Intelligent Methods in Engineering Sciences 3(3): 099-107, 2024

INTELLIGENT METHODS
IN ENGINEERING SCIENCES

https://www.imiens.org

International Open Access

September, 2024

e-ISSN 2979-9236

Research Article

https://doi.org/10.58190/imiens.2024.104

Classification of Raisin Grains Using Different Artificial Neural Network Methods

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ARTICLE INFO

Article history:
Received 11 August 2024
Accepted 13 September 2024

Keywords:
Artificial Neural Network,
Competitive layer neural network,
Pattern recognition artificial neural network,
Raisin classification,
Self-organizing map

ABSTRACT

In addition to its nutritional properties, raisins are also a beneficial food in terms of health due to its vitamins, minerals, antioxidants and phenolic compounds. Turkey ranks first in global raisin production with a production capacity of 24%. Many problems are encountered in the classification of raisins according to their type and quality by traditional methods. In order to overcome these problems, artificial intelligence systems, whose usage area is increasing day by day, are utilized. In this study, raisin grains were classified using 3 different Artificial Neural Network (ANN) methods using the 'Raisin' dataset from the UCI Machine Learning Repository. Performance measurements of Competitive Layer Neural Network (CLNN), Pattern Recognition Artificial Neural Network (PRNN) and Self-Organizing Map (SOM) methods used in classification were performed. In the obtained performance measurements, PRNN has the highest success, while SOM is weaker compared to the other two methods. CLNN, on the other hand, remains at similar levels to PRNN and offers a good alternative to PRNN.

1. Introduction

Raisins are an important food source containing plenty of carbohydrates, vitamins and minerals such as potassium, calcium and iron [1], [2]. In addition to its nutritional properties, raisins are also a beneficial product in terms of health. Its antioxidants and phenolic compounds are known to have positive effects against diseases such as cardiovascular diseases and cancer [3]. Global raisin production was 1.3 million tons in 2022/2023. Turkey ranks first in raisin production, accounting for 24% of global production. Turkey is followed by China (14%), Iran (14%), USA (13%) and India (11%). Uzbekistan, Argentina, South Africa and Chile are the other countries producing between 3% and 5% [4].

Nowadays, the classification of products according to their type and quality by traditional methods is both more costly and longer due to the increase in production quantities and labor costs. In addition, a certain standard cannot be obtained due to fatigue, inattention and personal differences in classification with traditional methods. Pricing and determining the quality of raisins is also one of the most important challenges between sellers and buyers [5]. In order to overcome these problems, artificial intelligence systems, which have started to be used in many areas of our lives, have started to be utilized. Different branches of artificial intelligence are utilized in the classification of raisin grains.

In the literature; Quantum machine learning (QML) [6], Extreme Learning Machine (ELM) [7], Support Vector Machine (SVM) [8], Graph Neural Network (GNN) [9], Convolutional Neural Network (CNN) [10], CNN-SVM [11], Single Shot MultiBox Detector (SSD) [12], Logistic Regression (LR) [13] are the current classification methods. Particle Swarm Optimization (PSO) [5], Stacked Autoencoder and Rotation Forest [14], Least Squares Support Vector Machine (LSSVM) [15], Deep Learning Algorithms [16], Artificial Neural Networks (ANN) [17] are some of the methods used in the classification of raisins.

Backes and Hocastehnazhand (2024), analyzed 15 different classes of bulk raisins. Texture features of the images were used for classification and evaluation was performed using the Particle Swarm Optimisation (PSO) method. Three different classifiers, SVM, Linear Discriminate Analysis (LDA) and K-nearest neighborhood, were used for modelling. The best results were achieved using SVM and LDA modelling as 99.33% and 99.73%, respectively [5].

