Intelligent Wheat Types Classification Model Using New Voting Classifier

Abdelaziz A. Abdelhamid[1], El-Sayed M. El-Kenawy[2], Abdelhameed Ibrahim[3], Marwa M. Eid[4]

[1] Computer Science Department, Faculty of Computer and Information Sciences, Ain Shams University, Cairo, 11566, Egypt
[2] Department of Communications and Electronics, Delta Higher Institute of Engineering and Technology, Mansoura, 35111, Egypt
[3] Computer Engineering and Control Systems Department, Faculty of Engineering, Mansoura University, 35516, Mansoura Egypt
[4] Faculty of Artificial Intelligence, Delta University for Science and Technology, Mansoura 35712, Egypt
Emails: abdelaziz@cis.asu.edu.eg; skenawy@ieee.org; afai79@mans.edu.eg; marwa.3eeed@gmail.com

Abstract

When assessing the quality of the grain supply chain's quality, it is essential to identify and authenticate wheat types, as this is where the process begins with the examination of seeds. Manual inspection by eye is used for both grain identification and confirmation. High-speed, low-effort options became available thanks to automatic classification methods based on machine learning and computer vision. To this day, classifying at the varietal level is still challenging. Classification of wheat seeds was performed using machine learning techniques in this work. Wheat area, wheat perimeter, compactness, kernel length, kernel width, asymmetry coefficient, and kernel groove length are the 7 physical parameters used to categorize the seeds. The dataset includes 210 separate instances of wheat kernels, and was compiled from the UCI library. The 70 components of the dataset were selected randomly and included wheat kernels from three different varieties: Kama, Rosa, and Canadian. In the first stage, we use single machine learning models for classification, including multilayer neural networks, decision trees, and support vector machines. Each algorithm's output is measured against that of the machine learning ensemble method, which is optimized using the whale optimization and stochastic fractal search algorithms. In the end, the findings show that the proposed optimized ensemble is achieving promising results when compared to single machine learning models.

Keywords: Neural network; Support vector machine; Decision tree; Voting ensemble.

1. Introduction

The agricultural industry is the backbone of many poor countries' economies. The vast majority of work is done without using any kind of high-tech equipment. The purification of seeds plays a significant part in this process and could be improved. Seed classification is often done based on human knowledge. Expert judgment and patience are required for manual wheat type determination. In cases where several seeds in a batch seem the same, telling them apart by eye might be difficult [1-4]. The transformation of the grain supply chain necessitates the development of a system for assessing the quality of wheat harvests [5]. The objective is to produce more wheat of a higher grade. The labeling of seeds necessitates germination tests [6]. The seeds underwent a purity test, which is necessary for determining a seed lot's genetic and physical integrity. Because of the potential for genetic contamination during mechanical mixing and incorrect labeling, it is important

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

to preserve the purity of the original wheat cultivar [7]. Taxonomic categorization and nondestructive grain feature analysis are used to conduct the testing of classifications [8, 9]. The seed testing process involves two levels of classification: species and varietal. Due to the similarities amongst wheat varieties, determining the varietal level can be difficult. The grain's characteristics may also be influenced by its growing conditions [5]. The actual classification test technique remains a low-throughput operation, with accuracy depending on the expert's skill and expertise. As the Internet has grown and larger datasets have become more widely used, machine learning methods have become a topic of research in a wide range of academic fields [4]. A human operator would have a tough time making sense of or working with such data without the aid of specialized tools or automated software operations. To address these needs, many organizations are turning to machine learning [10] for classification, regression, and prediction tasks. When comparing items with just subtle differences in color, texture, and morphology, a single classifier does not perform better [11]. The current study employs an ensemble method to solve this issue. Ensemble approaches aim to improve model prediction by merging numerous models into a single, highly dependable model. Common ensemble methods include boosting, bagging, and stacking. Because of their ability to reduce bias and variance while enhancing model accuracy, ensemble approaches are ideally suited to regression and classification. The architecture in Figure 1 shows the overview of this research paper.

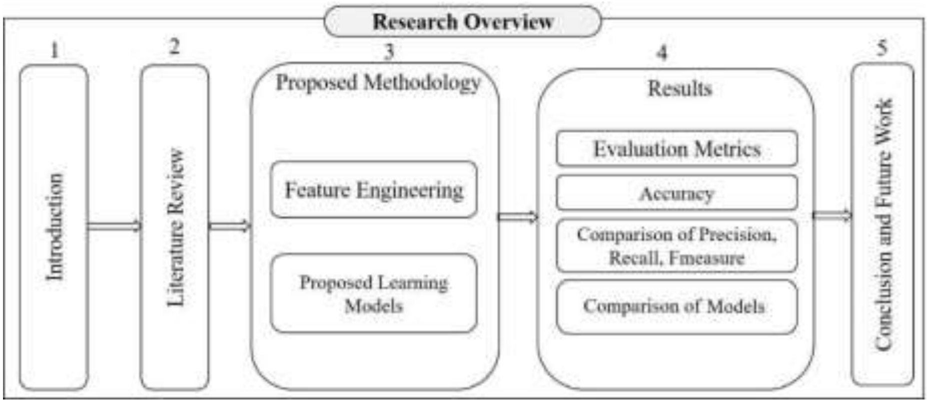

Figure 1: Research Paper Overview.

