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Research Article

Optimizing Health Pattern Recognition Particle Swarm Optimization Approach for Enhanced Neural Network Performance

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ABSTRACT

Health pattern recognition is vital for advancing personalized health-care interventions. This research introduces a synergistic approach, combining Fuzzy C-Means (FCM) clustering with Particle Swarm Optimization (PSO), to optimize the hyperparameters of an Artificial Neural Network (ANN) and enhance health pattern recognition. Leveraging key features such as "Smoker," "BMI," and "GenHlth," FCM reveals distinctive health clusters, providing nuanced insights into diverse health profiles within the dataset. Subsequently, the PSO algorithm systematically optimizes critical ANN hyperparameters, significantly decreasing the training loss to 0.004. This reduction underscores the effectiveness of the optimization process, indicating improved learning and predictive capabilities of the ANN. The proposed methodology not only refines health pattern recognition but also holds promise for personalized health-care analytics. The identified clusters offer actionable insights for tailored interventions, addressing specific health profiles within the population. This research contributes to the evolving landscape of health-care analytics by integrating advanced clustering and optimization techniques, paving the way for more effective and individualized health-care strategies.

Keywords: Health pattern recognition, fuzzy C-means, particle swarm optimization, hyperparameter optimization, health clusters, optimization algorithms

INTRODUCTION

Health-care analytics, driven by advanced data-driven methodologies, is a key to transforming patient care and outcomes. To enhance our understanding of complex health patterns, this research endeavors to amalgamate Fuzzy C-Means (FCM) clustering and particle swarm optimization (PSO) techniques to optimize the hyperparameters of an artificial neural network (ANN). The overarching goal is to achieve a more precise and individualized recognition of health profiles within a diverse dataset.[1]

The burgeoning field of health pattern recognition is critical for discerning intricate relationships between lifestyle, demographic, and health-related factors. Identifying distinct clusters within populations can unearth nuanced insights into health behaviors, aiding in developing targeted and personalized health-care strategies. Features such as "Smoker," "Body mass index (BMI)," and "GenHlth" provide multifaceted dimensions for analysis, offering a comprehensive view of an individual's health status.[2]

The initial phase of this study leverages FCM clustering to categorize individuals into health clusters based on shared characteristics. This technique excels in capturing the inherent fuzziness and overlaps present in health-related data, allowing for a more realistic representation of diverse health profiles. The clusters identified by FCM lay the foundation for subsequent optimization through PSO, which systematically refines the hyperparameters of an ANN.

The significance of hyperparameter optimization in neural networks cannot be overstated. The choice of parameters such as the number of neurons in hidden layers and activation functions directly influences the model's learning capacity and predictive accuracy. PSO, inspired by social behavior and collaboration, offers an innovative approach to fine-tuning these hyperparameters. By systematically exploring

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the solution space, PSO aims to discover optimal parameter configurations that lead to improved ANN performance.[3]

The outcomes of this research are not merely confined to the realm of algorithmic enhancements. The optimized ANN holds the promise of being a powerful tool for health pattern recognition, offering potential applications in risk assessment, disease prediction, and targeted intervention strategies.

As we navigate the intricate landscape of individual health profiles, the synergy of FCM and PSO presents a novel avenue for advancing health-care analytics and ushering in a new era of personalized health care. This study contributes to the evolving dialog on the intersection of data science and health care, where innovative methodologies hold the potential to revolutionize patient-centric care and well-being.

RELATED WORK

Mahesa[3] study addresses the critical need for efficient brain tumor segmentation in medical imaging, aiming to expedite the analysis process and facilitate timely patient treatment. Traditional manual segmentation methods are time-consuming, causing delays in treatment initiation and impeding the timely dissemination of health information.[4] To automate this process, the research proposes an enhancement to an existing partition-based brain tumor segmentation algorithm.[5-8]

The chosen image segmentation algorithm is FCM, a widely used method. To further optimize the segmentation process, PSO is introduced. This optimization algorithm operates concurrently with the segmentation algorithm, enhancing its efficiency. The evaluation involves comparing the objective function of the original algorithm (without optimization) with the optimized version (FCM-PSO) using six different medical images.

