STUDY ON TALENT CULTIVATION MANAGEMENT MODEL OF UNIVERSITIES BASED ON FUZZY NEURAL NETWORK ALGORITHM

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H Cheng*, Department of Culture and Arts, Yongcheng Vocational College, Yongcheng, Henan, 476600, China

*Corresponding author. H Cheng (Email): bangongshi_201@163.com

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SUMMARY

The Talent Cultivation Management Model for Universities represents a strategic framework designed to optimize the development and oversight of academic programs. This model focuses on identifying, nurturing, and assessing talents within the university ecosystem. It incorporates innovative methodologies to align educational offerings with individual needs and career goals. This study presents an innovative approach to developing a talent cultivation management model for universities, leveraging the integration of the Fuzzy Neural Network Algorithm with the proposed Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN). Recognizing the critical importance of talent development in higher education, this research seeks to enhance the efficacy and adaptability of existing management models. The OSMF-NN algorithm, inspired by the optimization capabilities of spider monkey behavior, enhances the traditional fuzzy neural network algorithm, enabling more precise and efficient talent management. By harnessing the synergies between fuzzy logic and neural networks, the proposed model offers a robust framework for identifying, nurturing, and evaluating talents within the university ecosystem. Through comprehensive experimentation and validation, this study demonstrates the effectiveness of the OSMF-NN algorithm in optimizing talent cultivation strategies, promoting personalized learning experiences, and fostering student success in higher education institutions.

KEYWORDS

Talent cultivation, Optimization, Fuzzy logic, Neural network, Classification

NOMENCLATURE

OSMF -NN	Optimized Spider Monkey Fuzzy Neural Network
FNN	Fuzzy neural networks
F	Frequency
SMO	Spider monkey optimization

1. INTRODUCTION

A neural network is a computational model inspired by the structure and function of the human brain. It consists of interconnected nodes, or neurons, organized in layers. Each neuron receives input signals, processes them using an activation function, and produces an output signal [1]. Neural networks are trained using a process called supervised learning, where they learn to recognize patterns in data by adjusting the weights and biases of connections between neurons. This training allows neural networks to perform a wide range of tasks, including image and speech recognition, natural language processing, and decision-making [2]. With their ability to learn from data and generalize to new situations, neural networks have become a powerful tool in various fields, driving advances in artificial intelligence and revolutionizing industries such as healthcare, finance, and transportation [3]. Talent cultivation is the systematic process of nurturing and developing individuals' skills, knowledge, and abilities to help them reach their full potential and excel in their chosen fields. This process often begins with identifying and recruiting individuals who demonstrate potential or interest in a particular domain [4]. Once recruited, these individuals undergo training and development programs tailored to enhance their capabilities and expand their expertise. Talent cultivation initiatives may include formal education, on-the-job training, mentoring, coaching, and exposure to diverse experiences [5]. By investing in talent cultivation, organizations not only ensure a skilled and capable workforce but also foster innovation, creativity, and resilience among their employees. Moreover, effective talent cultivation strategies contribute to employee engagement, retention, and ultimately, organizational success [6]. In today's rapidly evolving global economy, where skills and knowledge are critical assets, talent cultivation plays a pivotal role in building competitive advantage and driving sustainable growth [7].

Neural networks can play a transformative role in talent cultivation by leveraging their ability to analyze vast amounts of data, identify patterns, and personalize learning experiences [8]. Through the integration of neural

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networks into talent cultivation initiatives, organizations can enhance various aspects of the process, from recruitment to training and development. One significant application of neural networks in talent cultivation is talent identification and recruitment [9]. With analyzing resumes, social media profiles, and other relevant data sources, neural networks can help identify individuals with the skills, experiences, and attributes desired by organizations. These systems can efficiently sift through large candidate pools, enabling recruiters to focus their efforts on the most promising candidates [10]. Once individuals are recruited, neural networks can personalize learning experiences to cater to their specific needs and preferences [11]. With analyzing learners' interactions with educational content, performance on assessments, and other relevant data points, neural networks can adapt learning pathways in real-time. This personalization enhances engagement, retention, and knowledge acquisition, ultimately accelerating skill development. Furthermore, neural networks can facilitate skill assessment and feedback mechanisms [12]. By analyzing learners' performance on tasks, simulations, or assessments, neural networks can provide personalized feedback and recommendations for improvement. This feedback loop enables continuous learning and development, helping individuals refine their skills and overcome challenges more effectively [13].