2. Literature Review

There has been some study into the possibility of utilizing machine algorithms to classify seeds. These analyses used many machine classifiers, all of which performed exceptionally well. For the categorization of seeds and cereals, machine learning approaches have already been implemented in several manufacturing chains with positive results [12-14]. Using well-trained multilayer neural network classifiers, the research in [15] demonstrates the potential and use of machine vision for identifying forms, sizes, and varieties. They classified the seeds using Weka's function, Bayes, meta, and lazy techniques. Taking the characteristics of wheat seeds into account, the authors of [16] suggested a fuzzy theory-based method for classifying wheat seeds. We resorted to a taboo search strategy. Using an artificial neural network, the authors of [17] achieved an accuracy of 92.1% and 85.72 %, respectively, when categorizing wheat seeds using VLC. Authors in [18] have studied the seed's morphology, coloration, and textural qualities. Classifying seeds might be challenging if there is just a slight variation in their external appearance. The quantity of cereal grains produced is proportional to the size of the individual grains and the number of ears harvested. Manually counting seeds and measuring their morphology is a time-consuming process. As a result, many image processing-based methods for accurate grain morphometry have been presented [19, 20].

In [21], the authors developed a workstation to facilitate grain analysis for classification, and in [22], they present a video colorimetry approach to aid in determining cereal grain colour. In [22], 400 samples of four different types of chickpea seeds—Kaka, Piroz, Ilc, and Jam—were used to classify chickpea seed varieties according to their morphological characteristics. The commercial viewpoint suggests that rice quality evaluation might benefit from the application of machine vision constructed from pre-existing neural network models [23]. Here, nine different types of rice are used to demonstrate how neural networks may be used to classify rice varieties by their seeds. They also developed a technique for extracting 13 morphological features, 6 color features, and 15 texture

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

features from color photographs of seeds, and their model has achieved an overall classification accuracy of 92%. The k-nearest neighbors classifier requires storing the entire training set, which can be prohibitively expensive when the set is huge. In order to classify plants, the authors have turned to deep learning models [24-26]. Ubbens and Stavness's research in this field [27] demonstrates one trend.)e other is related to high-throughput phenotyping and plant identification, and it is the difficulty of identifying and monitoring plant diseases [28, 29]. The authors of [30] describe a wide variety of voting methods for evaluating groups of bagging-trained classifiers. Classes are determined with the use of multilayer perceptrons. One approach is to use ensembles of classifiers instead of just one. Several classifiers are merged to produce a single, more accurate output in the well-known ensemble approaches of bagging [31] and boosting [32]. Reconciliation is the process of combining classification models, and it was bagging that was used in the studies by the authors of [33], who analyzed the effectiveness of various voting procedures. Machine vision systems for assessing the quality of food grains take into account the factors listed in Table 1.

3. Proposed Methodology

The proposed methodology is shown in Figure 2. In this figure, three base classifiers were employed. These classifiers are decision trees (DT), multilayer perceptron (MLP), and support vector machines (SVM). These classifiers are used in a voting ensemble model, where the votes are optimized in a hybrid metaheuristic optimization algorithm composed of the whale optimization algorithm (WOA) algorithm and the stochastic fractal search (SFS).

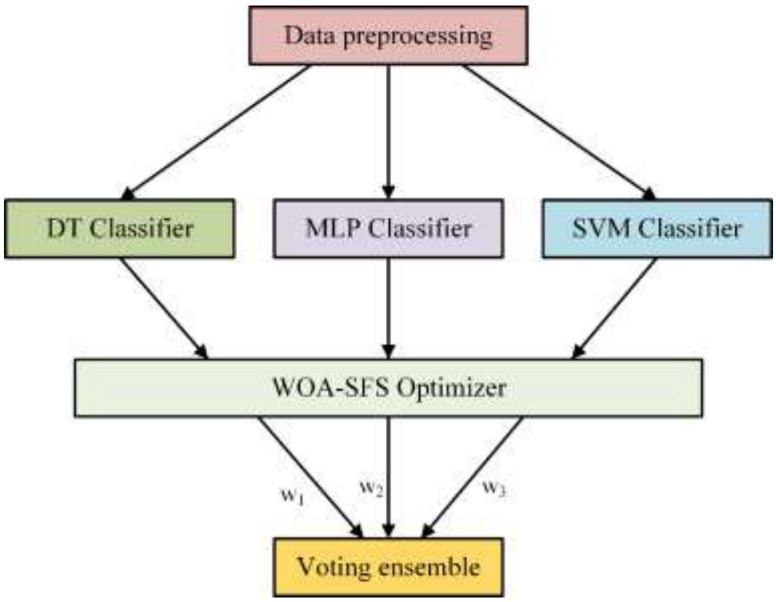

Figure 2: Overview of research methodology.