Raihen and Akter (2024), investigated different machine learning and deep learning methods for classification. These methods are GaussianNB, Decision Tree, K-Nearest Neighbor, Random Forest, SVM,

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XGBoost, LightGBM, and AdaBoost, Logistic Regression, Artificial Neural Network and Deep Learning Network. The effectiveness of the study was evaluated using standard metrics such as F1 score and ROC area under the curve (AUC). It was reported that AdaBoost and LightGBM methods achieved an accuracy of 90.30 and 98.40 per cent and an ROC curve score of approximately 90 per cent, respectively [16].

Kılıçarslan (2022), proposed a hybrid model using Rotation Forest (RF) and Stacked Autocoder (SOC) deep learning algorithms to predict the types of raisin grains. As a result of the experimental evaluation in the study, it was stated that the hybrid RO method achieved high success with 91.50% performance compared to classical data mining methods and deep learning methods. [14].

Çınar et al. (2020), developed a machine vision system to distinguish between two different raisin varieties (Keçimen and Besni) grown in Turkey. They subjected 900 raisin grains to different pre-processing steps and extracted 7 morphological features using image processing techniques. Then, models were created using LR, MLP and SVM machine learning techniques and performance measurements were made. It was stated that the highest classification accuracy was obtained from SVM with 86.44% [18].

Khojastehnazhand and Ramezani (2020), analyzed the quality of bulk raisins using image processing technique. Different texture feature algorithms combined with different modelling methods were used to evaluate the system performance. The results of the study showed that the SVM classifier using Gray Level Run Length Matrix (GLRM) features gave more accurate classification results. [19].

Yu et al. (2012), presented an approach based on combined color and texture features to classify raisins. They used least squares support vector machine (LSSVM), linear discriminant analysis and soft independent modelling of class analogy to build classification models. Their results show that the best performance is obtained with LSSVM with an average correct response rate of approximately 95% [15].

Mollazede et al. (2012), investigated the quality classification of raisins using image processing and data mining-based classifiers. They investigated four different data mining-based techniques, namely ANN, SVM, Decision Trees (DTs) and Bayesian Networks (BNs) to classify raisins. Among these techniques, ANN has the highest classification accuracy with 96.33% [17].

In this study, three different ANN methods were used to classify the raisins of Keçimen and Besni varieties produced in Turkey according to their varieties. The proposed ANN methods are Competitive Layer Neural Network (CLNN), Pattern Recognition Artificial Neural Network (PRNN) and Self-Organizing Map (SOM) methods. Classification with the proposed ANN methods was carried out according to 7 different morphological features obtained from 900 raisin grains of Keçimen and Besni varieties taken from the UCI Machine Learning Repository.

2. Material and Methods

In this study, 900 raisin data from the UCI Machine Learning Repository were classified using CLNN, PRNN and SOM artificial neural network methods. The process steps required for the classification of raisin grains are given in Figure 1.

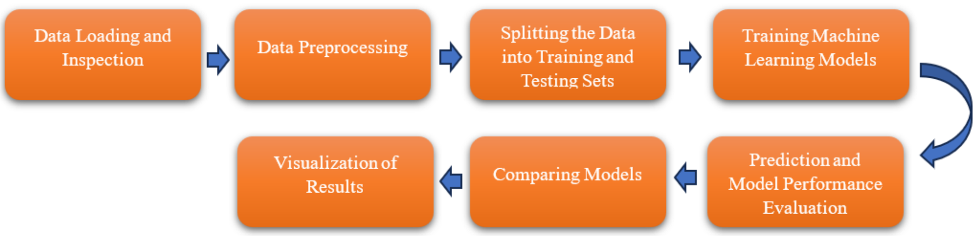

Figure 1. Classification Steps of Dry Raisin Grains

2.1. Dataset

The “Raisin” dataset from the UCI Machine Learning Repository was used for the classification of raisin grains [20]. The dataset created by Çınar et al. is composed of images of Keçimen and Besni raisin varieties grown in Turkey. The dataset consists of 450 pieces of Keçimen and 450 pieces of Besni raisins. For each raisin, 7 morphological features were extracted. Table 1 shows the 7 features and descriptions of the dataset.

