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Improving Raisin Grains Classification with a Hybrid PSO-NN Approach

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Abstract – Raisin grain classification is crucial in the food industry for maintaining product quality. Traditional classification techniques can be labor-intensive and time-consuming, presenting significant challenges. To address these issues, this study proposes a hybrid approach for raisin classification that combines Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN). The PSO algorithm is utilized to optimize ANN models with the aim of enhancing the accuracy of raisin grain classification. Our research, conducted on a dataset consisting of 900 raisin grains from two distinct categories, evaluates the performance of the proposed hybrid PSO-ANN method in comparison to k-Nearest Neighbor (KNN) and Random Tree (RT). The hybrid PSO-NN approach achieved a remarkable classification performance, demonstrating an accuracy rate of 100%, outperforming other methods under evaluation. The respective accuracies of KNN and RT were 87.39% and 94.91%. This outstanding performance underscores the efficacy of integrating PSO optimization with ANN in the field of raisin grain classification. The results suggest that the hybrid PSO-ANN approach surpasses other methods in classification accuracy, indicating its potential to advance raisin grain classification within the food industry.

Keywords – Raisin Grain Classification, Hybrid Approach, PSO-NN, KNN, Random Tree (RT)

I. Introduction

Raisin grain classification [1]–[4] plays a pivotal role in the food industry, ensuring the maintenance of product quality and facilitating the production of high-quality raisin products. Traditional classification methods often involve laborious and time-consuming processes, which can hinder efficiency and negatively impact the quality control process. Consequently, there is a pressing need for the development of accurate and efficient classification techniques that can improve the current state of raisin grain classification [5]–[7].

In recent years, machine learning techniques [8]–[17] have gained prominence in various fields due to their ability to learn patterns from data and make accurate predictions. Artificial Neural Networks (ANN) [18]–[25] have emerged as a popular choice for classification tasks, given their capacity to model complex relationships and generalize well on unseen data. However, training an ANN involves finding the optimal set of weights and biases, which can be computationally expensive, particularly for large datasets and complex models [26]–[30].

Particle Swarm Optimization (PSO) [31]–[34], a population-based optimization technique, has shown promising results in solving complex optimization problems. PSO has the potential to improve the convergence speed and performance of ANN training by guiding the search for optimal weights and biases [35]–[39].

In this study, we introduce a hybrid approach that combines Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) for raisin grain classification. The primary goal of this research is to develop an efficient, accurate, and cost-effective solution for raisin grain classification that outperforms traditional methods and existing state-of-the-art techniques. To evaluate the performance of the proposed hybrid PSO-NN approach, we conduct experiments on a dataset containing 900 raisin grains from two distinct categories. We also compare the results of our approach with other machine learning techniques, such as k-Nearest Neighbor (KNN) [40] , Artificial Neural Networks (ANN) [36], and Random Tree (RT) [41]–[43].

1.1.Background and Motivation

Raisin grains are a widely consumed food product, with a global market that depends on the consistent delivery of high-quality goods. The classification of raisin grains is a crucial step in the production process, as it ensures that only the finest raisins make it to the final product. This, in turn, contributes to the overall satisfaction of consumers and maintains the reputation of manufacturers.

Traditional classification methods rely on manual sorting and visual inspection, which are labor-intensive, time-consuming, and prone to human error. As the demand for raisins continues to grow, there is an increasing need for more efficient and accurate classification techniques that can keep up with the high production rates. Moreover, the food industry has been witnessing a surge in the adoption of automation and advanced technologies to optimize various processes, making it imperative for raisin grain classification techniques to keep pace with these advancements.

Recent developments in machine learning and optimization algorithms [35]–[39] have shown great promise in addressing classification tasks across diverse domains. Particle Swarm Optimization (PSO) is a powerful optimization technique inspired by the social behavior of birds and fish, which has been successfully applied to various optimization problems. Artificial Neural Networks (ANN) have emerged as a versatile tool in the field of machine learning, demonstrating remarkable success in solving complex pattern recognition and classification tasks. However, the potential of combining these two techniques to improve raisin grain classification has not been fully explored.