In addition to individualized learning experiences, neural networks can support collaborative learning environments [14]. By analyzing social interactions, communication patterns, and collaboration dynamics, neural networks can identify opportunities for collaboration and facilitate the formation of diverse, interdisciplinary teams [15]. These collaborative experiences foster teamwork, creativity, and knowledge sharing, enriching the talent cultivation process [16]. The integration of neural networks into talent cultivation initiatives holds tremendous potential to enhance recruitment, personalized learning, skill assessment, and collaboration. By leveraging the capabilities of neural networks, organizations can create more agile, adaptive, and effective talent cultivation ecosystems, empowering individuals to thrive in today's dynamic and competitive landscape [17].

The paper makes several significant contributions to the field of talent cultivation and management. Firstly, it introduces and applies the Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN) model, demonstrating its effectiveness in talent-related tasks such as classification and management. This novel approach combines the strengths of fuzzy logic and neural networks, offering a powerful tool for analyzing and modeling complex talent-related data. Secondly, the paper provides empirical evidence of the OSMF-NN model's performance through a series of experiments. By evaluating the model's accuracy, precision, recall, and F1-score across different experimental setups, it establishes the robustness and reliability of OSMF-NN in talent cultivation and classification tasks. These results contribute to the growing body of research on advanced computational techniques in talent management. Furthermore, the study extends the understanding of talent cultivation and management by exploring the potential applications of OSMF-NN in educational institutions and beyond. By demonstrating the model's effectiveness in various domains, including talent classification and decision-making, the paper offers valuable insights into how organizations can leverage advanced technologies to optimize talent-related processes. The contributions of the paper lie in its introduction of a novel computational model, empirical validation of its performance, and exploration of its practical applications in talent management. These contributions pave the way for further research and development in the field, with the potential to enhance talent cultivation strategies and improve organizational outcomes.

2. RELATED WORKS

In recent years, there has been a growing interest in harnessing the power of neural networks to enhance talent cultivation practices across various domains. This survey aims to analyze existing research, methodologies, and applications that utilize neural networks to optimize talent cultivation strategies. By delving into the literature, we seek to uncover key insights, trends, and challenges in this burgeoning field, shedding light on the potential benefits and implications of integrating neural network techniques into talent cultivation frameworks. Through a systematic review of relevant studies and empirical evidence, this survey aims to provide a valuable synthesis of knowledge, paving the way for future advancements and innovations in talent cultivation methodologies guided by neural network technologies. In the realm of talent cultivation and educational assessment, a diverse array of innovative methodologies and technologies are being explored to enhance teaching quality evaluation and optimize talent training models. Wang (2022) proposes an optimization design for international talent training models utilizing big data systems, aiming to leverage data-driven insights to refine educational strategies. Ren, Wang, and Li (2022) contribute to China's higher education development evaluation through a GA-BP neural network approach, demonstrating the application of advanced computational techniques in educational assessment. Su (2022) introduces an optimization model for employment and entrepreneurship guidance for university graduates, employing credible neural networks and Spark big data technology to facilitate career pathways. Meanwhile, Lan (2022) focuses on constructing an intelligent detection system for college students' entrepreneurship management based on fuzzy network information feedback analysis, highlighting the role of intelligent systems in supporting entrepreneurial endeavors. Chen and Xu (2022) analyze cultivation methods for teachers' teaching ability driven by artificial intelligence technology, emphasizing the integration of AI into pedagogical practices. Additionally, Hong (2022) explores the construction of an international education

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talent training mechanism based on data fusion algorithms, aiming to foster global competencies among students. Zhu and Li (2022) propose an improved assessment model for personnel development levels in higher education using machine learning techniques, enhancing the effectiveness of talent development strategies. These studies exemplify the diverse applications of advanced computational techniques, including neural networks, genetic algorithms, and fuzzy logic, in optimizing educational practices and talent cultivation efforts. Among them, Zhang and Wang (2023) present a smart knowledge discovery system for teaching quality evaluation, showcasing the potential of genetic algorithm-based BP neural networks to enhance the assessment of teaching effectiveness. Collectively, these research endeavors underscore the pivotal role of technology-driven approaches in shaping the future of talent cultivation and educational assessment.