Table 1. Raisin Dataset Characteristics and Descriptions

Variable Name	Role	Type	Description
Area	Feature	Integer	Gives the number of pixels within the boundaries of the raisin.
MajorAxisLength	Feature	Continuous	It measures the environment by calculating the distance between the boundaries of the raisin and the pixels around it.
MinorAxisLength	Feature	Continuous	Gives the length of the main axis, which is the longest line that can be drawn on the raisin.
Eccentricity	Feature	Continuous	Gives the length of the small axis, which is the shortest line that can be drawn on the raisin.
ConvexArea	Feature	Integer	It gives a measure of the eccentricity of the ellipse, which has the same moments as raisins.
Extent	Feature	Continuous	Gives the number of pixels of the smallest convex shell of the region formed by the raisin.
Perimeter	Feature	Continuous	Gives the ratio of the region formed by the raisin to the total pixels in the bounding box.
Class	Target	Categorical	Kecimen and Besni raisin.

2.2. Competitive Layer Neural Network

Competitive Layer Neural Network (CLNN) was first proposed by Ritter to solve spatial feature binding and sensory segmentation problems [21], [22]. This model is based on a combination of competitive and collaborative processes in a Recurrent Neural Network (RNN) architecture, which can separate a set of input features into distinct groups [22]. Due to competitive interactions between layers, each feature is ambiguously assigned to a layer and feature binding is performed by a collection of competitive layers [23].

The CLNN contains a number of layers, with neurons in each layer. The neurons in each layer are connected to each other and the connection weights are assumed to be independent of any layer. Between different layers, only neurons arranged in a row are connected. Neurons in each layer must be co-operative, while neurons in each row must be competitive. In the competitive layer, only one neuron is activated when a certain input is received, while the others remain inactive. This reflects a 'winner takes all' strategy [24], [25]. Figure 2 shows the basic components of the CLNN system.

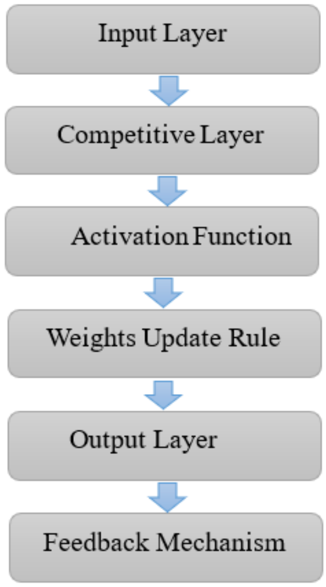

Figure 2. Basic Components of The CLNN System

In CLNN, the network receives an input vector, usually consisting of high-dimensional data. Each neuron calculates the distance between the incoming input and its own weights. The calculated distance determines how close the neuron is to the input. The lowest of the calculated distances is selected and is called the 'winning neuron'. The winning neuron is the neuron that best fits the input data. The weights of the winning neuron are updated towards the input vector. The neighbors of the winning neuron are also updated using a certain neighborhood function. Thus, similar inputs are better organized. This process is repeated for the entire training dataset. Once training is complete, the network can be used to classify or group new data.

2.3. Pattern Recognition Artificial Neural Network

Pattern Recognition Artificial Neural Network (PRNN) studies how machines can observe the environment, learn to distinguish patterns of interest from their background, and make sound and reasonable judgements about categories of patterns [26].

In the neuron model of PRNN, the multilayer hierarchical network consists of many layers of cells. In the multilayer hierarchical network, there are forward and backward connections between cells. Thus, the network can be trained for the optimal solution to a given problem [27], [28]. There are three elements that influence the success of PRNN techniques; the volume of data, the method applied, the designer and the user. The task in PR is to create a system capable of processing big data. The way to solve the challenges of PR is the choice of the analysis model, such as pre-processing, schema and post-processing or decision-making model [27]. Figure 3 shows the basic components of the PRNN system.

