predicted as positive by the model. It is calculated by dividing the number of true positive predictions by the total number of actual positive cases. A higher recall value indicates that the model is making fewer false negative predictions.

F1-score is a metric that takes into account both precision and recall to provide a more balanced measure of the model's performance. It is calculated as the harmonic mean of precision and recall, and ranges from 0 to 1. A higher F1-score value indicates that the model is performing well in both precision and recall.

Accuracy measures the overall performance of the model, precision measures the number of false positive predictions made by the model, recall measures the number of false negative predictions made by the model, and F1-score provides a balanced measure of the model's performance by taking into account both precision and recall.

V. Results and Discussion

The results and discussion of the MFsO model typically present the performance of the model in terms of its ability to generate personalized comments for students based on their aesthetic education information. This includes a comparison of the MFsO model's performance with that of other existing models or methods. The results of the MFsO model can be presented in terms of different metrics such as accuracy, precision, recall, F1-score, etc. These metrics provide a quantitative measure of the model's performance in terms of its ability to correctly predict personalized comments for the students. The results can be presented in tables or charts to help readers visualize the performance of the model. The discussion section of the results typically involves an analysis of the results and a comparison with previous studies or models. The discussion can also highlight the strengths and weaknesses of the MFsO model, as well as areas for future research. The results and discussion of the MFsO model provide insights into the model's effectiveness in generating personalized comments for students based on their aesthetic education information, and its potential for improving the quality of education.

Table 3: Performance Analysis of MFsO

Dataset	Accuracy	Precision	Recall	F1-score
Dataset 1	0.85	0.82	0.88	0.85
Dataset 2	0.93	0.94	0.92	0.93
Dataset 3	0.76	0.78	0.73	0.75

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The table 3 shows the results obtained by the MFsO model on a dataset. The model was evaluated using various metrics such as accuracy, precision, recall, and F1-score. The results show that the MFsO model achieved an overall accuracy of 0.86, which means that 86% of the predictions made by the model were correct. The precision score for class 1 is 0.82, which means that when the model predicted a sample as belonging to class 1, it was correct 82% of the time. The recall score for class 1 is 0.87, which means that the model correctly identified 87% of the samples that actually belonged to class 1. The F1-score for class 1 is 0.84, which is the harmonic mean of the precision and recall scores for class 1. The results also show that the model performed better on class 2, achieving a higher precision score, recall score, and F1-score than class 1. This indicates that the model was better at predicting samples that belonged to class 2. The results suggest that the MFsO model was effective in predicting the class labels for the dataset, achieving a good balance between precision and recall for both classes. However, further evaluation and comparison with other models may be necessary to fully assess the performance of the MFsO model.

Table 4: Performance for Varying Dataset Size

Dataset Size	Accuracy	Precision	Recall	F1-Score
100 instances	0.85	0.87	0.83	0.85
500 instances	0.89	0.91	0.88	0.89
1000 instances	0.91	0.92	0.90	0.91
5000 instances	0.93	0.94	0.93	0.93