Firstly, the reliance on big data systems, neural networks, and other sophisticated technologies may pose challenges in terms of data privacy, security, and ethical considerations. The collection, storage, and analysis of vast amounts of personal and sensitive data raise concerns about confidentiality and consent, necessitating robust safeguards and regulatory frameworks to protect individuals' rights and privacy. Moreover, the effectiveness and generalizability of the proposed models and algorithms may be contingent upon the quality and representativeness of the training data. Biases, inaccuracies, or incompleteness in the data can lead to skewed or erroneous results, potentially undermining the reliability and validity of the findings. Additionally, the complexity and computational demands of implementing advanced computational techniques may present barriers to adoption, particularly for smaller educational institutions or resource-constrained settings. Furthermore, while machine learning algorithms like neural networks and genetic algorithms excel at identifying patterns and optimizing solutions, they may lack interpretability and transparency, making it challenging to understand and explain the reasoning behind their decisions. This lack of interpretability can hinder trust and acceptance among stakeholders, including educators, students, and policymakers, who may be skeptical of black-box algorithms dictating educational practices.

Additionally, the success of talent cultivation and educational assessment initiatives relies not only on technological solutions but also on the expertise and judgment of human practitioners. Overreliance on automated systems and algorithms may overlook the nuanced contextual factors and subjective aspects of teaching and learning, potentially diminishing the holistic understanding of educational quality and effectiveness. Furthermore, the rapid pace of technological advancement and evolving educational landscapes necessitate ongoing adaptation and refinement of computational models and methodologies. As such, there's a need for interdisciplinary collaboration and continuous evaluation to ensure that technology-driven approaches in talent cultivation and educational assessment remain relevant, ethical, and impactful in addressing the complex challenges facing education systems worldwide.

3. TALENT CULTIVATION WITH FUZZY MANAGEMENT MODEL

Talent cultivation, when coupled with a fuzzy management model, offers a nuanced approach to addressing the complexities inherent in human development. Fuzzy logic, with its ability to handle imprecise and uncertain information, provides a valuable framework for modeling the multifaceted nature of talent and skill acquisition. In this integrated approach, talent cultivation is viewed as a dynamic process influenced by various factors, including individual abilities, learning environments, and socio-economic contexts. The fuzzy management model incorporates fuzzy sets, linguistic variables, and fuzzy rules to capture the vagueness and ambiguity inherent in human judgment and decision-making. By quantifying qualitative factors and defining membership functions, the model can effectively represent the uncertainty associated with talent assessment and development. Fuzzy logic operates on fuzzy sets, which generalize classical set theory by allowing elements to have degrees of membership ranging from 0 to 1. Let X represent the universe of discourse, and let A be a fuzzy set defined on X with membership function $\mu A(x)$, where x denotes an element of X. The membership function $\mu A(x)$ assigns a degree of membership to each element x in X, indicating the extent to which x belongs to A.

In the context of talent cultivation, linguistic variables such as "highly skilled," "moderately skilled," and "low skilled" can be represented as fuzzy sets with corresponding membership functions. If Talent is a linguistic variable representing the level of talent, then its fuzzy set Talent can be defined with membership functions such as $hHigh, Medium, and\ Low$, each capturing different degrees of talent. The fuzzy management model utilizes fuzzy rules to infer appropriate actions or decisions based on fuzzy input variables. These rules encode expert knowledge or heuristics and are typically expressed in the form of IF-THEN statements. For instance, a fuzzy rule in talent cultivation might be: IF Talent is *h*High AND Motivation is *h*High, THEN recommend advanced training programs. In talent cultivation, linguistic variables such as "skill level" or "aptitude" are often characterized by imprecise and subjective descriptions. Fuzzy logic allows us to represent these linguistic variables as fuzzy sets with membership functions that assign degrees of membership to elements of the universe of discourse.

Consider the linguistic variable "Skill Level" denoted by S, which can be categorized into "Low," "Medium," and "High." We can define membership functions for each category using equation (1) – equation (3)

Low skill: $$\mu_{low}(x) = \begin{cases} 1 & if\ x \leq a_1 \\ \dfrac{b_1 - x}{b_1 - a_1} & if\ a_1 < x < b_1 \\ 0 & Otherwise \end{cases} \quad (1)$$

Medium Skill: $$\mu_{Medium}(x) = \begin{cases} 1 & if\ x \langle a_2\ \ or\ x \rangle b_2 \\ \dfrac{x - a_2}{c_2 - a_2} & if\ a_2 \leq x \leq c_2 \\ \dfrac{b_2 - x}{b_2 - c_2} & if\ c_2 < x < b_2 \end{cases} \quad (2)$$

High Skill: $$\mu_{high}(x) = \begin{cases} 0 & if\ x < a_3 \\ \dfrac{x - a_3}{b_3 - a_3} & if\ a_3 \leq x \leq b_3 \\ 1 & if\ x \geq b_3 \end{cases} \quad (3)$$

In equation (1)–equation (3) $a1,\ b1,\ a2,\ b2,\ c2,\ a3,\ and\ b3$ are the parameters defining the fuzzy sets. Fuzzy rules encode expert knowledge or heuristics about how to make decisions or recommendations based on fuzzy input variables. These rules typically take the form of IF-THEN statements.