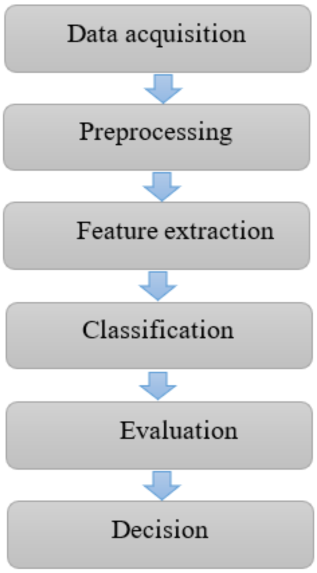

Figure 3. Basic Components of The PRNN System

2.4. Self-Organizing Map

Self-Organizing Map (SOM) is an automated data analysis method [29]. SOM refers to a class of neural network algorithms in the unsupervised learning category. SOM was introduced in 1981-82 by Professor Teuvo Kohonen, founder of the Neural Network Research Centre, and since then many versions and implementations of SOM have been developed [30]. Each input data item will select the model that best matches the input item, and this model as well as a subset of its spatial neighbors in the grid will be modified for better matching. As in Vector Quantization (VQ), the modification is concentrated on a selected node containing the winning model. On the other hand, since an entire spatial neighborhood in the grid around the winning model is modified at once, the local ranking of the models in this neighborhood will increase due to the smoothing action. Different successive inputs cause corrections in different subsets of models. The local ranking actions will gradually spread over the grid [31-33]. Figure 4 shows the basic components of the SOM system.

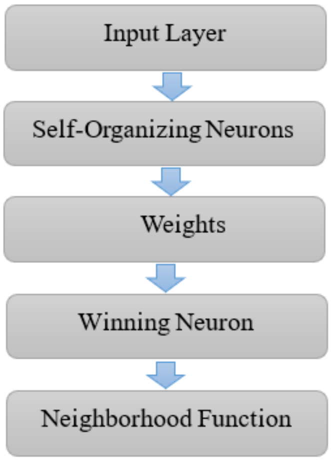

Figure 4. Basic Components of The SOM System

The SOM receives an input data. Then all neurons calculate their distance from the input, the neuron with the lowest distance becomes the winning neuron. The weights of the winning neuron and neighboring neurons are updated towards the input data. The update is usually determined by a learning rate and neighborhood function. This process is repeated for the whole dataset.

3. Experimental Study

In the dataset used in the study, raisins are expressed with two different classes as Besni and Keçimen. Two different raisin varieties were classified according to their varieties using CLNN, PRNN and SOM artificial neural network methods. Comparison of the performances of 3 different ANN methods used in the study was carried out according to accuracy, recall, precision and F1-score criteria. The calculation formulas for the performance success criteria are given in Equations 1-4 below.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

$$\text{F1} - \text{Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

In the equations; TP (True Positive), FP (False Positive), TN (True Negative) and FN (False Negative).

The feature values of 14 grape berries belonging to the ‘Raisin’ raisin dataset used in the study are given in Table 2.

Table 2. Dataset Example

Area	MajorAxisLength	MinorAxisLength	Eccentricity	ConvexArea	Extent	Perimeter	Class
87524	442,2460114	253,291155	0,819738392	90546	0,758650579	1184,04	Kecimen
75166	406,690687	243,0324363	0,801805234	78789	0,68412957	1121,786	Kecimen
90856	442,2670483	266,3283177	0,798353619	93717	0,637612812	1208,575	Kecimen
45928	286,5405586	208,7600423	0,684989217	47336	0,699599385	844,162	Kecimen
79408	352,1907699	290,8275329	0,56401133	81463	0,792771926	1073,251	Kecimen
49242	318,125407	200,12212	0,777351277	51368	0,658456354	881,836	Kecimen
42492	310,1460715	176,1314494	0,823098681	43904	0,665893562	823,796	Kecimen
137583	649,541485	273,2602815	0,907201118	142650	0,731637667	1590,354	Besni
117592	533,2928563	288,5583194	0,840966033	123587	0,730067672	1432,006	Besni
95546	487,1782819	251,960243	0,855874944	99166	0,722782014	1276,807	Besni
96582	446,7052035	278,325498	0,782171631	100113	0,706597603	1216,979	Besni
61409	403,7012948	209,3658885	0,855007371	67286	0,597392869	1083,477	Besni
154242	585,9280742	337,5992453	0,817323783	158371	0,7216	1530,315	Besni
134303	600,7662711	288,3849296	0,877252896	138133	0,74243622	1497,515	Besni

