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Guava Fruit Grading and Sorting using Optimized Artificial Neural Networks

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ABSTRACT- Agriculture and food industry are the backbone of any country. Food industry is the prime contributor in agricultural sector. Thus, automation of Guava fruit grading and sorting is the need of the hour. Since, artificial neural networks are best suited for automated pattern recognition problems; they are used as a classification tool for this research. Back propagation is the most important algorithm for training neural networks. But, it easily gets trapped in local minima leading to inaccurate solutions. Therefore, some global search and optimization techniques were required to hybridize with artificial neural networks. One such technique is Genetic algorithms that imitate the principle of natural evolution. So, in this article, a hybrid intelligent system is proposed for Guava fruit grading and sorting in which artificial neural networks are merged with genetic algorithms. Results show that proposed hybrid model outperformed the existing back propagation based system.

Keywords*:* Guava fruit grading and sorting; artificial neural networks; Particle Swarm Optimization; Hybrid intelligent system; Pattern recognition

I. INTRODUCTION

For consumption of vegetable and fruits by humans, guava is one of the most produced and consumed fruit across the globe which is nearly 55 million tons in 2019. Guava is adopted as a crop in many parts of Asia including India with the lead of 45% of the total worldwide production. These facts lay the basis that the profits to the farmers would be high enough, however, the margins are quite below the expected profits. The possible reasons include slow and manual methods of assessing the fruit quality. This task is a tedious one and requires a lot of labor to work on it prior to the fruit being taken to the market for selling. As a result, the task of inspecting and grading the fruit shall be done as quickly as possible, since the shelf-life of the fruit is extremely less. Also, there shall be an accurate way to grade and sort the guava fruit. A large number of studies have been conducted however, artificial neural networks (ANN) for pattern recognition are the best suited approach when human kind of expertise is required.

As the main objective of this research work is to speed up the human subjective task of guava fruit quality evaluation, therefore, ANN have been utilized. Although, ANN are a quite effective artificial intelligent classifier, these sometimes are unable to find the global minima/maxima in the search space and suffers from the problem of finding local solution as the best one. In such cases, it is better to optimize the process of training the ANN through some optimization techniques. One promising technique is genetic algorithms (GA) that tries to find global solution in the solution space and thus speeds up the process of training.

The remaining article is organized as follows: briefs of background is provided in Section 2, the materials and methods are presented in Section 3, results and discussions are demonstrated in Section 4, and lastly, the conclusions are briefed in Section 5.

II. BACKGROUND

In the past, several studies have been conducted in which effective fruit grading and sorting methods were investigated. These endeavors include studies pursued on apple (Unay and Gosselin, 2006; Zhu et al., 2007), grapes (Patterson, 2007; Kim 2009), citrus (Blasco et al., 2007), banana (Llobet et al., 1999), date (Khalid M. A. and Tamer, 2012; Hobani et al., 2003), pomegranate (Blasco et al., 2009), blueberry (Ahlawat et al., 2011), orange (Zaragoza, 2010), watermelon (Sadrnia et al., 2007; Ali et al., 2017), strawberry (Yamamoto et al., 2015), and litchi (He et al., 2017), and mango (Gill and Singh, 2022) to name a few. Unay and Gosselin (2006) worked for the automatic grading

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and sorting of apples using ANN demonstrating a classification rate of 89.9 %. Similar investigation on apple fruit was performed by Cetişli and Büyükçingir (2013) utilizing a hybrid image processing based neuro-fuzzy technique for early detection of defects on the apple surfaces.

Many references of different fruit grading using ANN classifier are found in Janik et al. (2007), Ohali (2011), and Khalid and Tamer (2012). Another evidence to utilize ANN for detecting early the drying away of high market value fruit that is pomegranate by Motaveli et al. (2010).

Esehaghbeygi et al. (2010) introduced a method to categorize peaches into three grading classes: red-yellow, yellow-red, and yellow. The model successfully graded the peaches with recognition rates of 96%, 90% and 85-97%, respectively, for size, color and defect based grading. Whereas, Alipasandi et al. (2013) sorted three peach cultivars, namely, Anjiri peach, Shalil Nectarine and Elberta peach. The sorting model effectively reached classification rates of 98.5% and 99.3%, for mature and immature fruits, respectively. Common defects found in blueberries (like, fungal decay, shriveling or mechanical damage) was detected by Leiva et al. (2011). Accuracy rates of 96% and 90% were attained for fungal decay and for global damage in blueberries.