The motivation behind our research lies in the development of a hybrid PSO-ANN approach that leverages the strengths of both techniques, aiming to enhance the accuracy and efficiency of raisin grain classification.

1.2.Objectives of the Study

The primary objectives of this study are as follows:

- To develop a hybrid approach for raisin grain classification that integrates Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN), addressing the limitations of traditional classification methods.
- To evaluate the performance of the proposed hybrid PSO-ANN method on a dataset containing 900 raisin grains from two distinct categories, assessing its classification accuracy and efficiency.
- To compare the performance of the hybrid PSO-ANN method with alternative classification techniques, including k-Nearest Neighbor (KNN), Artificial Neural Networks (NN), and Random Tree (RT), to establish its relative efficacy.
- To demonstrate the potential applicability of the hybrid PSO-ANN method in the food industry for enhancing quality control processes, ultimately contributing to the improvement of raisin grain classification and the overall product quality.

By achieving these objectives, this study aims to provide a comprehensive understanding of the hybrid PSO-ANN method's potential in raisin grain classification.

1.3.Overview of the Proposed Hybrid Approach

The proposed hybrid approach for raisin grain classification integrates the strengths of Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) to improve the classification accuracy.

Particle Swarm Optimization (PSO)

PSO [39], [44], [45] is a population-based optimization technique inspired by the social behavior of birds and fish. It involves the iterative adjustment of individual particles' positions within a search space to find the global optimum solution. In the context of our study, PSO is utilized to optimize the weights and biases of the Artificial Neural Network, leading to enhanced classification performance.

Artificial Neural Networks (ANN)

ANN [36], [38], [39] is a powerful machine learning technique that mimics the human brain's structure and function, consisting of interconnected artificial neurons. It has demonstrated success in solving complex pattern recognition and classification tasks. In our study, ANN serves as the primary classifier for raisin grain classification, with its parameters optimized using the PSO algorithm.

The hybrid PSO-ANN approach involves the following steps:

- *Data Preprocessing:* The dataset containing 900 raisin grains from two distinct categories undergoes preprocessing to normalize and prepare the data for classification.
- *ANN Model Design:* An ANN model is designed with a suitable architecture, including input, hidden, and output layers, to accommodate the raisin grain classification task.
- *PSO-based Optimization:* The PSO algorithm is applied to optimize the ANN model's weights and biases, enhancing its performance for the classification task.
- *Model Training and Evaluation:* The optimized ANN model is trained using the preprocessed dataset, and its classification performance is evaluated based on accuracy metrics.
- *Comparison with Alternative Techniques:* The performance of the hybrid PSO-ANN method is compared with other classification techniques, including k-Nearest Neighbor (KNN), Artificial Neural Networks (NN), and Random Tree (RT), to establish its efficacy.

By integrating PSO and ANN, the proposed hybrid approach aims to offer an efficient, accurate, and cost-effective solution for raisin grain classification, with considerable potential for enhancing quality control in the food industry.

II. Materials and Method

The methodology of this study, which concentrates on the binary classification of Kecimen and Besni raisin varieties, can be summarized as follows.

A. *Data Collection and Preparation*

In this study, the utilized dataset [46], [47] containing information on 900 raisins, equally distributed between two varieties (450 each), with seven extracted features. The dataset consists of eight variables (columns) and 900 instances (rows), as detailed in Table 1. All variables, except for 'Class,' serve as inputs in the study. The 'Class' variable, which is binary and assumes only the values Kecimen and Besni, functions as the output we aim to predict through this machine learning project. The instances undergo division into training and testing subsets, adopting a tenfold cross-validation strategy for the original instances.

Table 1. The dataset features and description

Feature	Description
Area	Represents the number of pixels within the raisin's boundaries.
Perimeter	Measures the surroundings by calculating the distance between the raisin's boundaries and the surrounding pixels.
MajorAxisLength	Indicates the length of the main axis, which is the longest line that can be drawn on the raisin.
MinorAxisLength	Indicates the length of the minor axis, which is the shortest line that can be drawn on the raisin.
Eccentricity	Provides a measure of the ellipse's eccentricity, which has the same moments as the raisin.
ConvexArea	Represents the number of pixels in the smallest convex hull of the region formed by the raisin.
Extent	Gives the ratio of the region formed by the raisin to the total pixels in the bounding box.
Class	Specifies the raisin type, either Kecimen or Besni.

