Algorithm of Caries Level Image Classification using Multilayer Perceptron Based Texture Features

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***Abstract*—A number of patients with untreated caries only seek treatment at late stages when serious complications might have already developed and can lead to significant acute and chronic conditions with high cost of treatment. The purpose of this research is to be able to find out the level of caries based on X ray images by using image processing and machine learning methods. The image processing algorithm namely Gray Level Co-occurrence Matrix (GLCM) has been used to extract texture features and Multilayer Perceptron (MLP) methods to classify the X ray caries images. Lavenberg Marquard and Backpropagation Bayesian Regularization are used in this study. The conclusion obtained in this study is that the algorithm of classification using Multilayer Perceptron (MLP) based texture features can classify dental caries images in four classes. The best performance result is achieved the training accuracy of 99.20% and the testing accuracy of 98.30% by using Lavenberg Marquardt (LM) model with hidden layer 10. In Backpropagation Bayesian Regularization (BR), the best results are found in hidden layer 10 as well (Training: 100%, Testing: 100%).**

Keywords*—*Dental Caries, Feature Extraction, GLCM, MLP, Classification

I. Introduction

In medicine, Artificial Intelligence (AI) has been gradually becoming more popular and widely applied in diagnosing and treating patients more quickly and accurately, it also helps to reduce the risk of complications so that patients can speedy recovery. Among the wide scope of applications, AI has demonstrated magnificent performance to detect carious lesions in the field of dentistry as well. Most of the prior research has applied neural networks to process and analyze different types of dental X-ray images for detection and diagnosis of dental caries.

To detect caries lesions in bitewing radiographs, several image processing steps are used in caries classification research. Detection of proximal caries at the molar teeth has been done by using edge enhancement algorithm [1]. Research of segmentation on panoramic radiographs [2], automated teeth extraction from dental panoramic images using genetic algorithm [3], and caries detection using multidimensional projection and neural network [4] have been done in recent years.

Artificial neural network systems can be created to help doctors work so that the classification of normal teeth and caries teeth can be easier and faster to do [5]. The uses of different machine learning algorithms for diagnosis of dental caries have been reviewed in several studies [6], [7], [8].

In our previous research, the features extraction performances of dental caries image are analyzed by using Gray Level Cooccurrence Matrix (GLCM) algorithm for contrasted two types of caries is based on the theory of GV Black, namely: dental caries Class 3 and Class 4. The study aims to determine the pixel value and quantization value of the GLCM used for an automated classification system of dental caries types. The analysis is conducted by using variations of pixel distances and quantization value to perform features on the image in values such as contrast, correlation, energy, and homogeneity. Then these values are used as input to the classification stage K nearest neighbor (KNN). Result performed on four data sets containing 60 images of each set is an accuracy value. The highest performance obtained is 80% of accuracy in 100 and 200 of pixel distances and 16 and 32 of quantization value. The pixel distances and quantization values are recommended to be used for an automated classification system of dental caries types based on X-ray images [9].

Next, our previous study was to analyze and discover the extraction results from Hu's moment invariants. After successfully extracting the features, the classification was carried out using Support Vector Machine (SVM) and KNN. The study employed radiographic images of four dental caries classes consisting of Class 1, 2, 3, and 4. A total of 198 images of dental caries were used as training data and 66 images as test data. The classification obtained accuracy value of the SVM and KNN. The highest accuracy was discovered in the Fine Gaussian model of the SVM classification method with 77.6%, while the lowest accuracy was depicted in the Cubic model with 57.4%. Meanwhile, the highest accuracy by using KNN is 100% of accuracy using Fine and Weighted KNN models.[10]. Comparison of SVM and KNN performances has been done based on texture features [11].

As in 2018, a study entitled Four Categories of Human Teeth Based on Biogeography-based Optimization Algorithm and Multilayer Perceptron was conducted by Mengmeng Yang et. all. The study used the Optimization Algorithm Multilayer Perceptron classification method. The study classification uses biogeography-based optimization algorithm (BBO) and Multilayer perceptron (MLP). First the extraction of the tooth image feature is done using an wavelet entropy (WE) then inserting the extracted filter into the MLP. The BBO algorithm is used to train MLP parameters to achieve the best performance. Results showed 83.75± 2.95%, 83.50± 5.16%, 84.00± 5.16%, and 84.75± 3.43% accuracy rates for incisor, canine, premolar, and molar identification [12].

Another study is dental caries diagnosis in digital radiographs using back-propagation neural network conducted by V. Geetha et. all., in 2020 with the classification of back-propagation neural networks. This experimental diagnostic system consists of Laplacian filtering, window based adaptive threshold, morphological operations, statistical feature extraction and back-propagation neural network. Back propagation neural networks are used for the classification of normal tooth surfaces or caries teeth. 105 images derived from intra-oral digital radiography were used, for artificial neural network training with 10-fold cross validation. Dental caries in this radiography, cannot be animated by a dentist. The performance of this dental caries analyzer algorithm is evaluated and compared with the basic method. Produced a system with an accuracy of 97.1%, false positive (FP) rate of 2.8%, receiver operating characteristic (ROC) area of 0.987 and precision recall curve (PRC) area of 0.987 with a learning rate of 0.4, momentum from 0.2 and 500 iterations with single hidden layer with 9 dots [13].

