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Machine Learning and Deep Learning Networks for The Classification of Rice Grain Images from Visual Testing

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Abstract

Quality assessment of rice is mandatory during the export of rice. It necessitates a Non Destructive Testing (NDT) Technique for acquiring rice grain images, feature extraction and classification techniques. In this work, visual images of rice grain images are collected from internet. Features are extracted using Discrete Wavelet Transform (Reverse Biorthogonal wavelet, Biorthogonal wavelet) and texture features. Generalized Recurrent Neural Network (GRNN) is used for the classification of rice grains from the above features. In order to further improve the performance of the classifier, squeezenet is used. The average sensitivity is 93.75%, the average specificity is 88.75% and the average accuracy is 90.625%. The performance of this SqueezeNet in deep learning is very high compared to the machine learning techniques.

Keywords:(Rice grain, quality assessment, DWT, GLCM, GRNN, squeezenet, sensitivity, specificity, accuracy

Biographical notes: (ABS)

1. Introduction

Cultivation of rice is the most important aspect of Indian agriculture. Rice is also exported to various countries from India. Stringent quality measurement is hence necessary. Conventionally, chemical techniques are used for the quality assessment of rice. Nowadays, the paradigm has shifted to Non-destructive Testing Technique (NDT). Visual testing is a common NDT technique that captures the visual image and these images are interpreted. As subjective inspection is prone to human fatigue and expertise, computer aided interpretation has to be developed.

The proposed work aims at developing machine learning and deep learning techniques for the assessment of the quality of rice. In the first approach, the work aims at feature extraction and classification. In the second case the work aims at developing a Convolutional Neural Network which accepts the input images extracts features and classifies the rice grains. Performance is measured in terms of sensitivity, specificity and accuracy.

Considerable work is carried out in the literature to assess the quality of rice grain. L.A.I.Pabamalie and H.L.Premaratne (2010)[1] used Artificial Neural Network for assessing the quality of rice grain. V.S.Kolkure and B.N.Shaikh (2016) provides an automatic evaluation method for the determination of the quality of rice granules. Deepika Sharma and Sharad D. Sawant (2017) provides a system that determines the quality of food. Initially, the grain samples run on the conveyor belt and then random images of grains are captured by the camera. The classification has been done according to color, shape and size. AnushaAnchan and ShabariShedthi B (2016) proposed an automated system is introduced which can be used for rice grain type identification and classification where digital imaging is recognized as an efficient technique to extract the features from rice grains in a non-contact manner. TanerCevik, Ali Mustafa Ali Alshaykha et al (2016) proposed a system that analyses the performance of GLCM-based classification on DWT-compressed fingerprint images. Yang Xiaojing, Jiao Qingju and Liu Xinke (2019) proposed the weight degeneracy phenomena in fundamental particle filter algorithm. However in all the above techniques, there is a room for improvement. Also the inherent limitations in machine learning can be eliminated only by using a deep learning technique[7,8,9].

2. Proposed Methodology

Steps involved in the proposed technique are as follows: To acquire the images of the rice grain, To create database such that it should contain both good and affected images, To identify suitable transforms for the decomposition of spatial domain images, To identify appropriate statistical parameters for the representation of features and to calculate the same, To develop a suitable classifier for the classification of rice grain images, To analyze the performance of the proposed technique in terms of sensitivity, specificity and accuracy and to develop a Convolutional Neural Network for the quality assessment of rice grain images and to compare its performance with the machine learning technique[10,11,12].

The data set consists of two different classes of images such as good grains and affected gains. In good grain images the rice grains were not broken where as in contrast the affected grain images had broken grains. These images are collected from the internet database.

The block diagram of the proposed work is shown in the Figure 1. Here the grain classification is carried out by two techniques namely machine Learning and Deep learning techniques. In machine learning, the proposed work aims at using reverse biorthogonal wavelets, biorthogonal wavelets and Gray Level Co-Occurrence Matrix (GLCM) for feature extraction and Generalized Regression Neural Network (GRNN) to classify the rice grain images. In the later technique, by virtue, convolutional layers identify the features and the fully connected layer classifies the rice grain images. Performance is measured in termsof sensitivity, specificity and accuracy.