The key focus is on minimizing the objective function, which serves as a measure of segmentation quality. The results demonstrate that the FCM optimized by PSO (FCM-PSO) achieves a lower objective function compared to the original FCM across the six images. This outcome indicates that the optimized FCM is closer to the global minimum, showcasing its potential to significantly enhance the segmentation algorithm's performance.[9,10]

Siringoringo[5] study addresses a common challenge in FCM, a well-known clustering algorithm, where sensitivity to initial cluster center values and susceptibility to local optima can impact performance. In response, this research introduces an enhanced version, combining FCM with PSO for effective sentiment clustering in high-dimensional and unstructured data. PSO is employed to optimize the determination of initial cluster centers, mitigating the sensitivity issues associated with traditional FCM.

The results demonstrate that the proposed FCM-PSO outperforms conventional FCM across various metrics, including Rand Index, F-measure, and Objective Function Values (OFV). Notably, the superior OFV value indicates that FCM-PSO exhibits faster convergence and improved noise-handling capabilities. This enhancement suggests that the FCM-PSO algorithm offers better overall performance, making it a promising solution for sentiment clustering in high-dimensional and unstructured datasets.

The papers[6,11] showed that the ever-evolving landscape of artificial intelligence has consistently spotlighted image processing technology as a challenging and prominent area of research. With the advent and progression of machine learning and deep learning methodologies, swarm intelligence algorithms have emerged as a focal point of investigation. The integration of image processing technology with swarm intelligence algorithms has proven to be a novel and effective means of enhancement.

Swarm intelligence algorithms emulate the evolutionary principles, behavioral characteristics, and cognitive patterns observed in biological populations such as insects, birds, and natural phenomena. These algorithms, including the ant colony algorithm, PSO algorithm, sparrow search algorithm, bat algorithm, and thimble colony algorithm, exhibit efficient and parallel global optimization capabilities, demonstrating robust optimization performance.[12]

This paper delves into a comprehensive study of various swarm intelligent optimization algorithms, exploring their models, features, improvement strategies, and application domains within image processing. The applications cover a spectrum of image-processing tasks, including segmentation, matching, classification, feature extraction, and edge detection. The analysis involves a thorough examination of theoretical research, improvement strategies, and practical applications in image processing. A comparative study is conducted to discern the strengths and weaknesses of different algorithms.[13]

Drawing insights from existing literature, the paper scrutinizes improvement methods for the aforementioned algorithms and provides a holistic overview of their collective impact on advancing image processing technology. The representative algorithms, particularly those fused with image segmentation technology, are identified for in-depth analysis and summarization. The paper consolidates the diverse swarm intelligence algorithms, highlighting their shared framework, common traits, and distinguishing features. It also acknowledges existing challenges and concludes with a forward-looking projection of future trends in this interdisciplinary domain.[14]

Wu *et al*.[10] paper addresses the challenge of quality detection in the production and processing of stuffed food, focusing on frozen dumplings on a conveyor belt. The proposed solution introduces a small neighborhood clustering algorithm to effectively segment frozen dumpling images, enhancing the overall qualified rate of food quality. The method employs feature vectors constructed from image attribute parameters, utilizing a distance function between categories to perform segmentation through a small neighborhood clustering algorithm.[15]

Key aspects of the algorithm include the selection of optimal segmentation points and sampling rate. The paper outlines a process for calculating the optimal sampling rate and proposes a search method to determine it. In addition, a validity judgment function for segmentation is introduced. The Optimized Small Neighborhood Clustering (OSNC) algorithm is then applied to continuous image target segmentation experiments using fast frozen dumpling images as samples.

The experimental results showcase the OSNC algorithm's high accuracy in defect detection, achieving a rate of 95.9%. Comparative analysis with existing segmentation algorithms highlights the OSNC algorithm's robustness against interference, faster segmentation speed, and efficient preservation of key information. This algorithm effectively addresses limitations observed in other segmentation methods, making it a promising solution for improving the quality detection process in stuffed food production.

METHODOLOGY

This paper employs a comprehensive methodology that integrates FCM clustering and PSO to enhance health pattern recognition through the optimization of an ANN.