Yet another contribution was made by Zakaria et al. (2012) to evaluate the maturity of mangoes. Here Linear Discriminant Analysis (LDA) was hybridized with ANN to classify the mangoes maturity-wise according to the number of weeks.

Qaqish et al. (2019) proposed an automatic classification system for grading and classifying guava fruits using image-processing techniques integrated with shape, color, and texture descriptors. During the preprocessing step, many morphological operations will be applied accompanied with filtering using various filters like the Wiener Filter.

Almadhor et al. (2021) presented an artificial intelligence (AI) driven framework to detect and classify the most common guava plant diseases. The proposed framework employs the 4E color difference image segmentation to segregate the areas infected by the disease. Furthermore, color (RGB, HSV) histogram and textural (LBP) features are applied to extract rich, informative feature vectors. The combination of color and textural features are used to identify and attain similar outcomes compared to individual channels, while disease recognition is performed by employing advanced machine-learning classifiers (Fine KNN, Complex Tree, Boosted Tree, Bagged Tree, Cubic SVM). The proposed framework is evaluated on a high-resolution (18 MP) image dataset of guava leaves and fruit. The best recognition results were obtained by Bagged Tree classifier on a set of RGB, HSV, and LBP features (99% accuracy in recognizing four guava fruit diseases (Canker, Mummification, Dot, and Rust) against healthy fruit).

Gill and Singh (2022) proposed a non-invasive mango fruit grading and sorting model that utilizes hybrid soft computing approach. Artificial neural networks (ANN), optimized with Antlion optimizer (ALO), are used as a classification tool. The quality of mangoes is evaluated according to four grading parameters: size (volume and morphology), maturity (ripe/unripe), defect (defective/healthy) and variety (cultivar). Besides, a comparison of proposed grading system with state-of-the-art models is performed. The system showed an overall classification rate of 95.8% and outperformed the other models. Results demonstrate the effectiveness of proposed model in fruit grading and sorting applications.

A handful of contributions were made in the field of guava fruit grading using artificial neural networks. From the survey, it is evident that fruit grading and sorting is not a generalized task and is rather specific to the fruit. Consequently, guava fruit with a high productivity share, provides the scope for the automation of its grading and sorting. Also, the classification tool used by many researchers was artificial neural networks. Since, the technique sometimes provides local solutions, needs optimization of the training phase. Genetic algorithms when used with ANN removes its drawbacks and assist in fast trainings of large volumes of data. In the current scenario efforts have been put to integrate both the techniques to blend the merits of classifier as well as the optimizer for guava fruit grading and sorting.

III. MATERIALS AND METHODS

Integrated artificial neural networks based guava fruit grading model, as depicted in figure 1, performs the chief steps as follows:

i) Pre-processing
ii) Image Segmentation
iii) Feature Extraction
iv) Classification

Before the start of the model, the input for the model in the form of a dataset has been prepared. There are a total of 50 images of guava fruit samples taken and the image dataset was formed.

3.1 Pre-processing

Images in the dataset were in raw form, those must be preprocessed before using in the model. So, the first step was to bring the images to a form ready for image segmentation. Prior to that the images have been resized to a uniform size of 100×100.

3.2 Image Segmentation

Image segmentation means the process of separating the region of interest (ROI) from the background of the image. It is also called background subtraction. In the present research work, the ROI is guava fruit in the image and rest

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all that do not contribute effectively to the classification step are background and have been separated using an old but efficient thresholding technique, Otsu thresholding method as proposed by Otsu (1979).

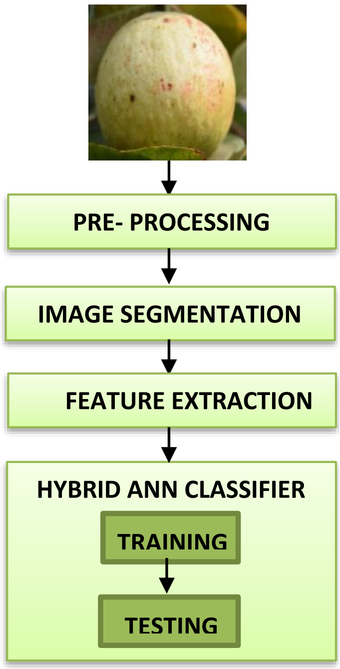

Figure 1: Proposed Artificial Neural Networks based Guava Fruit Grading Model

The method first computes the histogram of probabilities of intensity values of each pixel, thereafter mean and average of the probabilities are found to estimate the threshold value which is the global for all the pixels in the image. The mathematical steps are provided in figure 2.