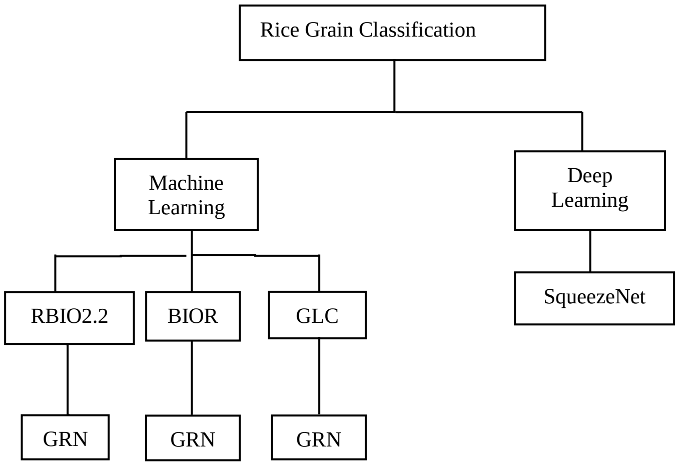

Figure 1: Block Diagram of proposed Work

In this work, rice grain images are transformed using Reverse Biorthogonal wavelets 2.2. Of the various wavelets Rbio2.2 is chosen because of its vanishing moments and its ability to detect the discontinuities. Have decomposed the original image into approximation co efficient, horizontal details, vertical details and diagonal details, the features are aggregated using statistical parameters namely mean, standard deviation, skewness and kurtosis. Mean provides the overall information present in the image, standard deviation provides information about the contrast, skewness and kurtosis measure the symmetry of the image.

Table 1: Statistical parameters from approximation co-efficient (Rbio2.2)

Image	Mean	Skewness	Kurtosis	Standard Deviation
Image_11	134.773	0.5805	15.8478	22.3857
Image_21	169.4591	1.1677	13.2241	38.0697
Image_31	215.4724	0.218	3.9508	14.0832
Image_41	146.4957	-1.4267	4.8153	53.893
Image_51	230.0697	-0.6017	4.3409	12.3532
Image_61	221.9932	-1.2438	6.8963	80.2708
Image_71	109.6363	1.8668	14.4683	55.8533
Image_81	148.8272	0.5293	20.9923	22.399
Image_12	175.7731	6.1963	6.9148	17.4929
Image_22	104.7339	-0.1324	1.6119	13.333
Image_32	142.6629	-1.7695	3.5832	57.6588
Image_42	228.1177	-0.3369	2.6408	20.0634
Image_52	161.8589	1.9967	10.5287	54.1144
Image_62	142.4172	0.1392	3.0263	46.2882
Image_72	166.1834	-1.7608	1.4318	16.4233

Image_82	38.8149	0.3537	1.9781	38.1508

Tables 1 to Table 4, shows mean skewness, kurtosis and standard deviation calculated for approximation co-efficient, horizontal detail, vertical detail and diagonal detail respectively.

Table 2: Statistical parameters from horizontal co-efficient (Rbio2.2)

Image	Mean	Skewness	Kurtosis	Standard Deviation
Image_11	-0.133	0.0024	5.2918	8.2433
Image_21	-1.6895	0.5638	2.9656	7.1909
Image_31	-0.0787	-0.3502	5.0274	7.3344
Image_41	-0.3021	4.4662	2.1147	14.0131
Image_51	-1.0304	1.1189	3.11	3.6045
Image_61	-0.3863	0.4801	3.1359	18.6829
Image_71	-0.084	0.0393	9.383	11.031
Image_81	-0.112	0.0713	4.2792	8.029
Image_12	0.4461	0.4599	3.5689	3.2927
Image_22	-0.1168	-1.464	1.7229	2.9895
Image_32	-0.0126	-0.3141	3.8211	15.6107
Image_42	-0.0276	1.2495	2.6946	3.9152
Image_52	-0.405	-0.086	5.9377	7.0139
Image_62	0.0033	0.0248	2.9951	2.8692
Image_72	-1.3161	4.305	16.956	5.0175
Image_82	-0.6128	0.3312	1.566	9.5282