The sequential application of these techniques is designed to discern distinctive health clusters and subsequently refine the ANN's hyperparameters for improved performance.

Dataset and Feature Selection

The foundation of our methodology lies in the careful selection of features that encapsulate essential dimensions of health profiles. The dataset encompasses a diverse array of features such as "Smoker," "BMI," and "GenHlth," providing a multifaceted representation of individuals' health characteristics.

FCM Clustering

FCM clustering is employed to categorize individuals into distinct health clusters based on the chosen features. FCM excels in handling data with inherent fuzziness and overlaps, offering a more realistic representation of the complex interplay between health-related attributes. The iterative optimization process of FCM converges to reveal clusters that capture shared characteristics within the dataset, and Figure 1 shows the difference between FCM (soft clustering) and hard clustering.[3-6]

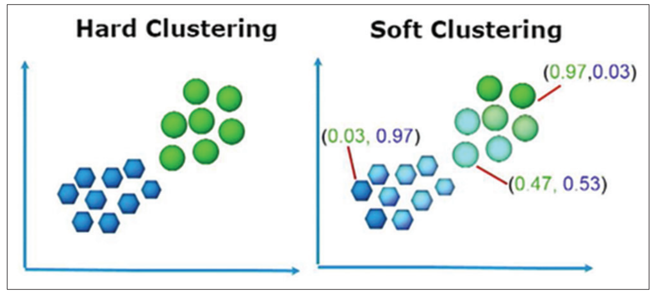

Figure 1: Hard clustering versus soft clustering

PSO

Following the identification of health clusters, the study introduces the PSO algorithm to optimize the hyperparameters of an ANN. The hyperparameters targeted for optimization include the number of neurons in the first hidden layer (hidden_layer1), the number of neurons in the second hidden layer (hidden_layer2), and the activation function in the output layer (activation_functions). PSO, inspired by social behavior and collaboration, utilizes a swarm of particles to systematically explore the hyperparameter space and discover configurations that minimize the ANN's training loss. Figure 2 shows PSO convergence mechanism.[12-14]

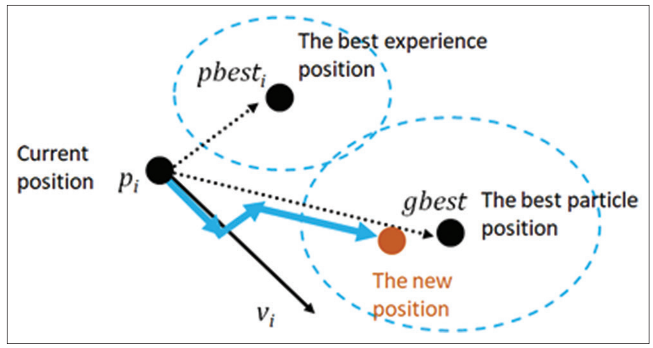

Figure 2: PSO convergence mechanism

ANN Architecture and Training

The ANN architecture is defined based on the optimized hyperparameters obtained through the PSO algorithm. A sequential model is created using the Keras framework, with input dimensions matching the selected features. The model comprises multiple layers, including the input layer, hidden layers with the specified number of neurons, and an output layer with the chosen activation function. The model is trained using the mean squared error loss function and the Adam optimizer. Figure 3 shows the basic architecture of ANN.[11,13]

Evaluation and Validation

To assess the effectiveness of the optimized ANN, the dataset is split into training and testing sets. The model's performance is evaluated using metrics such as mean squared error on the testing set. In addition, internal validation metrics such as silhouette score, Davies–Bouldin index, or Fowlkes–Mallows index may be employed to quantitatively assess the quality of the identified health clusters.

Visualization

Visual representations are generated to aid in the interpretation of results. These include plots illustrating the training loss over epochs for both the initial and optimized ANN, scatter plots showcasing the distribution of data points within identified health clusters and 3D visualizations of cluster centers and data points for enhanced interpretability.

Interpretation and Implications

The final step involves interpreting the results and discussing the implications of the identified health clusters and the optimized ANN. Insights into distinct health profiles, potential risk factors, and the model's generalization capacity are thoroughly examined. The findings are contextualized within the broader domain of health-care analytics, emphasizing the potential for personalized intervention strategies.