1. **Compute histogram and probabilities of each intensity level.**
2. **Set up initial class probability ωi(0) and class mean μi(0).**
3. **Step through all possible thresholds t=1…maximum intensity:**
    - 3.1. **Update ω_i and μ_i.**
    - 3.2. **Compute intra-class variance $\sigma_b^2(t)$**
4. **Desired threshold corresponds to the maximum $\sigma_b^2(t)$.**
5. **Compute two maxima (and two corresponding thresholds). $\sigma_{b1}^2(t)$ is the greater max and $\sigma_{b2}^2(t)$ is the greater or equal to maximum.**
6. **Compute Desired threshold = $\frac{threshold_1+threshold_2}{2}$.**

Figure 2: Otsu Thresholding

3.3 Feature Extraction

The next significant task was to extract certain values from the image that would really contribute to the classification or evaluation of guava fruit quality. This task of quantifying the image pixels with the values is known as feature extraction. Useful features to be extracted from the images are always application specific. There is no hard and fast rule to find the most effective feature set. However, the hit and trial method is used. In case of quality evaluation problems of fruit or vegetables, the color based and shape based features are the most contributing one. Consequently, in this research work, guava fruit image features have been extracted as provided in table 1. The red, green and blue components of the image have been extracted as the most eligible color features, therefore mean and standard deviation of red intensity pixel values, green intensity pixel values and blue intensity pixel values has been considered. Whereas six shape based features were extracted: area, major axis, minor axis, eccentricity, perimeter, and circularity ratio. The details of features are provided in table 1.

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Table 1: Color based and Shape based Features for Guava fruit Grading Model

Type	Feature	Description	Formula
1. Color based features	Mean_Red	Mean of 'R' component	$\mu = \frac{\sum_i^M \sum_j^N x}{M.N}$
	Mean_Green	Mean of 'G' component	
	Mean_Blue	Mean of 'B' component	
	Std_Red	Standard deviation of 'R' component	$SD = \sqrt{\frac{1}{n-1}\sum_i^n (x_i - \bar{X})^2}$
	Std_Green	Standard deviation of 'G' component	
	Std_Blue	Standard deviation of 'B' component	
2. Shape based features	Area	Number of pixels in the region described by the shape	$Area = \sum_{x,y} I(x,y)$
	Major axis	Largest distance connecting one point to another on the region boundary, going through the center of the region.	---
	Minor axis	Smallest distance connecting one point to another on the region boundary, going through the center of the region.	---
	Eccentricity	Measure of aspect ratio	$Ecc = \frac{major\ axis}{minor\ axis}$
	Perimeter	Distance around the boundary of object, calculated from segmented image. It consisted guava fruit boundary only.	$Perimeter = \sum_{x,y} \lvert x_i - x_{i+1} \rvert$
	Circularity ratio	The ratio of the area of a shape to the area of a circle having the same perimeter	$Cratio = \frac{area\ of\ shape}{area\ of\ circle}$

3.4 Classification

Classification was the final step. It was performed using the hybrid genetic algorithm based back propagation approach. The block diagram of the classification algorithm is shown in figure 3.