Table 3: Statistical parameters from vertical co-efficient (Rbio2.2)

Image	Mean	Skewness	Kurtosis	Standard Deviation
Image_11	-0.2965	-0.029	6.8518	13.0227
Image_21	0.0899	0.014	7.1857	10.2396
Image_31	0.137	0.7094	28.531	9.3924
Image_41	-0.5513	0.132	5.2428	21.4846
Image_51	0.1966	0.0635	10.6967	4.6133
Image_61	0.1847	-0.1772	4.7944	21.0257
Image_71	-0.2059	0.6785	12.3401	15.0265
Image_81	0.2934	-0.2778	4.7246	14.247
Image_12	0.2156	0.7054	6.3796	5.2791
Image_22	-0.0379	0.2303	2.6822	8.6048

Image_32	0.3668	-0.4823	23.1796	18.6355
Image_42	-0.017	0.0965	4.5591	5.4639
Image_52	-0.0539	-0.3768	7.035	9.4595
Image_62	0.015	0.1453	5.5319	3.7345
Image_72	-0.1339	0.1612	3.9192	4.0563
Image_82	-0.8904	0.1262	3.5164	11.5507

Table 4: Statistical parameters from diagonal co-efficient (Rbio2.2)

Image	**Mean**	**Skewness**	**Kurtosis**	**Standard Deviation**
Image_11	0.0184	0.3308	4.065	9.056
Image_21	0.1809	0.1258	3.1371	8.4801
Image_31	0.0152	0.2971	5.1461	6.2837
Image_41	0.0601	-0.4543	6.8722	15.5562
Image_51	0.0611	-0.8057	11.1613	2.2657
Image_61	0.1399	0.202	4.6525	16.9935
Image_71	-0.0554	0.1349	11.1485	9.896
Image_81	0.0154	-0.062	14.1232	7.8721
Image_12	0.0033	-1.1598	11.191	3.0574
Image_22	0.0088	-0.6186	3.4394	3.6987
Image_32	0.0885	0.2891	6.9109	14.1715
Image_42	0.0011	-0.3429	3.6195	3.6105
Image_52	-0.0051	0.3612	4.0002	5.2163
Image_62	0.0026	-0.2023	12.7797	1.7322
Image_72	0.0049	-0.3589	3.1257	1.9454
Image_82	-0.1045	0.123	4.2211	6.8638

3 Results and Discussion

Having determined the statistical parameters for approximation, horizontal detail, vertical detail and diagonal details, exemplars are created with 16 input parameters and class as the output parameter. 50% of the exemplars are used for training and remaining 50% is used for testing the proposed GRNN (Any reference related to GRNN). Performance is shown in terms of confusion matrix. Quantitative assessment is obtained in terms of sensitivity, specificity and accuracy.

Table 5: Confusion matrix for the test dataset (Rbio2.2)

Type	**Good**	**Affected**
Good	1	3

Affected	3	1
Sensitivity	25%	25%

Sensitivity is 25%, specificity is 25% and accuracy of classification is 25%. In order toimprove the above parameters, the input images are decomposed using biorthogonal wavelets

A) Classification Of Rice Grains Using Biorthogonal Wavelet(BIOR2.2)

To improve the sensitivity, specificity and accuracy the biorthogonal wavelet transform was used. In this work, rice grain images are transformed using Biorthogonal wavelets 2.2. Of the various wavelets Bior2.2 is chosen because of its vanishing moments and its ability to detect the discontinuities. Have decomposed the original image into approximation co efficients, horizontal details, vertical details and diagonal details, the features are aggregated using statistical parameters namely mean, standard deviation, skewness and kurtosis. Mean provides the overall information present in the image, standard deviation provides information about the contrast, skewness and kurtosis measure the symmetry of the image.