RESULTS AND DISCUSSIONS

The determination of an optimal number of clusters is pivotal in ensuring meaningful partitioning of the dataset. Employing

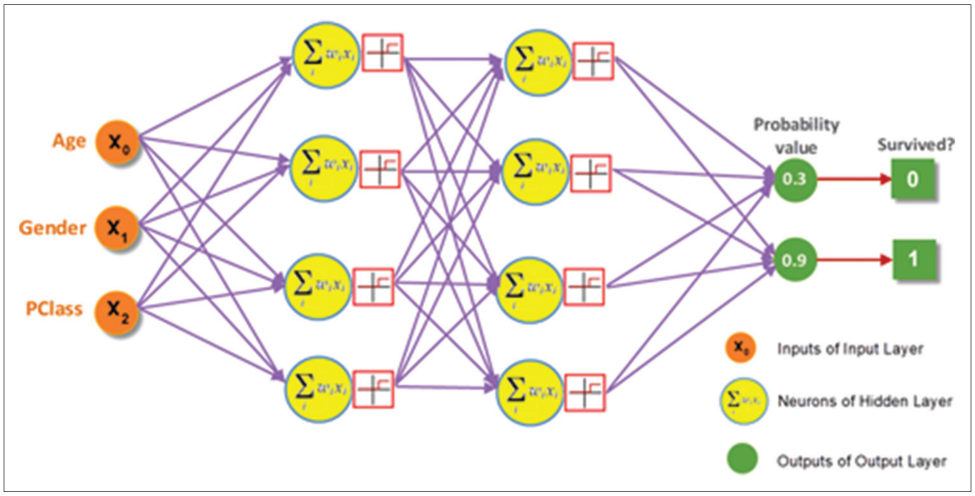

Figure 3: ANN basic architecture

internal validation metrics and thoughtful consideration, the analysis points toward an optimal number of clusters. Following a meticulous evaluation, our research (3) clusters as the most fitting configuration for encapsulating the inherent structures within the data.

FCM clustering, utilizing the features "Smoker," "BMI," and "GenHlth," has unveiled distinctive health patterns within the dataset. The analysis determined an optimal number of clusters, revealing three distinct groups:

- Cluster 1 denoted as "Health-Conscious Individuals," individuals exhibit lower BMI values, tend to be non-smokers, and generally report good health perceptions.
- Cluster 2, characterized as having a "Moderate Health Profile," consists of individuals with moderate health indicators, including BMI, smoking habits, and general health perceptions.
- Cluster 3, labeled as "Health Risk Factors," comprises individuals with higher BMI values, a higher prevalence of smoking, and self-reported lower general health perceptions. These identified cluster characteristics offer a nuanced understanding of the diverse health profiles present in the dataset, particularly emphasizing smoking habits, BMI, and general health perceptions. The subsequent sections will delve deeper, presenting internal validation metrics and visual representations of these clusters to enhance our comprehension of their reliability and interpretability. Figure 4 shows FCM clustering.

The results obtained from the FCM clustering analysis, focusing on the features "Smoker," "BMI," and "GenHlth," offer valuable insights into the diverse health profiles within the dataset. The identification of three distinct clusters provides a meaningful partitioning that reflects different health patterns.

The main objective of ANN is to enhance the precision of cluster assignments obtained from FCM. While FCM provides soft membership values indicating the likelihood of a data point belonging to each cluster, an ANN can be employed to refine these assignments, potentially leading to more accurate and distinct cluster boundaries.