The Raisin dataset, which is shown as an example in Table 2, was tested 10 times for CLNN, PRNN and SOM methods separately. Accuracy, Recall, Precision and F1-Score values were calculated for each test.

The result values obtained for the CLNN method are given in Table 3. The average and best result values obtained from all tests for the CLNN method are also given in Table 4. Class labels are expressed as Besni (0) and Keçimen (1) in return.

Table 3. Evaluation Results for CLNN Method

Test	Accuracy (%)	Precision (0) (%)	Precision (1) (%)	Recall (0) (%)	Recall (1) (%)	F1-Score (0) (%)	F1-Score (1) (%)
1	87.78	89.47	85.88	85.00	90.00	87.00	87.70
2	88.89	88.66	89.16	87.00	90.00	88.00	88.00
3	87.78	91.40	83.91	89.79	85.00	90.00	86.00
4	86.11	88.89	83.84	85.00	87.40	87.00	85.00
5	88.00	90.00	86.00	87.50	88.50	88.00	87.00
6	89.50	91.00	88.00	88.50	90.50	89.00	89.00
7	88.67	90.10	87.00	87.00	90.00	88.50	88.00
8	90.00	92.00	88.00	89.00	91.00	90.00	89.00
9	87.50	89.00	86.00	86.00	89.00	87.00	87.00
10	89.20	91.50	87.50	88.50	90.00	90.00	89.00

Table 4. Average and Best Result Values for The CLNN Method

Metric	Best Result (%)	Average (%)
Accuracy	90.00	88.34
Precision (0)	92.00	90.10
Precision (1)	89.16	86.43
Recall (0)	89.79	87.23
Recall (1)	91.00	88.14
F1-Score (0)	90.00	88.55
F1-Score (1)	89.00	87.27

The result values obtained for the PRNN method are given in Table 5. The average and best result values obtained from all tests for the PRNN method are also given in Table 6.

Table 6. Average and Best Result Values for The PRNN Method

Metric	Best Result (%)	Average (%)
Accuracy	89.50	88.12
Precision (0)	93.41	90.04
Precision (1)	88.00	85.93
Recall (0)	89.79	87.55
Recall (1)	90.00	88.28
F1-Score (0)	91.00	88.66
F1-Score (1)	89.00	87.20

The result values obtained for the SOM method are given in Table 7. The average and best result values obtained from all tests for the SOM method are also given in Table 8.

Table 5. Evaluation Results for PRNN Method

Test	Accuracy (%)	Precision (0) (%)	Precision (1) (%)	Recall (0) (%)	Recall (1) (%)	F1-Score (0) (%)	F1-Score (1) (%)
1	88.89	91.40	86.21	88.89	88.89	90.00	87.00
2	88.33	91.11	85.56	86.67	89.74	88.74	88.13
3	88.89	93.41	84.27	89.79	87.40	91.00	86.00
4	85.00	86.75	83.51	83.33	86.76	85.00	85.00
5	86.11	86.75	85.57	85.00	87.40	85.87	86.17
6	87.78	89.47	85.88	85.00	90.00	87.00	87.00
7	88.67	90.00	87.25	88.33	89.87	89.00	87.75
8	89.00	92.00	86.00	88.50	89.50	90.00	87.00
9	87.00	90.10	84.00	87.00	88.00	88.00	86.00
10	89.50	91.00	88.00	88.00	90.00	89.00	89.00