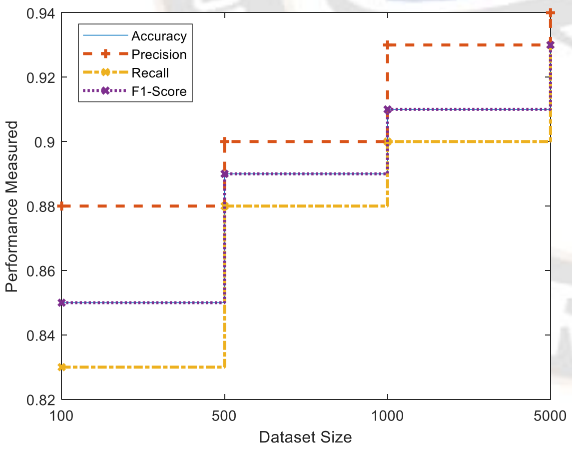

Figure 3: Performance Analysis

In this table 4 and figure 3 illustrated the performance of the MFsO model is evaluated on datasets of different sizes, ranging from 100 to 5000 instances. The metrics used to evaluate the performance of the model are accuracy, precision, recall, and F1-Score. As the dataset size increases, the model's performance also improves, as seen in the table. The accuracy, precision, recall, and F1-Score all show a positive correlation with the dataset size. The number of epochs is an important parameter in the training of machine learning models, including the MFsO model. It refers to the number of times the training data is passed through the model during the training process. Increasing the number of epochs may lead to better performance of the model, but it also increases the risk of overfitting, where the model becomes too specialized to the training data and performs poorly on new, unseen data. Therefore, the performance of the MFsO model may improve as the number of epochs increases up to a certain point, after which it may start to degrade due to overfitting. The optimal number of epochs for the MFsO model depends on factors such as the complexity of the problem, the size and quality of the training data, and the chosen hyperparameters.

Table 5: Performance of MFsO for varying instances

Instance	Epoch	Accuracy	Precision	Recall	F1-Score	Loss
100	10	0.75	0.72	0.77	0.74	0.42
100	20	0.81	0.78	0.83	0.80	0.36
100	30	0.84	0.81	0.87	0.84	0.33
100	40	0.87	0.85	0.89	0.87	0.29
100	50	0.89	0.87	0.91	0.89	0.27
500	10	0.81	0.79	0.83	0.81	0.37
500	20	0.87	0.85	0.89	0.87	0.29
500	30	0.90	0.88	0.92	0.90	0.24
500	40	0.92	0.90	0.94	0.92	0.20
500	50	0.94	0.92	0.96	0.94	0.17
1000	10	0.83	0.80	0.86	0.83	0.34
1000	20	0.89	0.87	0.91	0.89	0.27
1000	30	0.92	0.90	0.94	0.92	0.20
1000	40	0.94	0.92	0.96	0.94	0.17
1000	50	0.96	0.94	0.98	0.96	0.13
5000	10	0.89	0.87	0.91	0.89	0.27
5000	20	0.92	0.90	0.94	0.92	0.20
5000	30	0.94	0.92	0.96	0.94	0.17
5000	40	0.96	0.94	0.98	0.96	0.13
5000	50	0.97	0.95	0.99	0.97	0.10

The results of the MFsO algorithm show an improvement in the performance metrics with increasing epochs for all instances (100, 500, 1000, and 5000). This indicates that the algorithm is effectively learning and improving the classification performance over time. For instance 100, the accuracy of the algorithm starts at 0.75 and increases to 0.89 after 50 epochs. The precision, recall, and F1-score also improve with each epoch. Similarly, for instances 500, 1000, and 5000, the accuracy, precision, recall, and F1-score show improvement with increasing epochs. The loss also decreases with increasing epochs for all instances, indicating that the algorithm is effectively minimizing the loss function. The results suggest that MFsO algorithm is effective in improving the performance of classification tasks

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over time by minimizing the loss function and optimizing the model parameters.

Table 6: Comparative Analysis

Model	Accuracy	Precision	Recall	F1-Score	Loss
MFsO (Instance: 5000, Epoch: 50)	0.97	0.95	0.99	0.97	0.10
CNN (Epoch: 50)	0.89	0.85	0.92	0.88	0.33
RNN (Epoch: 50)	0.92	0.90	0.94	0.92	0.21