Table 6: Statistical parameters from approximation co-efficient (Bior2.2)

ge	**Mean**	**Skewness**	**Kurtosis**	**Standard deviation**
Image_11	154.8137	0.6286	12.9878	24.5339
Image_21	170.9792	1.4159	14.4832	36.533
Image_31	215.487	0.2638	4.4988	14.4007
Image_41	146.5084	-1.6127	7.7832	62.4006
Image_51	230.7331	-0.4015	5.3093	12.297
Image_61	221.9932	-0.3621	6.5993	88.3316
Image_71	109.6133	0.6801	25.9544	62.1864
Image_81	148.8214	0.68	24.7151	27.3476
Image_12	175.4455	1.8375	48.1074	17.6671
Image_22	104.7339	-0.1331	1.6195	15.1667
Image_32	142.6629	-1.6129	4.0891	65.1707
Image_42	228.117	-0.347	3.1457	21.944
Image_52	162.3191	2.0112	10.769	54.8769
Image_62	142.4165	0.1801	3.6254	46.2765
Image_72	166.7353	-2.6666	1.3057	18.0454
Image_82	39.4801	-0.4227	1.8879	16.2978

Tables 6- Table 9, shows mean, skewness, kurtosis and standard deviation calculated for approximation co-efficient, horizontal detail, vertical detail and diagonal detail respectively. Class '1' is used to indicate the good images and class '2' is used to indicate the affected grains.

Table 7: Statistical parameters from Horizontal co-efficient (Bior2.2)

Image	Mean	Skewness	Kurtosis	Standard Deviation
Image_11	-0.1146	-0.153	3.5573	5.7893
Image_21	-0.3331	0.1663	3.9903	5.4256
Image_31	-0.1123	-0.1363	5.5992	4.8769
Image_41	-0.3025	2.7585	1.8736	9.8948
Image_51	-0.3837	1.6066	3.0591	2.2929
Image_61	-0.3863	0.0797	2.6167	14.0364
Image_71	-0.1073	-0.0618	8.4847	7.554
Image_81	-0.1178	0.1075	4.235	5.983
Image_12	0.3888	0.4921	3.713	2.3073
Image_22	-0.1168	0.0735	1.7463	1.9089
Image_32	-0.0126	0.1512	9.6548	11.5431
Image_42	-0.0293	0.4501	10.2817	2.6169
Image_52	-0.1402	0.0643	5.0073	4.7162
Image_62	0.0024	-0.139	3.5356	1.5549
Image_72	-0.7761	3.8501	12.0385	2.3248
Image_82	0.0918	0.8122	1.7776	6.2474

Table 8: Statistical parameters from Vertical co-efficient (Bior2.2)

Image	Mean	Skewness	Kurtosis	Standard Deviation
Image_11	-0.6239	-0.0191	5.8852	9.5791
Image_21	0.0162	0.0095	5.1681	7.0864
Image_31	0.1403	0.0079	28.2104	6.5421
Image_41	-0.5652	0.4029	7.6717	14.7595
Image_51	0.2105	-0.2263	25.5784	2.6858
Image_61	0.1847	-0.2815	3.9	15.9742

Image_71	-0.2179	0.8644	31.2698	10.5471
Image_81	0.5637	-0.7649	8.0198	9.4988
Image_12	-0.024	0.9305	6.8715	3.5148
Image_22	-0.0379	0.2163	3.7518	5.0232
Image_32	0.3668	0.2697	20.9468	13.8405
Image_42	-0.0198	0.1701	3.6981	3.8588
Image_52	-0.0637	3.15E-04	5.9914	5.8638
Image_62	0.015	0.2403	8.2467	2.2755
Image_72	-0.13333	0.2738	4.0431	2.4525
Image_82	-0.1484	0.2434	3.1132	8.0175