A. Dataset

The seed dataset for the investigation was obtained from the UCI collection [42]. There are 210 wheat kernels in the assortment. Each instance also has seven extra attributes outside the class attribute. There are seven traits that are consistent across all samples (area, perimeter, compactness, kernel length, kernel width, asymmetry coefficient, and kernel groove length). There is no fluctuation in any of the attributes. You can see the characteristics of the dataset, such as the number of classes it contains and the machine learning techniques used to analyze it, in Figure 3. Seventy different components were analyzed, and they were all wheat kernels. The three types of wheat that were included in the collection were Kama, Rosa, and Canadian. Using a soft X-ray technique, we are able to get clear images of the kernel's inner structure. It's less expensive and less invasive than other high-tech imaging methods like scanning microscopy and laser technology. Photographs are captured on KODAK X-ray plates that measure 13 by 18 centimeters. In order to support their research, scientists from the Institute of Agrophysics of the Polish Academy of Sciences in Lublin patented wheat grain gathered in combination with their experiments. Kama (1), Rosa (2), and Canadian (3) are the three wheat classifications shown in Table 1.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

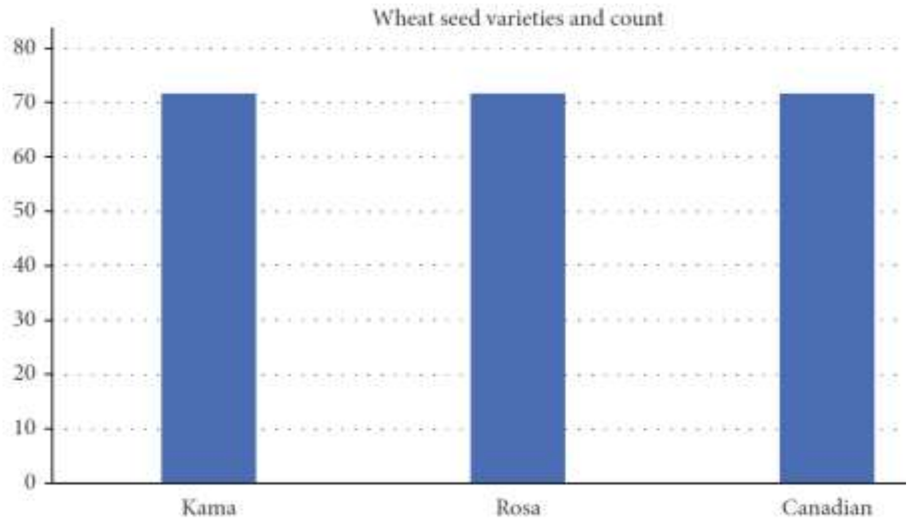

Figure 3: Count of different wheat seed varieties.

Table 1: Features considered in machine vision systems for food grain quality evaluation.

References	Grain	Features	Applications
[34–36]	Rice	Morphology	Variety-based classification
[37]	Popcorn	Color	Identification of microbial infection
[38, 39]	Chickpea	Morphology + color	Variety-based classification
[40, 41]	Wheat	Morphology	Variety-based classification

B. Support Vector Machines (SVM)

In classification, a support vector machine (SVM) is described as a family of closely comparable supervised learning techniques. To put it another way, if it is given a collection of training samples that have been labeled as belonging to one of two classes. For each possible classification of a given set of examples, the SVM training algorithm constructs a model to make predictions. To do classification, support vector machines (SVM) create a hyperplane or a series of hyperplanes in a high-dimensional space. The structure of the SVM process is depicted in Figure 4.

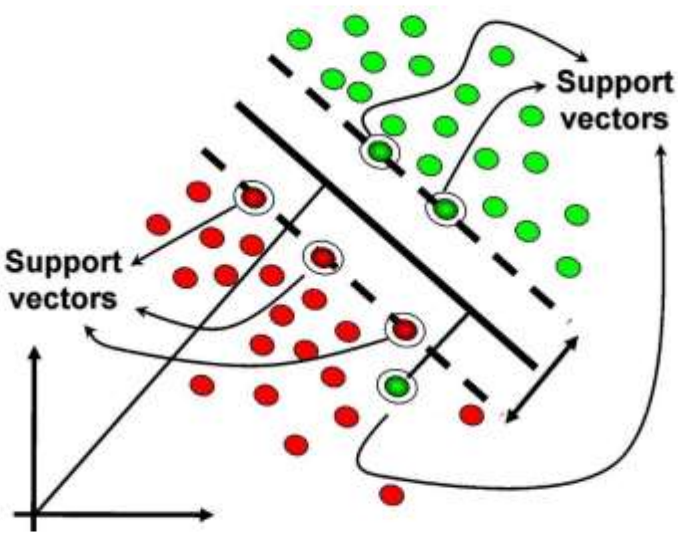

Figure 4: Structure of support vector machines.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

C. Multilayer Perceptron (MLP)

We have a neural network when a group of nodes, or neurons, are connected via synapses. Comparable to the human nervous system, artificial neural networks are used as estimation models. Every synthetic neural network consists of three distinct layers: an input layer, a hidden layer, and an output layer. The input layer comprises a set of nodes that take in data, and the technique's output is an activation function. In between the input and output layers is a hidden layer that assigns weights to the inputs. The output layer provides the final results. The structure of a multilayer neural network is shown in Figure 5.