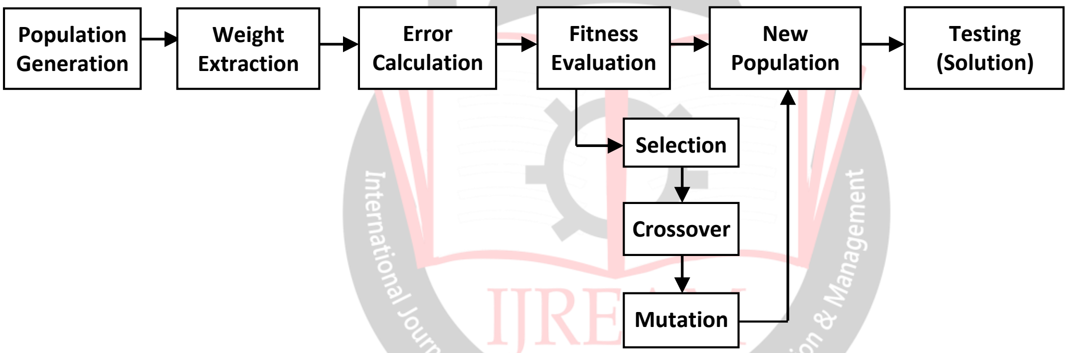

Figure 3: GA/BP based Hybrid Classifier

Genetic algorithms are population-based search and optimization techniques that follows the principle of natural genetics. By natural genetics one mean to say the evolution process where a population of a particular species adapts to its new contemplated environment based on the theory of survival of the fittest (Ceylan and Ozturk, 2005). GA are stochastic in nature. It means each time the algorithm is executed, from initiation till end, different number of parameters are set, different paths may be followed and tasks may be accomplished using different number of steps. Even different outcomes may be there as initial parameters are randomly generated. Another significant feature of GA is that they effectively utilize the information regarding next moves in an incremental way. This further helps in systematically exploring the search space, even though it is unknown in the beginning (Azadeh et al., 2006). In traditional optimization techniques (like, heuristic search, A* algorithm, backtracking, etc.,) the search space is always explored in one direction. Nevertheless, GA work on a population of points in different directions for exploring the search space (Huawang and Yong, 2009).

In order to understand how GA actually work, one must know how the natural evolutionary process works? For this purpose, suppose

P = {C1, C2 … Cn} represents the initial population of 'n' number of chromosomes such that each Ci is made up of 'm' number of genes as follows: $Ci = g1 \ |g2\ |g3| \ \dots \ |gm$. Chromosomes are also called individuals. Each chromosome or individual has some fitness value on the scale of adaptation. It means the better adapted an individual for its environment is, the fitter the individual is and hence, better are its chances to get selected for cross-over. From this initial population, two fittest individuals are chosen, known as parent1 and parent2. The two parents cross-over together to form a third (or fourth) individual,

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known as the child (children) of the parents. Sometimes, the children are not an exact combination their parents. They do possess their own qualities and this is known as mutation. But, the probability of mutation is very low. These new individuals are then kept in the population and the worst-fit are replaces by them. The population so formed is known as the new generation or population. After many such generations, it is assumed that more and more good individuals have been placed in the population and the best one is amongst them with the highest fitness, ever since the first generation. This best one is the global individual having the most optimal characteristics and is best suited to the environment for survival (Holland, 1975). On the basis of this natural process, genetic algorithms have been designed to solve optimization problem of the real world. As a result, every step of natural evolution is simulated through set of different operators.

In genetic algorithm domain, a specific terminology based on natural genetics is followed (Goldberg, 2008). The word 'chromosome' is used to represent the alternative solution for the problem. In present problem, features extracted from guava fruit images act as 'genes' and set of such genes form the chromosomes. Set of chromosomes further form the 'population' of alternative solutions. The term 'weight' signifies the importance assigned to inputs, fed to the network. 'Error' means difference in the forecasted and desired outputs. 'Fitness' is how close an individual (alternative solution) to the desired solution. More the fitness of the individual, more suitable candidate it is for the solution. Fitness is always inversely proportional to the error value. 'Selection' operator indicates finding the two fittest individuals out of population of alternatives. 'Crossover' operator implies merging of two parents (fittest alternatives) to reproduce a new offspring (new candidate solution). 'Mutation' operator means inculcating fresh features in the offspring to get diversity in the newly generated population.

The GA/BP NN algorithm works as follows:

Step 1: Generate random population of 'p' chromosomes (suitable solutions for the problem).

Step 2: Extract weights for input-hidden-output (l-m-n) layers from each chromosome x.

Step 3: Evaluate the fitness f(x) of each chromosome x in the population by reciprocating the cumulative error values obtained for each input set (weather forecasting data).

Step4: Create a new population by repeating following steps until the new population is complete

4.1 Selection: Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)

4.2 Crossover: Cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.

4.3 Mutation: With a mutation probability mutate new offspring at each position in chromosome.

4.4 Acceptance: Place the new offspring in the new population.

Step 5: Repeat steps 3 to 5 until stopping condition is met.

The output of classification step was in the form of text that specifies the class to which the guava fruit belonged to. Based on these classes, further grading was performed. The grading rules were: Assigning class A to non-defective guava fruit, class B to guava fruit having nominal surface defects and Class C to defective guava fruit. Hence, guava fruit grading was performed based on these rules.

IV. RESULTS AND DISCUSSION

An l-m-n architecture of 12-6-1 was used for simulation of neural networks as depicted in figure 4. The count of input neurons depends upon the number of feature extracted from the image, while the count of output neurons depend on the output values to be forecasted. For this scenario, the number of input neurons was 12 as the features extracted were 12 in count. Since, the network had shown minimum error values when number of hidden neurons were 6, so, m=6. Finally, the number of output neurons was taken as 1, because, there were three grading classes (Class A, Class B and Class C) and one of the three will be forecasted as output class.