Table 9: Statistical parameters from Diagonal co-efficient (Bior2.2)

Image	**Mean**	**Skewness**	**Kurtosis**	**Standard Deviation**
Image_11	-9.09E-04	0.2076	3.7689	4.416
Image_21	0.1797	-0.0139	3.2081	4.2355
Image_31	0.0231	-0.0233	8.371	3.2139
Image_41	0.0603	-0.4743	8.5305	6.5636
Image_51	0.0608	-0.1458	5.0534	0.7917
Image_61	-0.1399	0.0179	4.8793	8.1097
Image_71	-0.0575	-0.2591	11.3021	4.201
Image_81	0.0077	-0.518	12.1732	3.8617
Image_12	-4.43E-04	-1.0209	20.5133	1.1949
Image_22	0.0088	-0.0081	4.2557	1.1568
Image_32	0.0885	0.2544	6.334	6.7857
Image_42	1.53E-04	0.0359	6.589	1.4684
Image_52	-0.0046	-0.3813	5.5411	10.4679
Image_62	0.0025	-0.0739	16.9418	0.6256
Image_72	0.0053	0.1432	5.4675	0.5549
Image_82	-0.0999	0.1243	3.7276	2.7908

Having determined the statistical parameters for approximation, horizontal detail, vertical detail and diagonal details, exemplars are created with 16 input parameters and class as the output parameter. 50% of the exemplars are used for training and remaining 50% is used for testing the proposed GRNN. Performance is shown in terms of confusion matrix. Quantitative assessment is obtained in terms of sensitivity, specificity and accuracy. Table 10 provides the confusion matrix.

Table 10: Confusion matrix for the test dataset (Bior2.2)

Type	**Good**	**Affected**
Good	2	2
Affected	3	1
Sensitivity	50%	25%

Sensitivity is 50%, specificity is 25% and accuracy of classification is 37.5%. In order to improve the above parameters, texture features are obtained. The Table 11 describes the extracted features of the imagesand these features are used to train the GRNN.

Having determined the statistical parameters for contrast, correlation detail, energy detail and homogeneity details, exemplars are created with 16 input parameters and class as the output parameter. 50% of the exemplars are used for training and remaining 50% is used for testing the proposed GRNN. Performance is shown in terms of confusion matrix. Quantitative assessment is obtained in terms of sensitivity, specificity and accuracy.

Table 11: Extracted features of the dataset using GLCM classifier

Image	**Contrast**	**Correlation**	**Energy**	**Homogeneity**
image_11	2.9356	0.8445	0.5502	0.9452
image_21	0.6428	0.9688	0.4962	0.9681
image_31	1.8286	0.8941	0.191	0.8055
image_41	1.755	0.9001	0.521	0.9262
image_51	0.7726	0.9151	0.0778	0.7995
image_61	2.3602	0.9018	0.4637	0.9579
image_71	1.7375	0.8899	0.5464	0.9196
image_81	3.1672	0.8422	0.5299	0.9434
image_12	0.4911	0.8863	0.1453	0.8352
image_22	0.2386	0.9841	0.6516	0.9829
image_32	2.1693	0.8871	0.5656	0.9613
image_42	0.1799	0.8613	0.5697	0.9471
image_52	0.4408	0.9786	0.5143	0.9687

image _62	0.189 2	0.962 1	0.230 5	0.927 1
image _72	0.255 7	0.929 2	0.353 9	0.945 7
image _82	0.881 4	0.792 3	0.819	0.953 4

Table 12: Confusion matrix for the test dataset (GLCM).

Type	**Good**	**Affected**
Good	3	1
Affected	0	4
Sensitivity	75%	100%

From the Table 12 Sensitivity is 75%, specificity is 100% and accuracy of classification is 87.5%. In order to improve the above parameters, the input images are decomposed using GLCM. Hence in order to improve the performance further, features must be automatically generated and the feature map should be fed to the classifier.