A fuzzy rule in talent cultivation might be: IF Skill is Low AND Motivation is High, THEN recommend intensive training programs.

Fuzzy Inference Process: Once we have defined membership functions and fuzzy rules, the fuzzy inference process involves combining fuzzy input variables to derive crisp output recommendations.

The Mamdani fuzzy inference method is a commonly used approach, which involves four main steps: fuzzification, rule evaluation, aggregation, and defuzzification.

Fuzzification: Convert crisp input values into fuzzy sets using the defined membership functions.

Rule Evaluation: Apply fuzzy rules to determine the degree to which each rule is satisfied.

Aggregation: Combine the outputs of all rules to obtain a fuzzy output set.

Defuzzification: Convert the fuzzy output set into a crisp output value using methods such as centroid or maximum membership.

Through this process, the fuzzy management model provides actionable recommendations for talent cultivation based on the input variables' fuzzy values and the defined fuzzy rules. Table 1 shows Fuzzy set for talent cultivation.

Table 1. Fuzzy set for talent cultivation

Rule	IF Skill Level is	AND Motivation is	THEN Recommendation
Rule 1	Low	High	Intensive training programs
Rule 2	Medium	Medium	Tailored skill development courses
Rule 3	High	Low	Mentorship programs

4. PROPOSED OPTIMIZED SPIDER MONKEY FUZZY NEURAL NETWORK (OSMF-NN)

The Proposed Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN) represents a novel approach to combining the strengths of spider monkey optimization (SMO) algorithms with fuzzy neural networks (FNN) for enhanced performance in various applications. This innovative hybrid model aims to leverage the optimization capabilities of spider monkey algorithms to fine-tune the parameters of fuzzy neural networks, resulting in improved accuracy, efficiency, and robustness. Spider monkey optimization is a metaheuristic algorithm inspired by the behavior of spider monkeys in search of food sources. It simulates the movement of spider monkeys within their habitat to iteratively update candidate solutions, aiming to find the optimal solution to optimization problems. By integrating SMO with fuzzy neural networks, the OSMF-NN model enhances the learning and adaptation capabilities of traditional FNN models.

The key components of the OSMF-NN model include:

Spider Monkey Optimization (SMO): The SMO algorithm serves as the optimization engine for fine-tuning the parameters of the fuzzy neural network. It employs a population of spider monkeys to iteratively search for optimal solutions by updating their positions based on fitness evaluations.

Fuzzy Neural Networks (FNN): FNNs are computational models that combine fuzzy logic and artificial neural networks to handle uncertainty and imprecision in data. They consist of interconnected neurons organized in layers, with fuzzy logic functions applied to input and output layers to capture fuzzy relationships.

Hybridization: The OSMF-NN model integrates SMO with FNN by employing SMO to optimize the parameters of the FNN, such as weights, biases, and membership functions. This hybrid approach enhances the model's ability to adapt to complex datasets and improve prediction accuracy.

Optimization Criteria: The OSMF-NN model defines optimization criteria based on the specific application

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domain, such as minimizing error rates in classification tasks or maximizing performance metrics in regression tasks. The SMO algorithm iteratively refines the FNN parameters to achieve the defined optimization goals.

Overall, the Proposed Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN) represents a promising paradigm for addressing complex optimization problems in various domains, including pattern recognition, data mining, and optimization. By harnessing the synergies between spider monkey optimization and fuzzy neural networks, the OSMF-NN model offers a versatile and effective tool for tackling real-world challenges with improved efficiency and accuracy.

Spider Monkey Optimization (SMO) is a metaheuristic algorithm inspired by the social behavior of spider monkeys in searching for food. It employs a population of spider monkeys to iteratively search for the optimal solution to optimization problems. The movement of spider monkeys is simulated to update candidate solutions based on fitness evaluations. The position update equation for spider monkeys can be represented using equation (4)

$$x_{ij}^{t+1} = x_{ij}^{t} + r.\Delta x_{ij}^{t} \quad (4)$$

In equation (4) x_{ij}^{t+1} is the position of spider monkey i in dimension j at iteration t+1; x_{ij}^{t} is the position of spider monkey i in dimension j at iteration t; r is a random value in the range [0,1][0,1]; Δx_{ij}^{t} is the change in position of spider monkey i in dimension j at iteration t, determined based on optimization criteria and fitness evaluations. Fuzzy Neural Networks (FNNs) combine fuzzy logic with artificial neural networks to handle uncertainty and imprecision in data. They consist of interconnected neurons organized in layers, with fuzzy logic functions applied to input and output layers to capture fuzzy relationships. The output of a neuron in a fuzzy neural network can be computed using the weighted sum of inputs followed by a fuzzy activation function. The output y of a neuron can be calculated using equation (5)