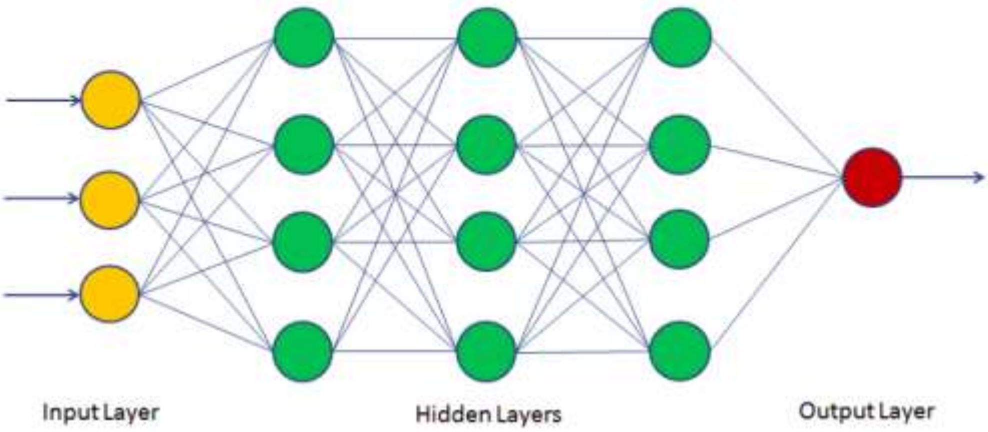

Figure 5: Structure of a multilayer neural network.

D. Decision Trees (DT)

Using a greedy search, decision tree learning finds the best possible branching points inside a tree to divide and conquer the problem. This partitioning is then iterated from the top down until all or the vast majority of entries fit neatly into predefined categories. The intricacy of the decision tree heavily influences the likelihood that all data points will be assigned to homogeneous groupings. Pure leaf nodes, or data points belonging to a particular class, can be more easily obtained in smaller trees. However, as a tree expands, it is harder to preserve this purity, and this often leads to too little information fitting within a specific subtree. This is known as data fragmentation, and it frequently results in overfitting. Therefore, decision trees favor tiny trees, which aligns with Occam's Razor's parsimony concept that "entities should not be multiplied beyond necessity." That is to say, decision trees should only get more intricate if required, as the simplest explanation is sometimes the most convincing. Pruning removes branches that divide on attributes of low value and is commonly used to accomplish both goals (reducing complexity and preventing overfitting). Cross-validation then provides an assessment of the model's fitness. The random forest technique is another method for maintaining the accuracy of decision trees; when the trees in the ensemble are uncorrelated, the classifier produces more accurate predictions. The structure of a decision tree is depicted in Figure 6.

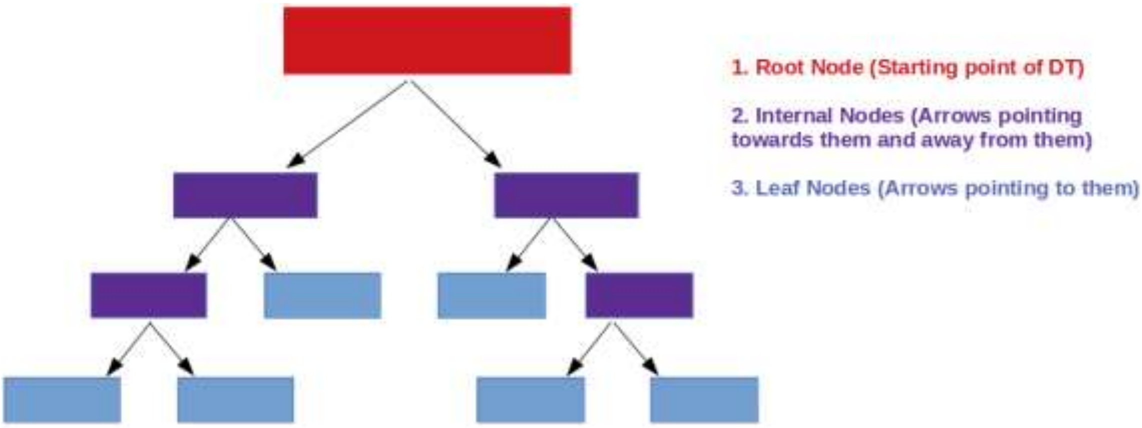

Figure 6: Structure of a decision tree.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

E. Whale Optimization Algorithm (WOA)

Australian researchers Mirjalili and Lewis devised the WOA swarm intelligence optimization method in 2016. Through the use of mathematical models, the 3e algorithm recreates the behavior of humpback whales as they hunt for food. The WOA team was motivated to create their program after learning about the bubble-net assault technique used by humpback whales. If a whale spots prey, it will dive to within 12 meters of the surface and then spiral upwards while bubbling to distract the fish. WOA's strengths lie in its straightforward premise, limited parameters, and robust search capabilities. It has been used in many other engineering areas, including optimization, parameter extraction, feature selection, and more, ever since it was first developed.