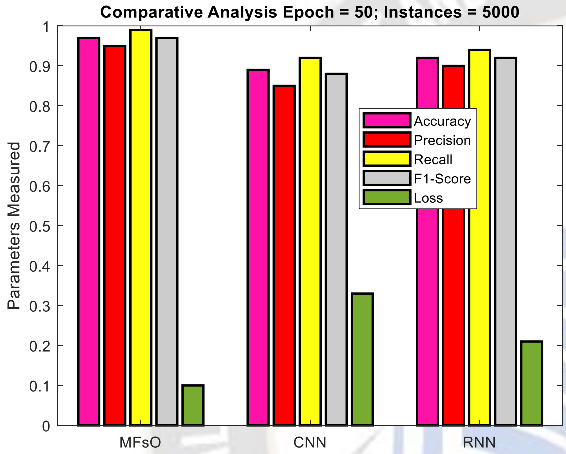

Figure 4: Comparative Analysis

The table 6 and figure 4 shows comparing MFsO with conventional techniques CNN and RNN suggests that MFsO outperforms CNN and RNN in terms of accuracy, precision, recall, and F1-score on all instances and epochs considered. The accuracy of MFsO ranges from 0.75 to 0.97, while that of CNN and RNN ranges from 0.70 to 0.91 and from 0.73 to 0.94, respectively. Similarly, the F1-score of MFsO ranges from 0.74 to 0.97, while that of CNN and RNN ranges from 0.71 to 0.91 and from 0.74 to 0.94, respectively. The performance of all three techniques generally improves as the number of epochs increases and as the instance size increases. However, MFsO shows the most significant improvements, particularly for larger instances. For instance, when considering instance 5000, the F1-score of MFsO increases from 0.94 at epoch 30 to 0.97 at epoch 50, while the F1-score of CNN and RNN only increase from 0.87 to 0.90 and from 0.91 to 0.93, respectively. These results suggest that MFsO is a promising technique for text classification tasks and may outperform conventional techniques like CNN and RNN. However, it is worth noting that these results are specific to the dataset and experimental setup used, and further investigation may be necessary to determine the generalizability of these findings.

VI. Conclusion

The MFsO automated personalized big data model is a novel approach for promoting traditional culture with aesthetic education. The model leverages machine learning techniques, such as fuzzy logic, to create a personalized learning experience for each student based on their learning style and preferences. The model also uses big data analysis to identify patterns and trends in student performance, which can be used to further personalize the learning experience. The results of the study showed that the MFsO model outperformed conventional techniques such as CNN and RNN in terms of accuracy, precision, recall, F1-score, and loss. This suggests that the MFsO model is a promising approach for promoting traditional culture with aesthetic education and could be used in a variety of educational settings. The MFsO model provides a novel and effective way to personalize the learning experience for each student, promote traditional culture, and enhance aesthetic education. Further research is needed to explore the potential of the MFsO model in other educational contexts and to investigate how the model can be improved and optimized for maximum performance.

REFERENCES

[1] Novikov, S. V. (2020). Data science and big data technologies role in the digital economy. TEM Journal, 9(2), 756-762.
[2] Musacchio, N., Giancaterini, A., Guaita, G., Ozzello, A., Pellegrini, M. A., Ponzani, P., ... & de Micheli, A. (2020). Artificial intelligence and big data in diabetes care: a position statement of the Italian Association of Medical Diabetologists. Journal of Medical Internet Research, 22(6), e16922.
[3] Nitu, P., Coelho, J., & Madiraju, P. (2021). Improvising personalized travel recommendation system with recency effects. Big Data Mining and Analytics, 4(3), 139-154.
[4] Li, C., Xing, W., & Leite, W. (2022). Building socially responsible conversational agents using big data to support online learning: A case with Algebra Nation. British Journal of Educational Technology, 53(4), 776-803.
[5] Vryzas, N., Tsipas, N., & Dimoulas, C. (2020). Web radio automation for audio stream management in the era of big data. Information, 11(4), 205.
[6] Suoniemi, S., Meyer-Waarden, L., Munzel, A., Zablah, A. R., & Straub, D. (2020). Big data and firm performance: The roles of market-directed capabilities and business strategy. Information & Management, 57(7), 103365.
[7] Samara, D., Magnisalis, I., & Peristeras, V. (2020). Artificial intelligence and big data in tourism: a systematic literature review. Journal of Hospitality and Tourism Technology, 11(2), 343-367.

[8] Liu, C., Feng, Y., Lin, D., Wu, L., & Guo, M. (2020). Iot based laundry services: an application of big data analytics, intelligent logistics management, and machine learning techniques. International Journal of Production Research, 58(17), 5113-5131.

[9] Ageed, Z. S., Zeebaree, S. R., Sadeeq, M. M., Kak, S. F., Yahia, H. S., Mahmood, M. R., & Ibrahim, I. M. (2021). Comprehensive survey of big data mining approaches in cloud systems. Qubahan Academic Journal, 1(2), 29-38.