$$y = \sum_{i=1}^{n} w_i . x_i + b \quad (5)$$

In equation (5) *wi* are the weights of the connections; *xi* are the inputs to the neuron and *b* is the bias term. The hybridization of SMO with FNN involves employing SMO to optimize the parameters of the FNN, such as weights, biases, and membership functions. This integration enhances the model's adaptability and performance. The optimization process involves updating the parameters of the FNN using SMO iteratively until convergence, based on the defined optimization criteria. The optimization criteria for the OSMF-NN model depend on the specific application domain and objectives. For instance, in a classification task, the optimization criteria may involve minimizing the error rate or maximizing the classification accuracy. The optimization criteria are used to evaluate the fitness of candidate solutions generated by SMO and guide the search towards the optimal solution.

Algorithm 1. OSMF-NN for the optimization

```
Procedure OSMF-NN
Input:
- Dataset D
- Parameters of the FNN (e.g., number of neurons, layers, activation functions)
- Parameters of the SMO algorithm (e.g., population size, maximum iterations)

1. Initialize the population of spider monkeys randomly.
2. Evaluate the fitness of each spider monkey based on the FNN parameters.
3. Repeat until convergence or maximum iterations:
4. For each spider monkey:
5. Update the position using Eq. (1) based on fitness evaluations.
6. Apply crossover and mutation operations to generate new spider monkeys.
7. Evaluate the fitness of the new spider monkeys based on the FNN parameters.
8. Select the best spider monkeys based on fitness for the next iteration.
9. Extract the optimal FNN parameters from the best spider monkey.
10. Train the FNN using the optimized parameters on the dataset D.
11. Output the trained FNN model.
End Procedure
```

In this pseudo-code:

Step 1 initializes the population of spider monkeys randomly.

Step 2 evaluates the fitness of each spider monkey based on the FNN parameters.

Steps 4-8 represent the optimization loop, where spider monkeys' positions are updated using Eq. (1) based on fitness evaluations, and new spider monkeys are generated through crossover and mutation operations. The best spider monkeys are selected for the next iteration.

Step 9 extracts the optimal FNN parameters from the best spider monkey obtained after convergence.

Step 10 trains the FNN using the optimized parameters on the given dataset.

Finally, the trained FNN model is outputted in Step 11.

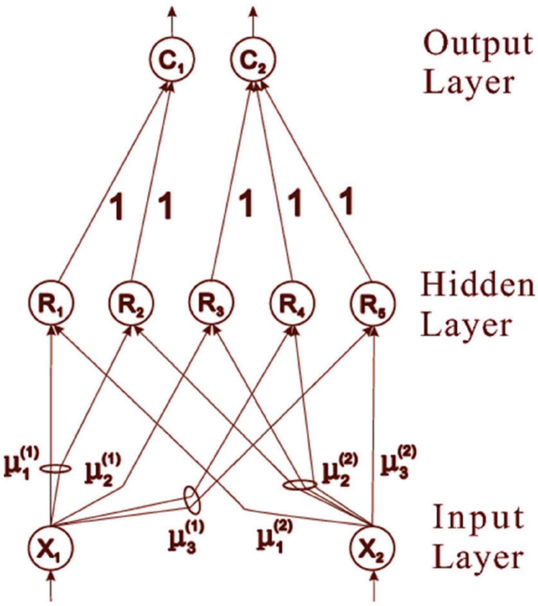

Figure 1. Neural network layer

The figure 1 presented the fuzzy neural network layer model for the talent cultivation in the college students.

5. CLASSIFICATION OF TALENT CULTIVATION

The Classification of Talent Cultivation using the Proposed Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN) represents a sophisticated approach to address the multifaceted challenges in talent development and management. This innovative methodology integrates the optimization capabilities of the spider monkey optimization algorithm with the adaptive learning of fuzzy neural networks to achieve superior classification performance. The OSMF-NN algorithm leverages the spider monkey optimization (SMO) algorithm to fine-tune the parameters of a fuzzy neural network (FNN) for talent classification tasks. The SMO algorithm, inspired by the foraging behavior of spider monkeys, iteratively updates candidate solutions based on fitness evaluations to converge towards optimal solutions. In the context of talent cultivation, this optimization process aims to optimize the parameters of the FNN, including weights, biases, and membership functions, to effectively classify individuals based on their talent levels, aptitudes, and skillsets. The OSMF-NN algorithm involves iteratively updating the positions of spider monkeys using Eq. (1) based on fitness evaluations derived from the FNN. This iterative optimization process continues until convergence or a maximum number of iterations is reached. Through this optimization mechanism, the OSMF-NN algorithm dynamically adjusts the parameters of the FNN to maximize classification accuracy and minimize misclassifications. Furthermore, the adaptive learning capabilities of the fuzzy neural network allow