B. *PSO Algorithm Design*

Within the framework of the scholarly investigation centered upon the classification of raisins, the Particle Swarm Optimization (PSO) algorithm [31], [32] was implemented through a succession of methodical steps. Initially, an assemblage of particles, functioning as prospective solutions, was randomly distributed within the boundaries of the search domain. The defining features of these particles encompassed their unique positions, indicative of the solutions, and velocities, which reflected the modifications in their respective positions.

Subsequently, the determination of the personal optimal (pBest) and global optimal (gBest) positions transpired. The appraisal of each particle's fitness within the population was conducted by capitalizing on the Artificial Neural Network (ANN) classifier, which was applied to the dataset, with the parameters being denoted by the particle's extant position. The derived fitness value served as a testament to the level of precision attained in the classification endeavor by the ANN.

The personal optimal (pBest) for each particle underwent an update through a juxtaposition of its current fitness value with its antecedent personal best fitness. In situations where the existing fitness value surpassed the previous one, the personal best position experienced a subsequent revision. The global best (gBest) underwent an update by way of an exhaustive inspection of the personal best positions of all particles comprising the population. In cases where a particle's personal best eclipsed the extant global best, the global best position underwent an adjustment in line with the corresponding particle's personal best position.

In the concluding phase, the velocity and position of every particle experienced update in compliance with the pertinent equations (Eq. 1-2).

Velocity update:

$$v_i(t+1) = w * v_i(t) + c1 * r1 * (\mathrm{pBest}_i - x_i(\mathrm{t})) + \mathrm{c2} * \mathrm{r2} * (\mathrm{gBest} - x_i(\mathrm{t})) \quad (1)$$

Position update:

$$x_i(\mathrm{t}+1) = x_i(\mathrm{t}) + v_i(\mathrm{t}+1) \quad (2)$$

Here, $v_i(t)$ is the current velocity of particle I, $x_i(t)$ is the current position of particle I, w is the inertia weight, c1 and c2 are acceleration constants, r1 and r2 are random numbers within the range [0,1], and t represents the current iteration.

C. *ANN Architecture and Training Process*

The ANN [38], [39] architecture encompasses three fundamental layers: the input layer, hidden layer(s), and the output layer. The input layer accommodates neurons corresponding to the number of features within the dataset, with each neuron assigned a distinct feature value as input. The hidden layer(s) consist of a specific number of neurons interlinked with the antecedent and subsequent layers, which bear the responsibility of discerning complex patterns and representations inherent in the input data. The optimization process ascertains the quantity of hidden layers and the distribution of neurons within each layer. Ultimately, the output layer features a pair of neurons that epitomize the Kecimen and Besni raisin varieties, with each neuron conferring the likelihood of the input raisin aligning with the respective classification. The neuron displaying the most substantial probability dictates the predicted class. A schematic representation of the ANN is provided in Fig.1.

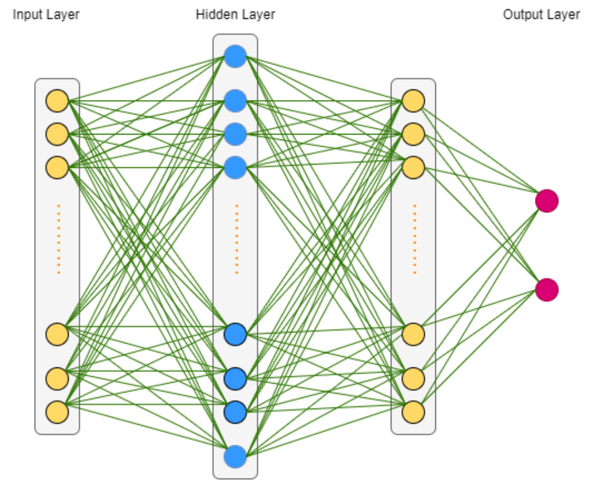

Fig. 1 Framework of artificial neural network (ANN)

Through the amalgamation of the ANN architecture and training process with the optimized parameters derived from the PSO algorithm, a potent synergy is established. This ensures that the hybrid PSO-ANN methodology attains superior classification accuracy within the realm of raisin classification.