From the Table 13 the sensitivity and specificity are equal to one for almost all test samples indicates that the network has more accuracy in identifying the good and affected grains. The average sensitivity is 93.75%, the average specificity is 88.75% and the average accuracy is 90.625%. Theperformance of this SqueezeNet in deep learning is very high compared to the machine learning techniques.

Table 13: Obtained results of SqueezeNet

Image_Name	**Sensitivity**	**Specificity**	**Accuracy**
test_image	75%	75%	75%
test_image1	100%	80%	87.5%
test_image2	100%	100%	100%
test_image3	100%	100%	100%

PERFORMANCE EVALUATION

The Table 14 describes the performances of the proposed techniques. The parameters in the below table are sensitivity, specificity and accuracy.

Table 14: Table for performances of proposed techniques

Type	**Sensitivity**	**Specificity**	**Accuracy**
RBIO2.2	25%	25%	25%
BIOR2.2	50%	25%	37.5%
GLCM	75%	100%	87.5%

SqueezeNet	93.75%	88.75%	90.625%

From the Table 14, the performance of the SqueezeNettechnique was very high compared to the RBIO2.2, BIOR2.2 and GLCM. The above is also shown in Figure 2.

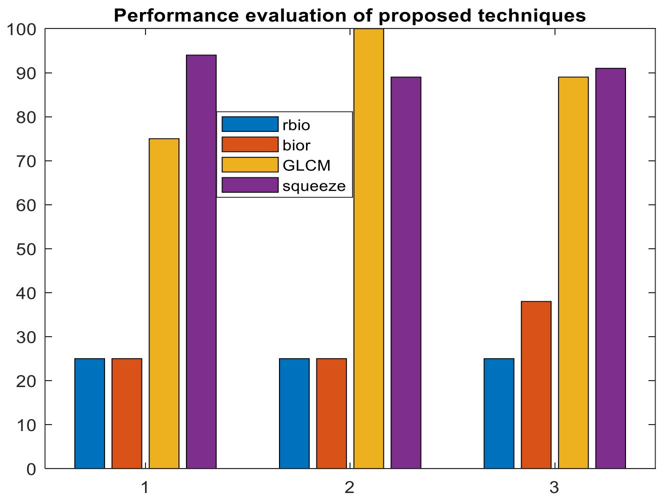

Figure 2: Performance Evaluation of the proposed techniques

It is found that sensitivity and accuracy are the highest for SqueezeNet; however, the specificity must be improved. It implies that though the SqueezeNet can classify all the good rice grain images as good, it could not classify the affected rice grains as affected.

4 CONCLUSION AND FUTURE WORK

In this work, both machine learning and deep learning techniques has been developed for the assessment of rice quality from visible images. Initially features were extracted from coefficients obtained through discrete wavelet transform with Reverse Biorthogonal 2.2 wavelet (RBIO2.2) classification is performed using General Regression Neural Network (GRNN). In order to improve the performance Biorthogonal 2.2 (BIOR2.2) wavelet was also used. In order to increase the performance heraldic features are extracted using Gray Level Co-Occurrence Matrix (GLCM) and the rice grains are classified using GRNN. Sensitivity and specificity are 75% and 100% respectively

By virtue, performance of the machine learning technique is dependent on the features which are extracted. To overcome the inherent limitations, Convolutional Neural Networks is developed for classification of rice grains. Of the various convolutional neural network architectures, SqueezeNet is chosen and developed for rice grain classification. Sensitivity, specificity and accuracy are 93.75%, 88.75%, 90.625% respectively.

The proposed algorithms are scalable in nature, the impact of large dataset on the performance of the proposed techniques can be studied. However, the work has stopped at simulation level. Also, modifications in SqueezeNet architecture also may improve performance of the classifier. Feasibility of other Convolutional Neural Networks can also be studied.

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