Table 7. Evaluation Results for SOM Method

Test	Accuracy (%)	Precision (0) (%)	Precision (1) (%)	Recall (0) (%)	Recall (1) (%)	F1-Score (0) (%)	F1-Score (1) (%)
1	88.89	89.69	87.95	87.50	90.00	88.78	88.07
2	90.00	91.40	88.51	90.00	90.00	90.00	89.00
3	84.44	85.15	83.54	82.67	86.67	83.89	84.09
4	83.33	81.52	85.23	81.00	86.00	81.76	85.00
5	87.50	88.00	86.00	85.00	90.00	86.90	87.00
6	85.00	86.00	84.00	83.00	87.00	84.00	85.00
7	89.20	92.00	86.00	88.50	90.00	90.00	87.00
8	86.00	88.50	83.50	84.00	87.00	85.25	85.00
9	84.50	82.00	87.00	82.50	86.50	82.90	86.00
10	87.80	89.00	86.70	86.00	90.00	87.00	87.50

Table 8. Mean and Best Result Values for The SOM Method

Metric	Best Result (%)	Average (%)
Accuracy	90.00	87.27
Precision (0)	92.00	88.33
Precision (1)	88.51	85.55
Recall (0)	90.00	85.45
Recall (1)	90.00	88.42
F1-Score (0)	90.00	86.65
F1-Score (1)	89.00	86.47

4. CONCLUSIONS

In this study, the classification of Keçimen and Besni grapes was studied by using the 'Raisin' dataset containing data of 900 raisin grains from the UCI Machine Learning Repository. The data of each raisin consists of 7 different raisin features such as Area, MajorAxisLength, MinorAxisLength, Eccentricity, ConvexArea, Extent, Perimeter and two different grape classes. Artificial neural network methods CLNN, PRNN, and SOM were used for the classification of raisin grains. The classification studies were developed in Python programming language using PyCharm IDE on Anaconda platform. Libraries such as Pandas, numpy, sklearn.model_selection, sklearn.neural_network, minisom and matplotlib were used for development.

The best result values for the analyzed methods are given in Table 9.

Table 9. Best Result Values for All Methods

Model	Accuracy (%)	Precision (0) (%)	Precision (1) (%)	Recall (0) (%)	Recall (1) (%)	F1-Score (0) (%)	F1-Score (1) (%)
CLNN	90.00	92.00	89.16	89.79	91.00	90.00	89.00
PRNN	89.50	93.41	88.00	89.79	90.00	91.00	89.00
SOM	90.00	92.00	88.51	90.00	90.00	90.00	89.00

When the results obtained from the methods are examined:

CLNN:

Accuracy: CLNN exhibited an accuracy rate ranging from 86.11% to 90.00%, which means it exhibited a similar performance compared to PRNN.

Precision and Recall: Precision values vary between 83.84% and 91.50%. It is seen that CLNN has a high precision value for class 1. Recall values also vary between 85% and 90%, which shows a good classification ability in general.

F1-Score: The F1 score is generally at similar levels to PRNN for classes 0 and 1. That is, CLNN also stands out as a model with balanced performance.

PRNN:

Accuracy: The method generally showed an accuracy rate of over 85%, with the highest recorded as 89.5.

Precision and Recall: Precision and recall values remained above 86% especially for class 1, indicating that the method has a strong ability to correctly identify class 1.

F1-Score: The F1-Scores are generally high for both classes 0 and 1. They range from 87.00% to 89.00%, especially for class 1. This shows that the model exhibits a balanced performance for both classes.

SOM:

Accuracy: SOM offers an accuracy rate ranging from 83.33% to 90.00%. These results generally show that it performs slightly lower than PRNN.