F. Stochastic Fractal Search (SFS)

While Fractal Search is effective in locating the answer, it has drawbacks. First, many moving parts need to be carefully considered, and second, particles don't share information with one another. There has been no evidence of interpersonal communication in FS; therefore, the search must be carried out. To hasten convergence to the minimum, the organization tries to share data across all members.

4. Results

To accomplish the classification through ML models, a number of Python3 libraries are used. These include NumPy, SciPy, scikit-learn, Keras, pandas, and Matplotlib. According to the available evidence [43-46], Scikit-learn is the most accessible and trustworthy machine learning library. NumPy, SciPy, and Matplotlib comprise the backbone of this package. In Figure 7 we see the steps taken to make a categorization. In this part, we provide the findings of our dataset analysis and the outcomes of our training and testing of the model with a variety of feature extractions. A confusion matrix, which details the ratio of correct to incorrect predictions made on the basis of training data with known true values, is necessary for evaluating a classifier's performance. In the case of a true positive (TP), both the actual value and the model's prediction are correct. In the case of a true negative (TN), both the actual and anticipated values are incorrect.

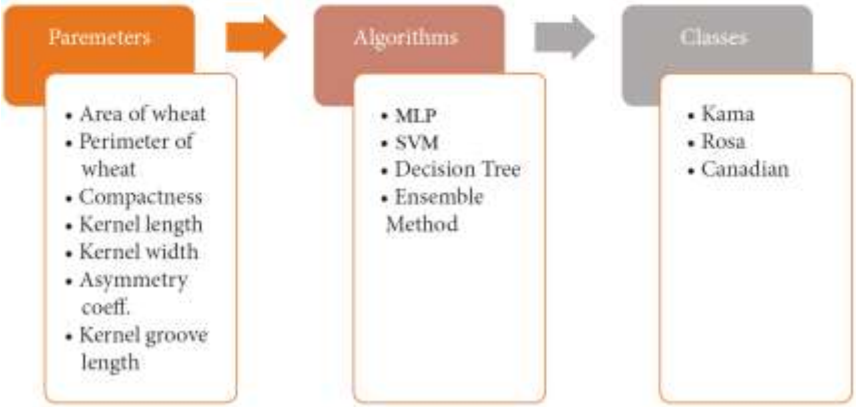

Figure 7: The steps of the classification process.

A comparison between the proposed approach and other machine learning models is presented in Table 6. This table shows the accuracy, sensitivity, specificity, pvalue, nvalue, and F-score better using the proposed optimized voting ensemble classifier.

Table 6: Classification results using the proposed method compared to other methods

	Accuracy	Sensitivity	Specificity	Pvalue	Nvalue	F-score
NN	0.9091	0.8889	0.9231	0.8889	0.9231	0.8889
SVM	0.8772	0.8889	0.8696	0.8163	0.9231	0.8511
DT	0.8696	0.8889	0.8571	0.8000	0.9231	0.8421

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

WOA-SFS	0.9391	0.9412	0.9375	0.9195	0.9545	0.9302

The statistical analysis presented in Table 7 shows the superiority of the proposed voting ensemble classifier. These results are better when the proposed optimized voting ensemble is employed.

Table 7: Statistical analysis of the results recorded by the proposed method

	NN	SVM	DT	WOA-SFS
Number of values	10	10	10	10
Minimum	0.9091	0.8672	0.8696	0.9391
25% Percentile	0.9091	0.8772	0.8696	0.9391
Median	0.9091	0.8772	0.8696	0.9391
75% Percentile	0.9091	0.8772	0.8696	0.9391
Maximum	0.9191	0.8772	0.8796	0.9391
Range	0.01	0.01	0.01	0
10% Percentile	0.9091	0.8682	0.8696	0.9391
90% Percentile	0.9181	0.8772	0.8786	0.9391
95% CI of median				
Actual confidence level	97.85%	97.85%	97.85%	97.85%
Lower confidence limit	0.9091	0.8772	0.8696	0.9391
Upper confidence limit	0.9091	0.8772	0.8696	0.9391
Mean	0.9101	0.8762	0.8706	0.9391
Std. Deviation	0.003162	0.003162	0.003162	0
Std. Error of Mean	0.001	0.001	0.001	0
Lower 95% CI of mean	0.9078	0.8739	0.8683	0.9391
Upper 95% CI of mean	0.9124	0.8785	0.8728	0.9391
Coefficient of variation	0.3475%	0.3609%	0.3632%	0.000%
Geometric mean	0.9101	0.8762	0.8706	0.9391
Geometric SD factor	1.003	1.004	1.004	1
Lower 95% CI of geo. mean	0.9078	0.8739	0.8683	0.9391
Upper 95% CI of geo. mean	0.9123	0.8785	0.8728	0.9391
Harmonic mean	0.9101	0.8762	0.8706	0.9391
Lower 95% CI of harm. mean	0.9078	0.8739	0.8683	0.9391
Upper 95% CI of harm. mean	0.9123	0.8785	0.8728	0.9391
Quadratic mean	0.9101	0.8762	0.8706	0.9391
Lower 95% CI of quad. mean	0.9078	0.8739	0.8683	0.9391
Upper 95% CI of quad. mean	0.9124	0.8784	0.8728	0.9391
Skewness	3.162	-3.162	3.162	
Kurtosis	10	10	10	
Sum	9.101	8.762	8.706	9.391