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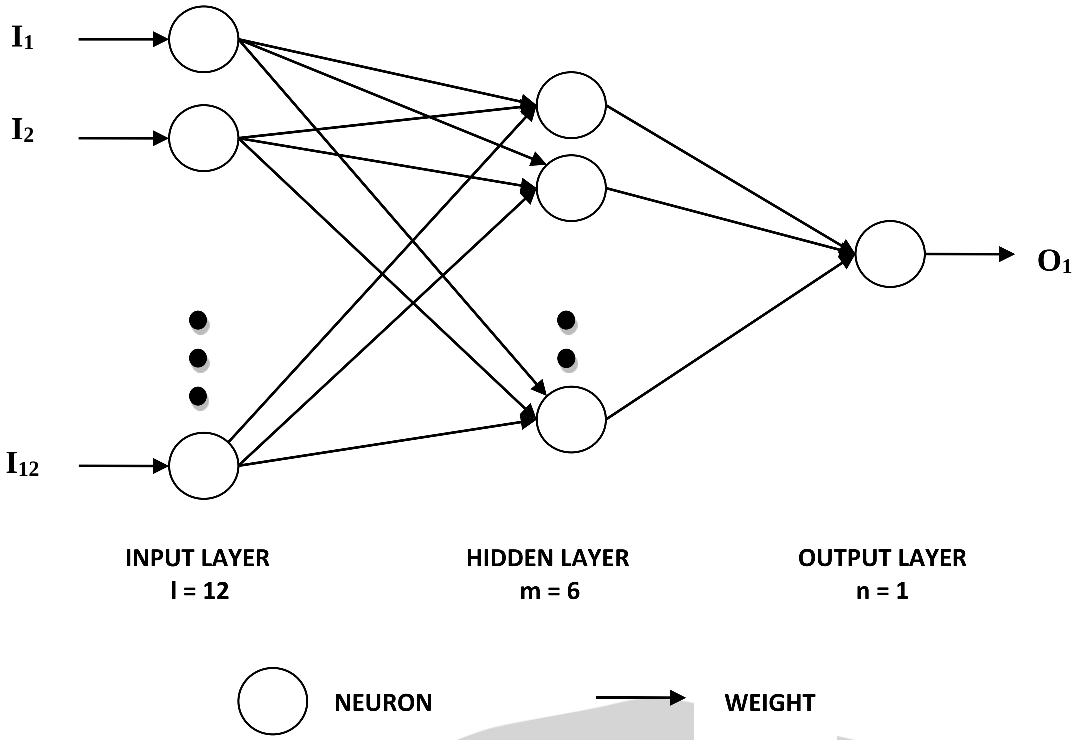

Figure 4: Neural Network Architecture for Guava Fruit Grading Model

The GA/BP guava fruit model worked in two fractions: Training and Testing. In the training phase, the 12-6-1 network was trained for inputs as well as outputs (supervised learning) to obtain weights. These weights along with different input values were then fed to the network for testing. In this study, inputs were guava fruit images and outputs were grade classes: Grade A-C. From the total 50 images, 35 were used for training purposes while 15 images for testing.

A summary of various techniques applied at each step of the guava fruit grading model are provided in table 2. Outputs of three samples corresponding to five phases are depicted in the last three columns of the table. While analyzing the outputs, the images acquired from natural scene are converted to gray scale images and then enhanced by Wiener filter in pre-processing phase. Afterwards background is separated to obtain the guava fruit object from images using Otsu threshold based method. The output is binary images. Otsu segmentation is well suited for background subtraction purposes. However, it did not provide sufficient information regarding the guava fruit defects as it is visible in the table too. Consequently, another segmentation technique: Sobel edge operator was applied.

Then, the color and shape based features were obtained in the feature extraction phase. Here, color based features assisted in classifying raw or ripe guavas so that the network could be trained to classify them. These were obtained directly from the RGB images. Shape based features were used to grade guavas according to size and defects. Area, major axis, minor axis and eccentricity, all depicted the size of guavas and were computed using the Otsu segmented image. Perimeter feature was utilized to extract the defect related information. It was computed both from Otsu segmented image (perimeter-O) and Sobel operator image (perimeter-S). The mango samples having surface defects had more difference in perimeter values, while, those with no defects were quite close. Using these features, the GA/BP NN was trained in the classification phase for 35 different images. After training, weights were extracted, which were fed along with new 15 images so as to grade them according to the rule discussed earlier.