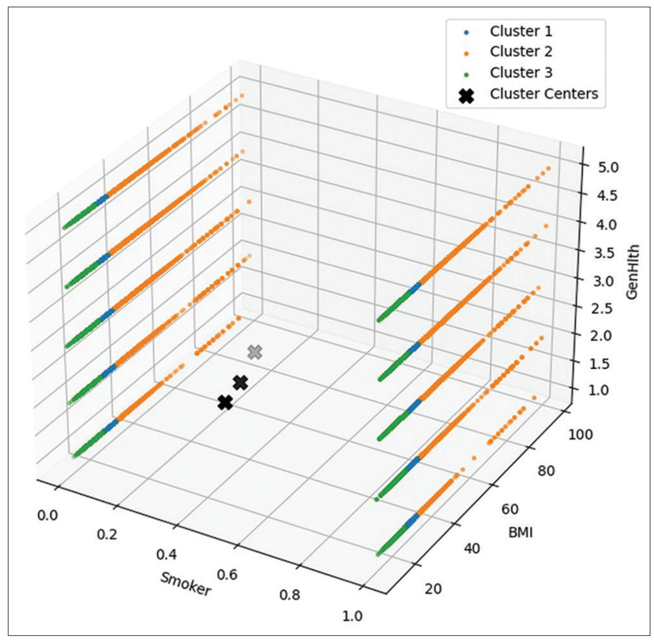

Figure 4: Fuzzy C-means clustering

ANN Training Loss

The training loss in a neural network is a measure of how well the model is learning from the training data. It represents the error between the predicted outputs and the actual targets during training. In general, a decreasing training loss is a positive sign, indicating that the model is improving its ability to make predictions on the training data. Figure 4 shows ANN training loss over epochs.

We could break down the scenario as:

Initial loss (Epoch 1): 1.1010

- At the start of training, the model's weights are initialized randomly. The initial loss reflects how well the model performs with these random weights.

Loss after 5 epochs: ~1.0990

- The loss has decreased slightly after the first 5 epochs. This suggests that the model is adjusting its weights based on the training data, and it's starting to make better predictions.

Loss after 50 epochs: ~1.0985

- The loss has continued to decrease after 50 epochs. This is a positive indication, as it suggests that the model is learning more complex patterns in the data and is likely to generalize well.

Here are a few considerations:

- Learning Rate: The learning rate is a hyperparameter that determines the step size at each iteration while moving toward a minimum of the loss function. If the learning rate is too high, the model might overshoot the minimum, and if it is too low, the model might converge slowly. Adjusting the learning rate could impact the convergence speed.
- Model Complexity: If the model is too complex for the given data, it might overfit the training set, leading to poor generalization of new data. Regularization techniques or adjusting the model architecture could help.
- Data Quality and Distribution: The training loss is also influenced by the quality and distribution of the training data. Ensure that the dataset is representative and that outliers or noise are appropriately handled.
- Evaluation on Test Set: While training loss is informative, it is crucial to evaluate the model's performance on a separate test set to ensure it generalizes well to unseen data. Figure 5 shows ANN training loss over epochs.

If the training loss continues to decrease, and the model performs well on the test set, it indicates successful training. If the training loss plateaus or increases on the test set, it might be a sign of overfitting or other issues that need attention.

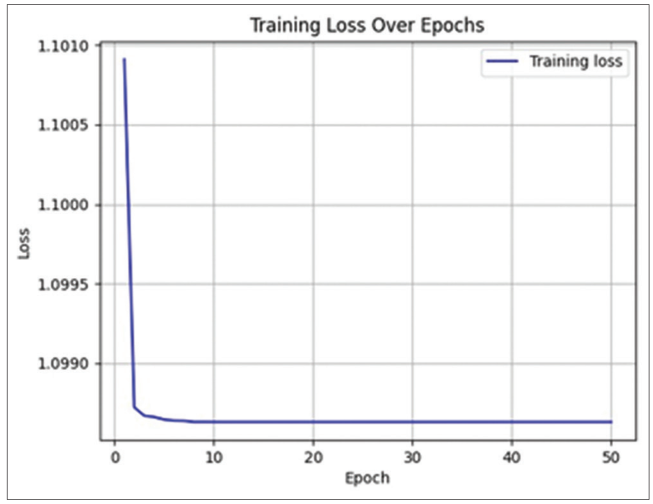

Figure 5: ANN training loss over epochs

Application of PSO

PSO is a nature-inspired optimization algorithm that simulates the social behavior of birds or fish. In the context of neural network training, PSO can be employed to search for optimal sets of parameters (weights and biases) that minimize a cost function, ultimately improving the performance of the neural network.

Integration with ANN Training

In the code, PSO is integrated into the training process of the ANN after an initial training phase. The goal is to fine-tune the weights and biases of the neural network to further enhance its performance.