On the other hand, the Wilcoxon signed rank test is used to study the difference between the proposed approach and the other set of algorithms. The results of this test are listed in Table 8. In this table, the p-value proves this difference.

Table 8: Wilcoxon signed rank test of the recorded results of the proposed method

	NN	SVM	DT	WOA-SFS

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

Theoretical median	0	0	0	0
Actual median	0.9091	0.8772	0.8696	0.9391
Number of values	10	10	10	10
Wilcoxon Signed Rank Test				
Sum of signed ranks (W)	55	55	55	55
Sum of positive ranks	55	55	55	55
Sum of negative ranks	0	0	0	0
P value (two tailed)	0.002	0.002	0.002	0.002
Exact or estimate?	Exact	Exact	Exact	Exact
P value summary	**	**	**	**
Significant (alpha=0.05)?	Yes	Yes	Yes	Yes
How big is the discrepancy?				
Discrepancy	0.9091	0.8772	0.8696	0.9391

The plot shown in Figure 8 demonstrates the accuracy achieved by the proposed optimized voting ensemble classifier compared to the base models. As shown in this figure, the proposed approach is more effective.

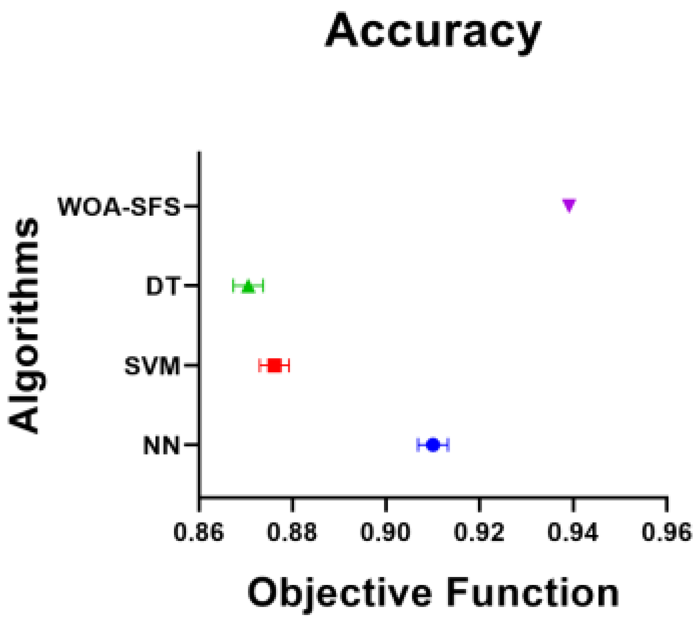

Figure 8: The accuracy of the proposed method compared to other methods

5. Conclusion

Using machine learning techniques for analyzing and categorizing grain seeds is becoming increasingly relevant. In this study, we describe a method for classifying wheat seeds based on seven distinct features: area, perimeter, compactness, kernel length, kernel width, asymmetry coefficient, and kernel groove length. The minute differences across seed types pose the most difficulty in categorization. Ensemble learning techniques are applied to this problem to increase prediction accuracy. We employ an ensemble machine learning technique using an optimized voting classifier to get the best possible classifier fit. The findings are compared using three different machine learning algorithms: the multilayer perceptron (MLP), the decision trees (DT), and support vector machines (SVM). Based on the outcomes, Using a voting system in an ensemble classifier allows for the best possible accuracy. Using other categorization algorithms will allow us to further refine our results' accuracy in the future.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

Funding: "This research received no external funding"

Conflicts of Interest: "The authors declare no conflict of interest."

References

[1] R. Tandon, D. S. Agrawal, and D. P. Goyal, "Sequential convolutional neural network for automatic breast cancer image classification using histopathological images," J. Crit. Rev.vol. 7, no. 15, p. 14, 2020.

[2] H. S. H. Chitra, S. Suguna, and S. N. Sujatha, "A survey on image analysis techniques in agricultural product," Indian Journal of Science and Technology, vol. 9, no. 12, 2016.

[3] M. R. Siddagangappa and A. P. A. H. Kulkarni, "Classification and quality analysis of food grains," IOSR Journal of Computer Engineering, vol. 16, no. 4, pp. 1–10, 2014.