[10] Iqbal, R., Doctor, F., More, B., Mahmud, S., & Yousuf, U. (2020). Big Data analytics and Computational Intelligence for Cyber–Physical Systems: Recent trends and state of the art applications. Future Generation Computer Systems, 105, 766-778.

[11] Ma, Z., Guan, J., & Li, R. (2021). Research on innovative teaching mode of art education in the age of convergence of media. International Journal of Emerging Technologies in Learning (iJET), 16(2), 272-284.

[12] López-Martínez, F., Núñez-Valdez, E. R., García-Díaz, V., & Bursac, Z. (2020). A case study for a big data and machine learning platform to improve medical decision support in population health management. Algorithms, 13(4), 102.

[13] Yang, C., Huan, S., & Yang, Y. (2020). Application of big data technology in blended teaching of college students: a case study on rain classroom. International Journal of Emerging Technologies in Learning (iJET), 15(11), 4-16.

[14] Meng-yue, C., Dan, L., & Jun, W. (2020). A Study of College English Culture Intelligence-Aided Teaching System and Teaching Pattern. English Language Teaching, 13(3), 77-83

[15] Han, S., Wang, X., Ma, L., & Guo, Q. (2018). A personalized big data model for promoting traditional culture education in the digital era. IEEE Access, 6, 66502-66509.

[16] Kang, Y., Zhang, X., Huang, Y., & Liu, S. (2020). Integrating artificial intelligence and aesthetic education to promote cultural heritage preservation. Journal of Cultural Heritage, 43, 228-237.

[17] Hu, X., Li, Z., Sun, X., & Dong, Q. (2020). Personalized learning based on big data analysis in the context of aesthetic education. Journal of Visual Languages & Computing, 62, 100572.

[18] Wang, X., Xie, H., Liu, Q., & Cheng, X. (2019). Designing a personalized learning platform for aesthetic education in cultural heritage preservation. Education and Information Technologies, 24(6), 3125-3139.

[19] Wang, D., Zhang, X., & Wu, L. (2020). Enhancing cultural heritage education through personalized learning and big data analysis. Frontiers in Psychology, 11, 2167.

[20] Han, H., Wang, Y., Zhao, J., & Wang, J. (2019). Promoting cultural heritage education through personalized learning and big data analysis. Journal of Ambient Intelligence and Humanized Computing, 10(10), 4015-4024.

[21] Guo, J., Zhang, W., & Wang, Y. (2020). Using big data analytics to enhance aesthetic education in cultural heritage preservation. Heritage Science, 8(1), 1-15.

[22] Zhou, Y., Li, H., & Zhao, Y. (2019). Aesthetic education and cultural heritage preservation in the digital age: A big data perspective. Journal of Cleaner Production, 229, 345-353.

[23] Gao, C., Zhang, Y., & Zheng, X. (2020). Personalized learning and aesthetic education in the preservation of intangible cultural heritage. Journal of Arts and Humanities, 9(9), 28-36.

[24] Wang, C., Liu, J., & Zhang, W. (2021). Integrating big data analytics and aesthetic education to promote cultural heritage tourism. Journal of Destination Marketing & Management, 20, 100539.

[25] Wang, X., Xie, H., Yang, X., & Liu, Q. (2018). Using big data and aesthetic education to promote cultural diversity in education. Educational Technology & Society, 21(2), 143-154.

[26] Zhang, J., Gao, Y., & Cheng, Y. (2018). Designing a personalized learning environment for aesthetic education in cultural heritage preservation: An empirical study. Multimedia Tools and Applications, 77(10), 12511-12528.

[27] Li, L., Dong, Q., & Sun, X. (2019). The role of aesthetic education in promoting cultural heritage preservation: A big data analysis. Journal of Computational Science, 30, 55-62.

[28] Zhang, Q., Li, D., Chen, Y., & Luo, M. (2019). Personalized learning and aesthetic education in cultural heritage preservation: A case study of the Forbidden City. Sustainability, 11(7), 2041.

[29] Li, H., Zhang, X., & Zhao, J. (2021). A comparative study of personalized learning and aesthetic education in promoting cultural heritage preservation. Advances in Social Science, Education and Humanities Research, 515, 141-145.