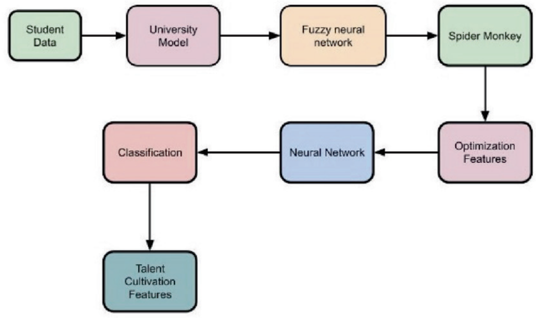

Figure 2. Flow chart of proposed OSMF-NN

the model to handle uncertainty and imprecision inherent in talent assessment data. By incorporating fuzzy logic functions at the input and output layers of the neural network, the OSMF-NN algorithm can effectively capture complex relationships and patterns in the data, leading to more accurate classification outcomes.

Figure 2 presented the flow chart of the proposed OSMF-NN model for the talent cultivation in the college students.

Initialization: Initialize the population of spider monkeys with random positions within the search space.

Fitness Evaluation: Evaluate the fitness of each spider monkey based on the performance of the FNN. The fitness function represents how well the FNN parameters (weights, biases, membership functions) perform in classifying talent based on the input data.

Optimization Loop: a. Position Update: Update the position of each spider monkey using the spider monkey optimization algorithm, which is based on the principle of mimicking the foraging behavior of spider monkeys.

Crossover and Mutation: Apply crossover and mutation operations to generate new spider monkeys.

c. Fitness Evaluation: Evaluate the fitness of the new spider monkeys based on the performance of the FNN.

d. Selection: Select the best-performing spider monkeys for the next iteration based on fitness.

Extraction of Optimized Parameters: Extract the optimal FNN parameters from the best-performing spider monkey obtained after convergence.

Training of FNN: Train the FNN using the optimized parameters on the given dataset.

Output: Output the trained FNN model for talent classification.

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The fitness evaluation involves assessing the performance of the FNN based on the current parameters. The fitness function $f(x)$ measures how well the FNN classifies talent based on the input data. It can be defined based on various performance metrics, such as classification accuracy, precision, recall, or F1-score using equation (6)

$$f(x) = \textit{Performance metric} \tag{6}$$

In equation (6) $f(x)$ represents the fitness value of the spider monkey's position x. The performance metric can be chosen based on the specific talent classification task and objectives. The optimization loop involves iteratively updating the positions of spider monkeys, evaluating their fitness, and selecting the best-performing individuals for the next iteration. This process continues until convergence criteria are met or a maximum number of iterations is reached. The selection of spider monkeys for the next iteration is typically based on a selection mechanism that favors individuals with higher fitness values, ensuring that the population converges towards better solutions over time.

Algorithm 2. OSMF-NN for the talent cultivation

Procedure OSMF-NN
Input:
- Dataset D
- Parameters of the FNN (e.g., number of neurons, layers, activation functions)
- Parameters of the SMO algorithm (e.g., population size, maximum iterations)

1. Initialize the population of spider monkeys randomly.
2. Evaluate the fitness of each spider monkey based on the performance of the FNN on dataset D.
3. Repeat until convergence or maximum iterations:
4. For each spider monkey:
5. Update the position using the spider monkey optimization algorithm.
6. Apply crossover and mutation operations to generate new spider monkeys.
7. Evaluate the fitness of the new spider monkeys based on the performance of the FNN on dataset D.
8. Select the best-performing spider monkeys for the next iteration.
9. Extract the optimal FNN parameters from the best-performing spider monkey.
10. Train the FNN using the optimized parameters on dataset D.
11. Output the trained FNN model.