[4] S. Agrawal and S. K. Jain, "Medical text and image processing: applications, issues and challenges," in Machine Learning with Health Care Perspective, V. Jain and J. M. Chatterjee, Eds., vol. 13, pp. 237–262, Cham: Springer International Publishing, Manhattan, NY, USA, 2020.

[5] C. Wrigley, "Cereal-grain morphology and composition," in Cereal Grains, C. Wrigley, I. Batey, and D. Miskelly, Eds., pp. 55–87, Woodhead Publishing, Cambridge, UK, 2nd edition, 2017.

[6] S. G. Elias, L. O. Copeland, M. B. McDonald, and R. Z. Baalbaki, Seed Testing: Principles and Practices, East Lansing: Michigan State University Press, East Lansing, MI, USA, 2012.

[7] S. Matthews, "Copeland, L.O. and McDonald, M.B. Principles of seed science and technology. 4th edn," Annals of Botany, vol. 89, no. 6, p. 798, 2002.

[8] W. S. Meyer and H. D. Barrs, "Non-destructive measurement of wheat roots in large undisturbed and repacked clay soil cores," Plant and Soil, vol. 85, no. 2, pp. 237–247, 1985.

[9] J. Acer, Rules Proposals for the International Rules for Seed Testing, Vol. 47, International Seed Testing Association, Switzerland, Europe, 2019 edition, 2019.

[10] M. Agrawal and S. Agrawal, "A systematic review on artificial intelligence/deep learning applications and challenges to battle against COVID-19 pandemic," Disaster Advances, vol. 14, no. 8, pp. 90–99, 2021.

[11] N. S. Visen, J. Paliwal, D. S. Jayas, and N. D. G. White, "AEautomation and emerging technologies," Biosystems Engineering, vol. 82, no. 2, pp. 151–159, 2002.

[12] D. I. Patricio and R. Rieder, "Computer vision and artificial intelligence in precision agriculture for grain crops: a systematic review," Computers and Electronics in Agriculture, vol. 153, pp. 69–81, 2018.

[13] P. Vithu and J. A. Moses, "Machine vision system for food grain quality evaluation: a review," Trends in Food Science & Technology, vol. 56, pp. 13–20, 2016.

[14] C.-J. Du and D.-W. Sun, "Learning techniques used in computer vision for food quality evaluation: a review," Journal of Food Engineering, vol. 72, no. 1, pp. 39–55, 2006.

[15] T. Tujo, "A predictive model to predict seed classes using machine learning," Int. J. Eng. Tech. Res., vol. 6, pp. 334–344, 2019.

[16] L. Li and S. Liu, "Wheat cultivar classifications based on tabu search and fuzzy C-means clustering algorithm," in Proceedings of the 2012 4th International Conference on Computational and Information Sciences, pp. 493–496, Chongqing, China, August. 2012.

[17] R. Choudhary, S. Mahesh, J. Paliwal, and D. S. Jayas, "Identification of wheat classes using wavelet features from near infrared hyperspectral images of bulk samples," Biosystems Engineering, vol. 102, no. 2, pp. 115–127, 2009.

[18] S. V. Neeraj Singh Visen, J. Jitendra Paliwal, D. Digvir Jayas, and N. D. G. White, "Image analysis of bulk grain samples using neural networks," Canadian Biosystems Engineering/Le Genie des biosystems au Canada, vol. 46, 2003.

[19] T. Tanabata, T. Shibaya, K. Hori, K. Ebana, and M. Yano, "SmartGrain: high-throughput phenotyping software for measuring seed shape through image analysis," Plant Physiology, vol. 160, no. 4, pp. 1871–1880, 2012.

[20] E. Komyshev, M. Genaev, and D. Afonnikov, "Evaluation of the SeedCounter, A mobile application for grain phenotyping," Frontiers of Plant Science, vol. 7, 2017.

[21] M. R. Neuman, E. Shwedyk, and W. Bushuk, "A PC-based colour image processing system for wheat grain grading," in Proceedings of the 3rd International Conference on Image Processing and its Applications, 1989, pp. 242–246, Warwick, UK, July 1989.

[22] S. Salah Ghamari, "Classification of chickpea seeds using supervised and unsupervised artificial neural networks," African Journal of Agricultural Reseearch, vol. 7, no. 21, 2012.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022