Based on the previous research and problems in the study, this study presents a solution by using GLCM with MLP to classify 4-level dental caries efficiently.

II. Methodology

The proposed classification algorithm of the caries level images has been developed by using GLCM and MLP methods. The features extraction process is done by employing the GLCM for extracting texture features and MLP is used for classification purposes. The following is a detailed explanation of the task process as described in Figure 1 of the research flow diagram.

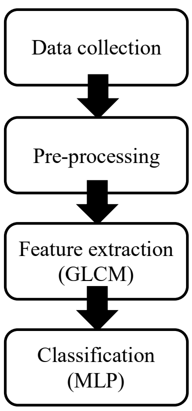

Fig. 1. Flowchart of the research

A. *Data and Tools*

In this study, we used 3 instruments, namely *hardware* (laptop) with Windows 10 Pro 64-bit specifications, Windows 10 Pro 64-bit, *processor* Intel® Caleron(R)- *Central Processing Unit* (CPU) N3150, 1.60 *GigaHertz* (GHz) with *Random Access Memory* (RAM) with a capacity of 4 *GigaBytes* (GB), Samsung Core i5 9400f Nvidia RTX 2060 6GB Computer with 16GB RAM and software in the form of MATLAB R2018b application. Image capture with Computed Radiography. The specifications of the tools can be seen in Table I.

TABLE I. Hardware Specifications

Hardware Memory	**Characteristic**	
	Laptop	***Computer***
Processor	4 Gb	16 Gb
Graphics	Intel® Caleron(R)- *Central Processing Unit* (CPU) N3150, 1.60 *GigaHertz* (GHz)	Core i5 9400f
Hardware	Integrated GPU	Nvidia RTX 2060 6GB

The research is started with the collection of dental caries images from experts. Collection of dental caries images is done by collaboration with experts (doctors) who are at the Dental and Oral Hospital of Universitas Muhammadiyah Yogyakarta. A total of 96 images for class 1, 72 images of class 2, 42 images of class 3 and 26 images of class 4 dental caries images were furthermore continued by preprocessing treatment with cropping and resize processes by previous studies [9].

B. *Pre-processing*

Pre-processing is carried out the augmentation process with the aim of varying the number of images. This magnification process consists of rotating the original image 180 degrees and flipping it horizontally. This procedure was chosen because the possible direction of the teeth is only vertical. The total imagery used after pre-processing is 396 images. Training data is as much as 90% of the total imagery, the rest is test data. The resolution of the image used is 445 x 1169 pixels. This process is similar to research that has been done before [10].

C. *Feature extraction*

For features extraction step, the study has employed the GLCM that also has succussed to be used in our previous studies [9], [10], [11]. The detail of the GLCM implementation has been presented in [9].

D. *Classification*

The Lavenberg Marquardt (LM) and Bayesian Regularization (BR) models are used in this research. The hidden layers which are used 3 level of layers (i.e. 5, 10 and 15, respectively). The 10-fold cross validation is used to manage the dataset for training and testing process.

E. *Results and Analysis*

The analysis can be done by comparing the image of teeth that have been known to have certain level of dental caries (1, 2, 3, 4), with the results of the classification of the proposed algorithm. The result of the algorithm is labeling on the testing image with the caries levels. Caries level 1 is the positive grade, and the caries levels 2 to 4 are the negative grade. The analysis of classification results is confusion matrix which has resulted accuracy, sensitivity, specificity, precision, and F-score. Calculation of the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) is referred to [14].

III. Result and Discussion

Table 2 is the average and the standard deviation calculation of GLCM features results for class 1, 2.3, 4 of caries images. The features are contrast, correlation, energy, and homogeneity which are consisted of the four orientations in the GLCM features. The features for the four orientations have the average and standard deviation of all used images as comparison of calculations that caries teeth class 1, class 2, class 3, and class 4.

The standard deviation calculation aims to find out the number of variations in the GLCM extraction feature data, which is a large difference from the sample value to the average. The differences in each value make it easier for the system to detect or classify test images. Feature extraction results can be seen in Table 2.

Based on Table 3, in hidden layer 1, the result has the best training on the ninth run with 81.30% while the best test on the third run with 86.40%. In layer 5, there is also the best training on the ninth run such as layer 1 with 97.30% but the best testing occurs in the fifth run with 96.60%. The next layer is 10, this layer has the best training on the sixth run with 99.20% while the best testing occurs in the third run with 98.30% as in layer 1. The confusion matrix of the LM can be seen in Figure 2. The analysis performance of the LM in the testing data has been tabulated in Table 4. The results have represented good performances in hidden layers 1 to 10. The accuracy results by using hidden layer 10 is better among the other used hidden layers.