In the table, sample 1 was graded as Class A because the mango had no surface defects and it is ripe. Sample 2 was classified as Class B, though it contained no surface defects but it was unripe (raw). The color based feature values depict the difference with the other two samples. Sample 3 was graded as Class C, since, it had surface defects. On comparing the perimeter-O and Primeter-S values for all the samples, it was obvious to put the sample 3 in Class C.

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Table 2: Step-wise Outputs for Guava fruit Grading Model

Sr. no.	Phase	Technique Applied	Output of Phase		
			Sample 1	Sample 2	Sample 3
1.	Image Acquisition	Own Camera Setup			
			↓	↓	↓
2.	Pre-processing	Resized			
			↓	↓	↓
3.	Feature Extraction	Color based Features			
		Mean_R	236	188.2220	207.8598
		Mean_G	202	212.7427	211.0254
		Mean_B	138	207.7930	170.1105
		Std_R	24.5176	50.8604	29.2215
		Std_G	34.3755	41.9398	37.9538
		Std_B	97.2350	75.0643	89.0373
		Shape based Features			
		Area	7917	3698	7739
		Major axis	118.6926	118.6904	124.6422
		Minor axis	85.7838	39.9413	79.2224
		Eccentricity	0.6911	0.9417	0.7720
		Perimeter-O	357.4630	274.5097	342.4924
		Perimeter-S	347.8061	275.9239	411.8478
			↓	↓	↓
4.	Classification	GA/BP Neural Networks	Normal	Defective	Unripe

The error versus iteration graph for back propagation neural networks (BPNN) and GA/BP neural networks is shown in figure 5 and 6, respectively. It is quite evident from the graph that GA/BP NN converged to solution earlier than BPNN. It took less than 190 iterations for GA/BP to converge while BPNN took more than 200 iterations for the same. Probable reason for late convergence of BPNN might be that it got trapped into local minima. This further led to slow training. The constant line after 80th iteration, in figure 5, undoubtedly supported the fact that BPNN suffers from local minima problem. Also, it is evident from figure 6 that GA/BP had eliminated this problem for guava fruit grading model.

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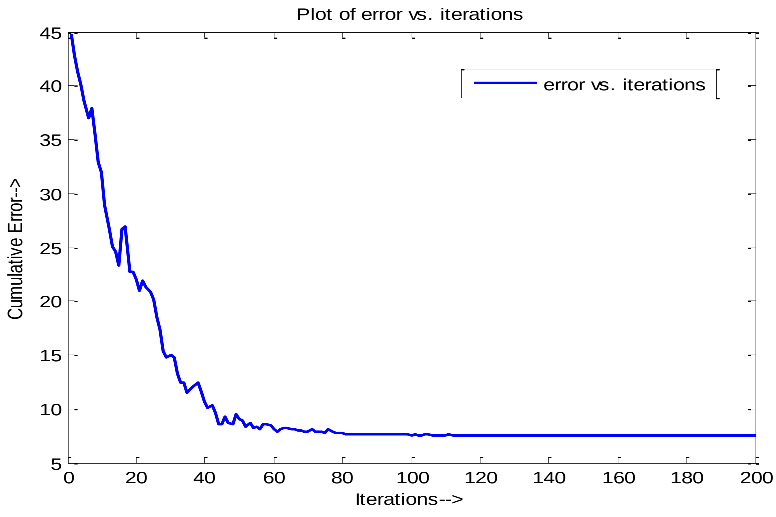

Figure 5: Error vs. Iteration graph for BPNN Approach

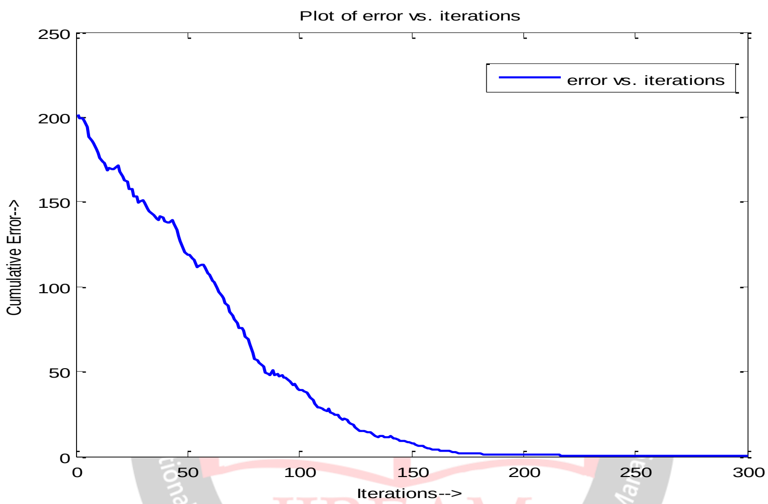

Figure 6: Error vs. Iteration graph for GA/BP NN Approach

Grading Class		Predicted Output		
		Grade A	Grade B	Grade C
Actual Output	Grade A	4	1	0
	Grade B	1	3	1
	Grade C	0	1	4