[23] C. Silva and U. Sonnadara, “Classification of rice grains using neural networks,” Proceedings of Technical Sessions, vol. 29, 2013.
[24] N. Abdel Samee, E. M. El-Kenawy, G. Atteia, M. M. Jamjoom, A. Ibrahim et al., "Metaheuristic optimization through deep learning classification of covid-19 in chest x-ray images," Computers, Materials & Continua, vol. 73, no.2, pp. 4193–4210, 2022.
[25] A. A. Abdelhamid and S. R. Alotaibi, "Optimized two-level ensemble model for predicting the parameters of metamaterial antenna," Computers, Materials & Continua, vol. 73, no.1, pp. 917–933, 2022.
[26] A. Kamilaris and F. X. Prenafeta-Bold´u, “Deep learning in agriculture: a survey,” Computers and Electronics in Agriculture, vol. 147, pp. 70–90, 2018.
[27] J. R. Ubbens and I. Stavness, “Corrigendum: deep plant phenomics: a deep learning platform for complex plant phenotyping tasks,” Frontiers of Plant Science, vol. 8, p. 2245, 2018.
[28] M. Brahimi, K. Boukhalfa, and A. Moussaoui, “Deep learnin for tomato diseases: classification and symptoms visualization,” Applied Artificial Intelligence, vol. 31, no. 4, pp. 299–315, 2017.
[29] K. P. Ferentinos, “Deep learning models for plant disease detection and diagnosis,” Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018.
[30] M. Van Erp, L. Vuurpijl, and L. Schomaker, “An overview and comparison of voting methods for pattern recognition,” in Proceedings of the 8th International Workshop on Frontiers in Handwriting Recognition, Niagara on the Lake, pp. 195–200, Niagra-on-the-Lake,ON, Canada, August 2002.
[31] L. Breiman, “Bagging predictors,” Machine Learning, vol. 24, no. 2, pp. 123–140, 1996.
[32] R. E. Schapire and Y. Singer, “Improved boosting algorithms using confidence-rated predictions,” in Proceedings of the 11th annual conference on Computational learning theory - COLT’ 98, pp. 80–91, Madison, WI, USA, July 1998.
[33] K. T. Leung and D. S. Parker, “Empirical comparisons of various voting methods in bagging,” in Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining - KDD ’03, p. 595, Washington, DC, USA, August 2003.
[34] S. J. MousaviRad, F. Akhlaghian Tab, and K. Mollazade, “Application of imperialist competitive algorithm for feature selection: a case study on bulk rice classification,” International Journal of Computer Application, vol. 40, no. 16, pp. 41–48, 2012.
[35] N. A. Kuchekar and V. V. Yerigeri, “Rice grain quality grading using digital image processing techniques,” Journal of Electronics and Communication Engineering, vol. 13, 2018.
[36] M. M. Agrawal and D. S. Agrawal, “Rice plant diseases detection & classification using deep learning models: a systematic review -,” J. Crit. Rev.vol. 7, no. 11, pp. 4376–4390, 2020.
[37] O. Yorulmaz, T. C. Pearson, and A. EnisÇetin, “Detection of fungal damaged popcorn using image property covariance features,” Computers and Electronics in Agriculture, vol. 84, 2021.
[38] O. D´ıaz, T. Ferreiro, J. Rodr´ıguez-Otero, and ´ A. Cobos, “Characterization of chickpea (cicer arietinum L.) flour films: effects of pH and plasticizer concentration,” International Journal of Molecular Sciences, vol. 20, no. 5, p. 1246, 2019.
[39] S. Sankaran, M. Wang, and G. J. Vandemark, “Image-based rapid phenotyping of chickpeas seed size,” Engineering in Agriculture, Environment and Food, vol. 9, no. 1, pp. 50–55, 2016.
[40] K. Laabassi, M. A. Belarbi, S. Mahmoudi, S. A. Mahmoudi, and K. Ferhat, “Wheat varieties identification based on a deep learning approach,” Journal of the Saudi Society of Agricultural Sciences, vol. 20, no. 5, pp. 281–289, 2021.
[41] A. Bhande and D. S. V. Rode, “Quality identification of wheat by using image processing,” International Journal of Engineering Science and Computing, vol. 6, 2016.
[42] UCI Machine Learning Repository, “UCI Machine Learning Repository: Seeds Data Set,” 2021, https://archive.ics.uci.edu/ml/index.php.
[43] X. Wei and Y. Cao, “Automatic counting method for complex overlapping erythrocytes based on seed prediction in microscopic imaging,” Journal of Innovative Optical Health Sciences, vol. 9, no. 5, Article ID 1650016, 2016.
[44] D. Saravagi, S. Agrawal, and M. Saravagi, “Opportunities and challenges of machine learning models for prediction and diagnosis of spondylolisthesis: a systematic review,” International Journal of Engineering Systems Modelling and Simulation, vol. 12, no. 2/3, pp. 127–138, 2021.
[45] Abdelhamid, A.A.; El-Kenawy, E.-S.M.; Khodadadi, N.; Mirjalili, S.; Khafaga, D.S.; et al., Classification of Monkeypox Images Based on Transfer Learning and the Al-Biruni Earth Radius Optimization Algorithm. Mathematics 2022, 10, 3614.
[46] Eid, M.M.; El-Kenawy, E.-S.M.; Khodadadi, N.; Mirjalili, S.; Khodadadi, E.; et al., Meta-Heuristic Optimization of LSTM-Based Deep Network for Boosting the Prediction of Monkeypox Cases. Mathematics 2022, 10, 3845.

Doi : https://doi.org/10.54216/JISIoT.070103
Received: March 28, 2022 Accepted: October 25, 2022