Precision and Recall: Precision values ranged from 81.52% to 92.00% for class 0, while they ranged from 83.50% to 88.51% for class 1. Especially the low precision value for class 0 suggests that this class has a higher probability of being misclassified.

F1-Score: The F1 scores are also lower compared to PRNN, indicating that the model provides lower balance for both classes.

The PRNN method shows the best performance by having the highest overall accuracy, precision, recall and F1 score values.

SOM generally gives lower results compared to other methods, especially in terms of precision and recall.

CLNN can be considered as a competitive alternative by showing similar performances to PRNN.

ROC curves for 3 methods are given in Figure 5.

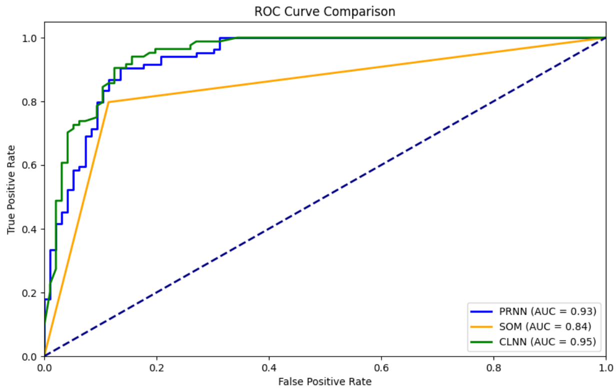

Figure 5. ROC Curves for 3 Methods

The ROC values obtained are quite good for PRNN and CLNN methods. The AUC values of these methods are above 0.9. However, the ROC curve of SOM showed a lower performance compared to other methods.

Confusion Matrices obtained for 3 different methods are given in Figure 6.

When the confusion matrices are examined, PRNN shows the best performance with high accuracy and few false predictions. SOM is slightly lower in correct predictions, but still shows acceptable performance. CLNN, although has good performance, has higher false positive and false negative rates.

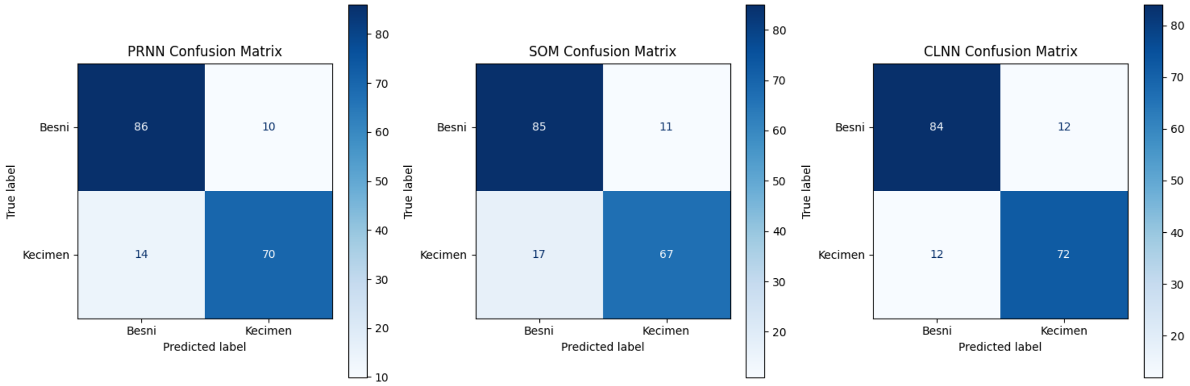

Figure 6. Confusion Matrix for 3 Methods

As a result, PRNN method has the highest success, while SOM is weaker compared to the other two methods. CLNN provides a good alternative, remaining at similar levels to PRNN. The choice of which method to choose may vary depending on the specific requirements of the application and the class balance.

Data Availability

The data is available on the public website of UCI Machine Learning Repository through this link: https://archive.ics.uci.edu/dataset/850/raisin

Acknowledgments

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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