(a) Confusion matrix for BPNN

Grading Class		Predicted Output		
		Grade A	Grade B	Grade C
Actual Output	Grade A	5	0	0
	Grade B	0	4	1
	Grade C	0	0	5

(b) Confusion matrix for GA/BP NN

Figure 7: Confusion Matrix for Accuracy Evaluation- BPNN vs. GA/BP NN

In order to compare the proposed GA/BP NN based guava fruit grading model with BPNN models, a quantitative analysis was performed. Confusion matrices for both the models were formed after the testing phase. As discussed earlier, 15 guava fruit images were taken for testing. The test set was so designed to include 5 images for every grading class. This employs 5 images

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of Grade A, 5 images of Grade B and 5 images of Grade C. From the confusion matrices of figure 7(a) and (b), classification parameters were computed for both the models, provided in table 3. Two types of parameters were considered: one to determine the overall performance and other to evaluate grading class-wise performance. The former type included accuracy and misclassification rate while the latter were true positive rate, false Positive rate, specificity, precision, and prevalence.

Table 3: Performance Evaluation of BPNN and GA/BP NN Guava fruit Grading Models

Parameter	Formulas	Output value for BPNN			Output for GA/BP NN		
1. Accuracy	$\frac{true\ positive + true\ negative}{total\ cases}$	73.33%			93.33%		
2. Misclassification rate	$\frac{false\ positive + false\ negative}{total\ cases}$	26.67%			6.67%		
		Grade A	Grade B	Grade C	Grade A	Grade B	Grade C
3. True Positive rate	$\frac{true\ positives}{actual\ positive\ cases}$	80.0%	60.0%	80.0%	100%	80.0%	100%
4. False Positive rate	$\frac{false\ positives}{actual\ negative\ cases}$	10.0%	20.0%	10.0%	0.0%	10.0%	0%
5. Specificity	$\frac{true\ negatives}{actual\ negative\ cases}$	70.0%	80.0%	70.0%	90.0%	100%	90.0%
6. Precision	$\frac{true\ positives}{forecasted\ positive\ cases}$	36.4%	27.3%	36.4%	35.7%	28.6%	35.7%
7. Prevalence	$\frac{actual\ positives}{total\ cases}$	33.3%	33.3%	33.3%	33.3%	33.3%	33.3%

On analyzing the tabular values, it was manifested that GA/BP NN outperformed BPNN, showing an overall accuracy rate of 93.33%. Moreover, the misclassification rate was quite low for GA/BP NN (6.67%) as compared to BPNN (26.67%). Grading class-wise parameters also showed better results for GA/BP NN than BPNN alone.

V. CONCLUSIONS

Automation of guava fruit grading is quite significant for increased shelf life of guava fruit, maintenance of fruit quality and less human involvement. In this article, an accurate guava fruit grading system was presented in which artificial neural networks were hybridized with genetic algorithms so as to eliminate the drawbacks of back propagation algorithm. A five step procedure was followed for grading: image acquisition, pre-processing, segmentation, feature extraction and classification. The guava fruit were assigned grading classes (Class A, B and C) automatically according to grading rules. The model has shown remarkable performance when compared with the existing back propagation neural networks. It has achieved an accuracy rate of 93.3% in contrast to BPNN with only 73.3% accuracy. Thus, the GA/BP NN guava fruit grading model is proposed for future perspectives.

VI. REFERENCES

[1] Almadhor, A., Rauf, H.T., Lali, M.I.U., Damaševi˘cius, R., Alouffi, B. and Alharbi, A., (2021), "AI-Driven Framework for Recognition of Guava Plant Diseases through Machine Learning from DSLR Camera Sensor Based High Resolution Imagery" Sensors 2021, 21, 3830, 1-19.

[2] Azadeh A., et al., (2016), "Integration of ANN and GA to predict electrical energy consumption", Proc. 32nd IEEE Conference on Industrial Electron., IECON, Paris, France.

[3] Bennedsen, B.S., Peterson, D.L. and Tabb, A., "Identifying Apple Surface Defects using Principal Components Analysis and Artificial Neural Networks", Transactions of American Society of Agricultural and Biological Engineers, vol. 50, no. 6, pp. 2257-2265, 2007.