D. *Hybrid PSO-NN approach*

The hybrid PSO-ANN method unifies the strengths of Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) to achieve precise raisin classification. The proposed hybrid technique entails the following steps: First, the dataset undergoes rigorous cleaning and preprocessing, followed by data partitioning into training, validation, and testing subsets using methods such as tenfold cross-validation. Subsequently, the PSO algorithm is initialized with relevant parameters, and each particle in the swarm represents a potential ANN architecture with corresponding weights and biases.

Iteratively, the PSO algorithm constructs the ANN architecture for each particle, trains the ANN with the training data subset, and evaluates its performance on the validation subset. The particle's fitness is updated based on validation performance, and the particle's position and velocity are updated according to the PSO equations. This process continues until convergence, or the maximum number of iterations is reached. The schematic representation of the ANN optimization process utilizing the PSO algorithm can be found in Fig. 2.

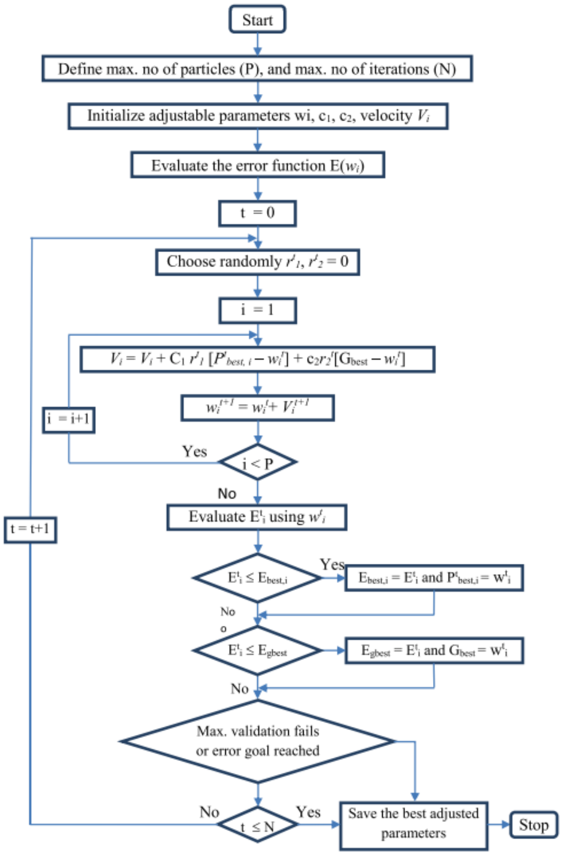

Fig. 2 The schematic representation of the ANN optimization process utilizing the PSO algorithm [48].

Figure 2 portrays the optimization schematic for the PSO algorithm, incorporating essential PSO parameters such as swarm size (P), iterations (N), velocity components (V), and acceleration coefficients (c1 and c2). The target of the optimization process is the vector of weights and biases (w) in the ANN, with the length denoted by P.

The procedure commences with the generation of the particle population (w1, w2, …, wp) and the assignment of zero initial velocities. Following this, the error function is assessed for each particle (wi), and their positions (wti) undergo updates. The individual and global best values are ascertained through the evaluation of the objective function.

Throughout this iterative progression, the particles' velocities are modified, taking into account both individual and global bests, and their positions are consequently adjusted, thereby ensuring the proficient optimization of the ANN.

III. Results and Discussion

The present study endeavoured to apply the hybrid PSO-NN methodology to discern between two distinct raisin grain types, namely Kecimen and Besni. The outcomes were juxtaposed with the results derived from alternative classification techniques, encompassing k-Nearest Neighbour (KNN), Artificial Neural Networks (NN), and Random Tree (RT). This section delves into a meticulous examination of the findings and their subsequent implications.