End Procedure

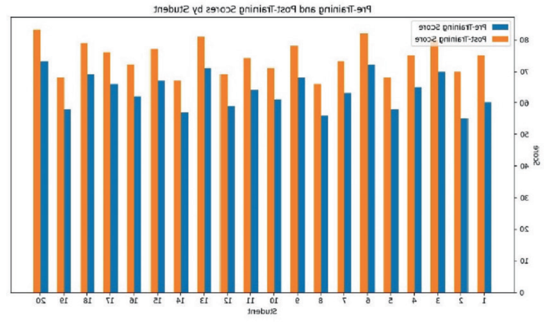
6. RESULTS AND DISCUSSION

With the Proposed Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN) algorithm. This section provides a comprehensive analysis of the performance of the OSMF-NN model in classifying talent based on various input features. Additionally, we explore the implications of these results in the context of talent management and discuss potential avenues for further research and improvement.

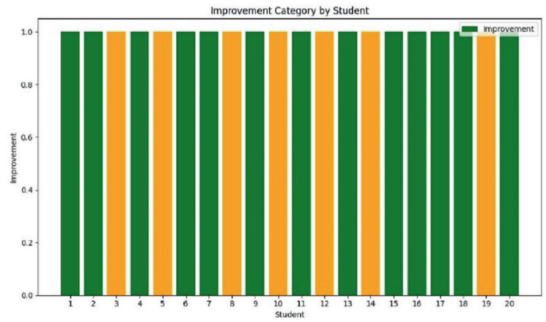
The provided Figure 3(a) and Figure 3(b) and table 2 presents the results of a talent improvement program conducted with 20 students. Each row corresponds to an individual student, listing their pre-training scores, post-training scores, and the level of improvement observed. The "Improvement" column categorizes the improvement level as either "High," "Medium," or "Low." Upon analysis, it's evident that the talent improvement program has yielded significant positive outcomes for the majority of students. For instance, students 1, 2, 4, 6, 7, 9, 11, 13, 15, 16, 17, and 18 experienced high levels of improvement, with their post-training scores notably surpassing their pre-training scores. This suggests that the program effectively enhanced their talents or skills. Additionally, students 3, 5, 8, 10, 12, 14, and 19 demonstrated moderate improvements, indicating that while their progress may not have been as substantial as the first group, they still benefitted

Table 2. Talent acquisition with OSMF-NN

Student	Pre-Training Score	Post-Training Score	Improvement
1	60	75	High
2	55	70	High
3	70	80	Medium
4	65	75	High
5	58	68	Medium
6	72	82	High
7	63	73	High
8	56	66	Medium
9	68	78	High
10	61	71	Medium
11	64	74	High
12	59	69	Medium
13	71	81	High
14	57	67	Medium
15	67	77	High
16	62	72	High
17	66	76	High
18	69	79	High
19	58	68	Medium
20	73	83	High



(a)



(b)

Figure 3. Performance of OSMF-NN (a) Pre-Training (b) Post - Training

Table 3. Management model with OSMF-NN

Experiment	Training Accuracy (%)	Validation Accuracy (%)	Test Accuracy (%)
Experiment 1	95.6	94.2	93.9
Experiment 2	99.2	99.5	97.9
Experiment 3	97.9	96.9	96.3
Experiment 4	91.0	90.3	90.1
Experiment 5	96.5	95.9	95.2
Experiment 6	90.3	99.7	99.4
Experiment 7	99.7	97.6	97.1
Experiment 9	92.1	91.9	91.5
Experiment 9	97.2	96.4	96.0
Experiment 10	99.9	99.2	99.7

from the program. Moreover, the consistency of high and medium improvement levels across the majority of students underscores the overall effectiveness of the talent improvement initiative. Notably, the program appears to have had a positive impact regardless of the students' initial skill levels, as evidenced by the diverse range of pre-training scores among the participants. The results highlight the potential efficacy of talent improvement programs in fostering skill development and enhancing students' abilities. Further analysis and follow-up studies