[4] Cetişli, B. and Büyükçingir, E., "Time Series Prediction of Apple Scab using Meteorological Measurements", Academic Journals: African Journal of Biotechnology, vol. 12, no. 35, pp. 5444-5451,2013.

[5] Ceylan H. and Ozturk H., (2005), "Estimating energy demand of Turkey based on economic indicators using genetic algorithm approach", J. Energy Conversion and Management, vol. 30, no. 7, pp. 1003-1012.

[6] Goldberg, D. E., "Genetic Algorithms in Search, Optimization and Machine learning", ed. 3rd, Dorling Kindersley Pvt. Ltd. with Pearson Education Inc., pp. 120-125, 2008.

[7] Holland, J. H., "Adaptation in Natural and Artificial Systems", published by University of Michigan Press, Ann Arbor, MA, 1975.

[8] Huawang S. and Yong D., (2009), "Application of an improved genetic algorithms in artificial neural

 DOI : 10.35291/2454-9150.2023.0157

networks", Proc. International Symposium on Inform. Process. (ISIP'09) Huangshan, China, pp. 263-266.

[9] Gill, J. and Singh, R.P., (2022), "Non-invasive Grading and Sorting of Mango (Mangifera indica L.) using Antlion Optimizer based Artificial Neural Networks", International Journal of Image and Graphics, 2022.

[10] Janik, L.J., Cozzolino, D., Dambergs, R., Cynkar, W. and Gishen, M., "The prediction of total anthocyanin concentration in red-grape homogenates using visible-near-infrared spectroscopy and artificial neural networks", Analytica Chimica Acta, vol. 594, no. 1, pp. 107–118, 2007.

[11] Khalid, M.A. and Tamer, A.A.A., "Date Fruits Classification using MLP and RBF Neural Networks", International Journal of Computer Applications, vol. 41, no. 10, pp. 36-41, 2012.

[12] Llobet, E., Hines, E.L., Gardner, J.W. and Franco, S., "Non-Destructive Banana Ripeness Determination using a Neural Network-based Electronic Nose". Measurement Science and Technology, vol.10, no.6, pp.538–548, 1999.

[13] Mercol, J. P., Gambini, J. and Santos, J.M., "Automatic Classification of Oranges using Image Processing and Data Mining Techniques", 2007.

[14] Motevali, A., Minaei, S., Khoshtaghaza, M.H., Kazemi, M. and Nikbakht, A. M." Drying of Pomegranate Arils: Comparison of Predictions from Mathematical Models and Neural Networks". International Journal of Food Engineering, issue.6, vol. 3, pp.1-20, 2010.

[15] Qaqish , R.K., Al-Alaya , A. and Adnan , D., (2019), "Automated Guava Classification Technique using Artificial Neural Network and Artificial Ant Colony"

[16] Ohali, Y. A., "Computer Vision based Date Fruit Grading System: Design and Implementation", Journal of King Saud University – Computer and Information Science, vol. 23, pp. 29–36, 2011.

[17] Otsu, N., "A Threshold Selection Method from Gray-Level Histograms", IEEE transactions on Systems, Man, and Cybernetics, vol. 9, no. 1, pp. 62-66, 1979.

[18] Rajasekaran S and Vijayalakshmi P., "Neural Networks, Fuzzy Logic and Genetic Algorithms", Prentice Hall of India, New Delhi, pp. 253-265, 2004.

[19] Rasekhi, R. and Raoufat, M. H., "Sorting Orange Fruit by Machine Vision and Neural Networks Techniques", CIOSTA CIGR V Conference, 2011.

[20] Salim, S. N. M., Shakaff, A.Y. M., Ahmad, M.N. and Adom, A.H., "A Feasibility Study of using an Electronic Nose as a Fruit Ripeness Measuring Instrument", 1st International Workshop on Artificial Life and Robotics, pp. 7 – 11.

[21] Sobel, I.E., "Camera Models and Machine Perception", Ph.D. Dissertation, Stanford University, Palo Alto, Calif, 1970.

[22] Unay, D. and Gosselin, B., "Artificial Neural Network based Segmentation and Apple Grading by Machine Vision", IEEE, 2005.

[23] Zakaria, A. et al., "Improved Maturity and Ripeness Classifications of Mangifera Indica cv. Harumanis Mangoes through Sensor Fusion of an Electronic Nose and Acoustic Sensor", Sensors 2012, vol. 12, pp. 6023-6048, 2012.

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