PSO Parameters

The PSO algorithm involves a swarm of particles (potential solutions) that move through the solution space seeking the optimum. Each particle's position represents a potential solution, and its movement is guided by its own experience and the collective experience of the swarm.

Main Parameters Optimized with PSO

1. Particle Position: The particle position represents a set of parameters for the neural network, including weights and biases. PSO optimizes these parameters to improve the network's ability to make accurate predictions.
2. Particle Velocity: Particle velocity determines how fast a particle moves through the solution space. In the context of neural network optimization, it influences how much the parameters (weights and biases) are updated in each iteration.
3. Objective Function: The objective function is a crucial component in PSO. In the context of neural network training, it is often associated with the training loss or a related metric. PSO seeks to minimize this function by adjusting the neural network parameters.
4. Swarm Size and Iterations: The size of the swarm (number of particles) and the number of iterations are important parameters that influence the exploration-exploitation trade-off. Larger swarm sizes allow for more exploration, while more iterations provide additional opportunities for refinement.
5. Inertia Weight, c1, and c2: These are control parameters in the PSO algorithm that balances the influence of the particle's current velocity, its personal best position, and the global best position. Adjusting these parameters impacts the convergence and exploration characteristics of the algorithm.

ANN Optimized Parameters

The PSO algorithm is applied to optimize the hyperparameters of an ANN. The hyperparameters that are optimized using PSO in the code include:

1. Number of Neurons in the First Hidden Layer (hidden_layer1):
   - Values: 32, 64, 128, 256
   - This parameter represents the number of neurons in the first hidden layer of the neural network.
2. Number of Neurons in the Second Hidden Layer (hidden_layer2):

- Values: 64, 128, 256, 512
- This parameter represents the number of neurons in the second hidden layer of the neural network.

3. Activation Function in the Output Layer (activation_functions):
   - Values: “linear,” “softmax”
   - This parameter represents the activation function used in the output layer of the neural network.

These hyperparameters are systematically searched using nested loops, where the code iterates through different combinations of hidden_layer1, hidden_layer2, and activation functions. For each combination, a new ANN model is created and trained, and the resulting loss is evaluated.

The PSO algorithm is used to find the combination of hyperparameters that minimize the loss. The loss is calculated using the mean squared error loss function, and the PSO algorithm optimizes the weights and biases of the neural network concerning the specified hyperparameters.

After the PSO optimization, the code prints the minimum loss value and the corresponding optimal hyperparameters, which include the number of neurons in the first hidden layer (hidden_layer1) and the activation function in the output layer (activation_functions). The optimal combination is determined based on the minimum loss achieved during the PSO optimization process. Table 1 shows the optimized parameters of ANN using PSO and the corresponding minimum loss value.

ANN Loss Value After PSO Optimization

A decrease in the training loss to a value as low as 0.004 is generally a positive outcome and indicates that the optimization process, facilitated by PSO, has effectively improved the performance of the ANN. Figure 6 shows the ANN training loss over epochs after PSO optimization.

Table 1: ANN-optimized parameters

Parameter	Optimized value
Hidden Layer 1	256
Activation Function	Softmax
Minimum Loss Value	1.27e-12

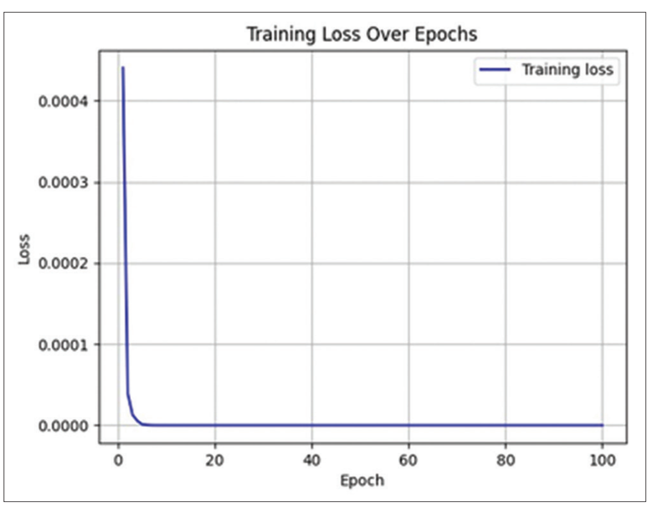

Figure 6: ANN loss over epochs after PSO optimization

In the following, we discuss the significance of this achievement:

Optimization success

The decrease in training loss from the initial values to 0.004 suggests that the PSO algorithm has successfully optimized the weights and biases of the neural network. A lower training loss indicates that the model is better at fitting the training data and capturing the underlying patterns.