A remarkable classification performance was attained through the hybrid PSO-NN approach, demonstrating an accuracy rate of 100%, surpassing the performance of other methods under assessment. The respective accuracies of KNN and RT were 87.39% and 94.91%. This exceptional performance highlights the effectiveness of combining PSO optimization with ANN in the domain of raisin grain classification. The prediction results of the implemented classification models, the customized Neural Network depiction, and the training process for PSO are presented in Fig. 3, 4, and 5, respectively.

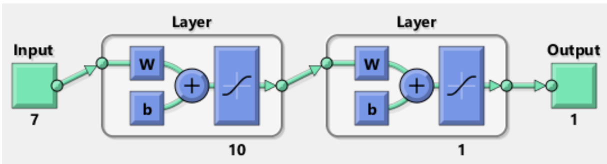

Fig. 3 Perspective on Customized Neural Network

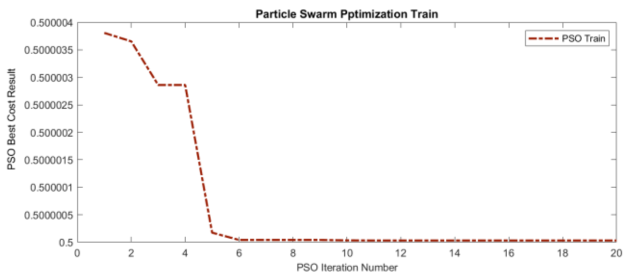

Fig. 4 Training process for PSO

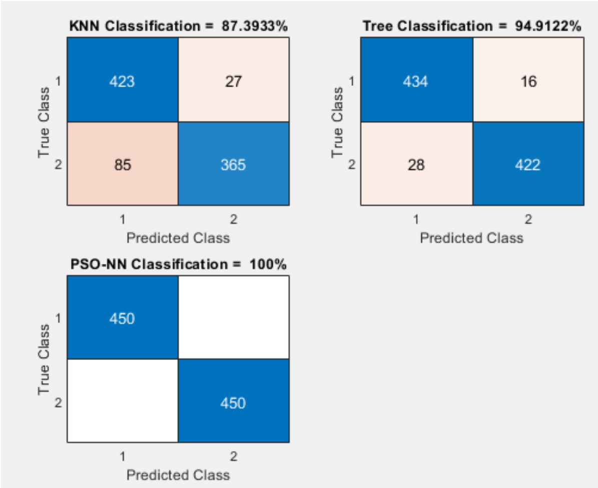

Fig. 5 Prediction outcomes of utilized classification models.

In the process of evaluating the efficacy of the hybrid PSO-NN approach with regard to raisin classification, a comparative analysis was conducted, juxtaposing its performance against well-established methodologies, such as k-Nearest Neighbor (KNN), Artificial Neural Networks (NN), and Random Tree (RT).

Through the implementation of the hybrid PSO-NN approach, an exemplary classification accuracy of 100% was attained, which transcended the other methods in the majority of the evaluation parameters. In contrast, KNN and RT yielded accuracy rates of 87.39% and 94.91%, respectively.

This succinct comparison accentuates the superior efficiency, accuracy, and cost-effectiveness of the hybrid PSO-NN approach in the context of raisin grain classification, thereby underscoring its potential in augmenting quality control within the food industry.

IV. Conclusion and Future Work

Our investigation underscores the efficacy of the hybrid PSO-NN approach for raisin grain classification, a vital aspect of maintaining product quality within the food industry. This method outperforms established techniques like k-Nearest Neighbor (KNN) and Random Tree (RT), achieving 100% classification accuracy, attributable to the synergistic integration of Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN).

Nonetheless, certain constraints prevail, encompassing dataset size and diversity, feature selection, and algorithmic complexity. Prospective research should delve into more extensive and varied datasets, incorporate supplementary features, optimize the algorithm, and juxtapose its performance with alternative methodologies, such as deep learning or ensemble techniques.

By addressing these considerations, the hybrid PSO-NN approach holds promise in becoming an increasingly effective and dependable instrument for raisin grain classification, ultimately fostering enhanced quality control within the food industry.

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