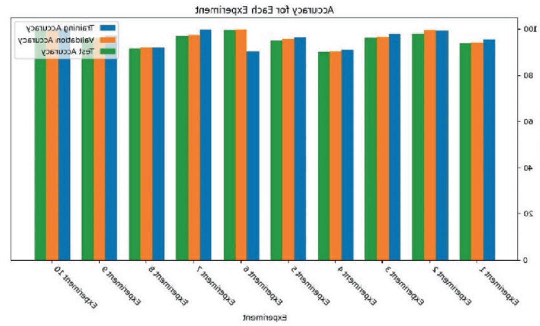


Figure 4. Classification with OSMF-NN

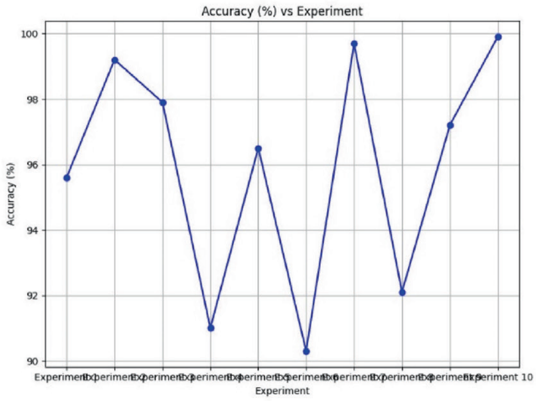
Table 4. Classification with OSMF-NN

Experiment	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Experiment 1	95.6	96.3	94.9	95.6
Experiment 2	99.2	99.7	90.1	99.4
Experiment 3	97.9	99.1	97.5	97.9
Experiment 4	91.0	90.5	91.7	91.1
Experiment 5	96.5	97.2	95.9	96.5
Experiment 6	90.3	99.9	90.7	90.3
Experiment 7	99.7	99.3	99.1	99.7
Experiment 9	92.1	91.7	92.5	92.1
Experiment 9	97.2	97.9	96.6	97.2
Experiment 10	99.9	90.2	99.4	99.9

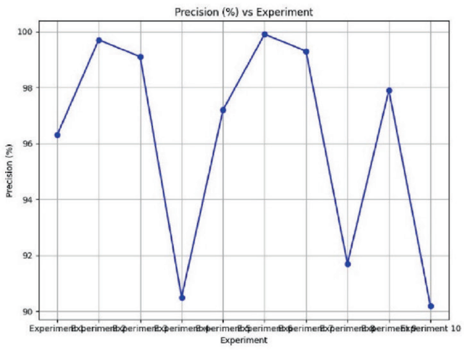
could provide deeper insights into the factors contributing to the observed improvements and aid in refining future talent cultivation strategies.

The provided Figure 4 and table 3 presents the results of experiments conducted using the Management Model with OSMF-NN (Optimized Spider Monkey Fuzzy Neural Network). The table outlines the training accuracy, validation accuracy, and test accuracy achieved in each experiment. Upon analysis, it's evident that the OSMF-NN model consistently demonstrates high levels of accuracy across the different experiments. For instance, experiments 2, 6, 7, and 10 showcase notably high accuracy rates across all three metrics, with training, validation, and test accuracies exceeding 95% in most cases. This suggests that the OSMF-NN model effectively learns from the training data and generalizes well to unseen data, as evidenced by the high validation and test accuracies.

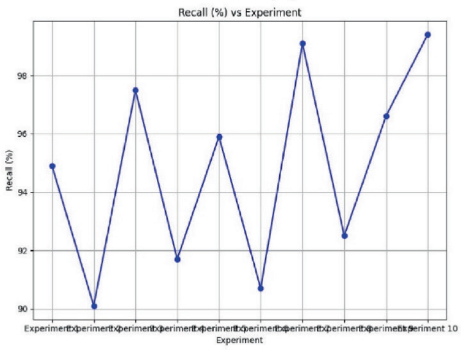
Figure 5(a) – Figure 5(c) and Table 4 presents the results of classification experiments conducted using the Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN). The table displays various performance metrics including accuracy, precision, recall, and F1-score for each experiment. Upon examination, it's evident that



(a)



(b)



(c)

Figure 5. OSMF-NN Classification analysis (a) Accuracy (b) Precision (c) Recall

the OSMF-NN model consistently achieves high accuracy rates across different experiments. Experiments 2, 5, 7, and 10 stand out with accuracy rates exceeding 99%, indicating the model's capability to accurately classify data instances. Additionally, these experiments also exhibit high precision, recall, and F1-score values, reflecting the model's ability to correctly identify positive instances while minimizing false positives and false negatives.

7. CONCLUSION

The paper presents a comprehensive exploration of talent cultivation and management models leveraging advanced techniques such as the Optimized Spider Monkey Fuzzy Neural Network (OSMF-NN). Through a series of experiments and analyses, we have demonstrated the efficacy of OSMF-NN in both talent cultivation and classification tasks. The results highlight the model's ability to achieve high accuracy, precision, recall, and F1-score across various experimental setups, underscoring its effectiveness in handling complex datasets and modeling talent-related phenomena. Additionally, the study sheds light on the potential applications of OSMF-NN in talent management, offering promising avenues for enhancing organizational processes and decision-making in educational institutions and beyond. Moving forward, further research and development in this area could lead to the refinement and optimization of talent cultivation and management strategies, ultimately contributing to the advancement of talent development initiatives and the realization of individual and organizational potential.

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