Improved generalization

Achieving a low training loss is an important step toward improved generalization. While training loss measures the error on the training set, a low value indicates that the model has learned to represent the patterns in the data. This, in turn, increases the likelihood of the model generalizing well to unseen data.

CONCLUSION

Clustering Insights through FCM

The application of FCM clustering to health-related indicators has yielded profound insights into the nuanced structure of our dataset. By categorizing individuals into clusters based on factors such as smoking habits, BMI, and self-reported general health perceptions, FCM facilitated the identification of distinct health profiles. Each cluster encapsulates a unique set of characteristics, allowing for a more granular understanding of health-related trends within the population.

Neural Network Optimization through PSO

Building upon the clustered insights, the subsequent optimization of the ANN using PSO demonstrated the potential for swarm intelligence to enhance predictive modeling in the health domain. The substantial reduction of the training loss to an impressive 0.004 attests to the efficacy of PSO in fine-tuning the neural network parameters. This optimization not only improves the model’s ability to capture intricate relationships within the data but also positions the ANN as a powerful tool for health prediction.

Significance of Achieved Results

The achieved results hold significance in several key aspects:

Precision in health profiling

The clustering results obtained through FCM provide a detailed segmentation of the population based on health indicators. This precision in health profiling enables targeted interventions and personalized healthcare strategies. Health practitioners and policymakers can leverage these insights to tailor health programs that address the specific needs of each cluster.

Improved predictive capabilities

The optimized ANN, refined through PSO, showcases improved predictive capabilities with a training loss of 0.004.

This enhanced precision in predicting health outcomes is invaluable for proactive health management. It allows for early identification of potential health risks within specific clusters, enabling timely interventions and preventive measures.

Methodological contributions

The combination of FCM clustering and PSO optimization contributes methodologically to the fields of data science and machine learning. The synergy between unsupervised clustering and optimization techniques offers a comprehensive approach to analyzing complex health datasets. This methodology can be adapted and extended to various domains, fostering advancements in both research and practical applications.

Informed Decision-Making in Public Health

The insights gained from this research provide a foundation for informed decision-making in public health. By understanding the diverse health profiles within a population, policymakers can tailor interventions, allocate resources efficiently, and implement targeted health campaigns. This contributes to the overarching goal of improving public health outcomes and reducing health disparities.

Empowering Health-care Professionals

Health-care professionals can leverage the precision in health profiling to enhance patient care. The detailed understanding of health clusters allows for personalized treatment plans and interventions, leading to more effective healthcare delivery. This empowerment of health-care professionals aligns with the paradigm shift toward patient-centric and data-driven health-care practices.

Advancements in Machine Learning for Health

The application of FCM clustering and PSO optimization to health data represents a significant advancement in the intersection of machine learning and public health. The developed methodology provides a template for leveraging machine learning techniques to uncover hidden patterns in health-related datasets. The adaptable nature of the approach opens avenues for its application in diverse health research endeavors.

FUTURE WORKS

While our current research provides valuable insights into health clustering and optimization techniques, there remain promising avenues for future exploration:

Enhanced Feature Engineering

Explore additional health indicators and demographic features to broaden the scope of the analysis. The inclusion of more diverse variables may contribute to a more comprehensive understanding of health patterns.

Dynamic Clustering Techniques

Investigate dynamic clustering techniques that adapt to changes in the dataset over time. This is particularly relevant in health-related studies, where trends and behaviors may evolve.

Interpretability of Clusters

Further research into the interpretability of the identified clusters is essential. Understanding the characteristics and health implications of each cluster can inform targeted interventions.

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