After LM, then there is a BR whose confusion matrix can be seen in Figure 3. BR also has 3 layers as well, namely layers 1, 5 and 10. In BR, layer 1 (Table 5), the best training occurred in the fifth run with 79.80% while the second run became the best test with 86.40%. In the next layer (layer 5), the fourth run has a perfect score with 100% accuracy, but the fourth run is not the best training. The best training came in fifth with almost perfect accuracy with 97.40%. In the last layer, training and testing get perfect accuracy (100% accuracy) achieved by the eighth run for training and the seventh run for testing. The analysis performance of the BR model based on the used testing data are tabulated in Table 6. The results have represented good performances in hidden layers 1 to 10. The accuracy results by using hidden layer 10 is also better among the other used hidden layers. Based on Tables 3 and 5, the time of training duration of LM model is better than the BR model.

TABLE II. GLCM FEATURE EXTRACTION RESULTS

No.	**GLCM Features**		**Average ± Standard Deviation**			
			Class 1	***Class 2***	***Class 3***	***Class 4***
1	Contrast	0o	39.21 ± 17.55	53.54 ± 21.84	56.77 ± 18.49	88.53 ± 19.24
		45th	70.30 ± 23.45	79.53 ± 29.62	54.87 ± 20.33	85.19 ± 20.16
		90th	72.09 ± 20.84	68.78 ± 18.73	45.56 ± 13.06	66.79 ± 13.15
		135th	72.08 ± 22.85	82.13 ± 30.68	54.42 ± 19.62	85.56 ± 20.99
2	Correlation	0o	0.45 ± 0.21	0.26 ± 0.21	0.00 ± 0.14	-0.04 ± 0.14
		45th	0.021 ± 0.20	-0.13 ± 0.20	-0.05 ± 0.15	-0.11 ± 3.61
		90th	0.01 ± 0.16	0.01 ± 0.16	0.13 ± 0.16	0.25 ± 7.19
		135th	0.00 ± 0.19	-0.16 ± 0.18	-0.05 ± 0.16	-0.12 ± 10.82
3	Energy	0o	0.015 ± 0.02	0.01 ± 0.01	0.00 ± 0.00	0.01 ± 0.00
		45th	0.01 ± 0.00	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 3.60
		90th	0.01 ± 0.01	0.01 ± 0.00	0.00 ± 0.00	0.01 ± 7.21
		135th	0.01 ± 0.01	0.00 ± 0.00	0.01 ± 0.00	0.01 ± 10.81
4	Homogeneity	0o	0.37 ± 0.07	0.32 ± 0.04	0.28 ± 0.04	0.41 ± 0.04
		45th	0.25 ± 0.05	0.24 ± 0.04	0.26 ± 0.04	0.39 ± 3.58
		90th	0.26 ± 0.04	0.27 ± 0.03	0.31 ± 0.03	0.47 ± 7.18
		135th	0.25 ± 0.05	0.24 ± 0.04	0.26 ± 0.03	0.39 ± 10.79

(a) (b) (c)

Fig. 2. Confusion matrix of GLCM trainlm (a) Hidden Layer 1, (b) Hidden Layer 5, (c) Hidden Layer 10

TABLE III. CLASSIFICATION RESULT OF LAVENBERG MARQUARDT MODEL

Folds	Hidden Layer 1			Hidden Layer 5			Hidden Layer 10		
	Training	*Testing*	*Time*	*Training*	*Testing*	*Time*	*Training*	*Testing*	*Time*
1	77.50%	78.00%	0.00.00	82.10%	78%	0.00.00	98.50%	93.20%	0.00.00
2	79.20%	81.45%	0.00.00	97.10%	94.90%	0.00.00	97.30%	91.50%	0.00.00
3	75.80%	**86.40%**	0.00.00	93.30%	84.70%	0.00.00	98.90%	**98.30%**	0.00.00
4	76.10%	74.60%	0.00.00	96.00%	94.90%	0.00.00	98.10%	94.90%	0.00.00
5	80.30%	69.50%	0.00.00	96.80%	**96.60%**	0.00.00	98.10%	86.40%	0.00.00
6	76.90%	76.30%	0.00.00	96.40%	89.80%	0.00.00	**99.20%**	94.90%	0.00.00
7	79.20%	67.80%	0.00.00	90.50%	76.30%	0.00.00	98.70%	84.70%	0.00.00
8	76.50%	79.70%	0.00.00	96.80%	81.40%	0.00.00	97.30%	94.90%	0.00.00
9	**81.30%**	76.30%	0.00.00	**97.30%**	88.10%	0.00.00	98.70%	94.90%	0.00.00
10	79.00%	78.00%	0.00.00	94.10%	84.70%	0.00.00	96.80%	91.50%	0.00.00
Mean	78.18%	76.81%	0.00.00	94.04%	86.94%	0.00.00	98.16%	92.52%	0.00.00

TABLE IV. PERFORMANCE ANALYSIS OF LAVENBERG MARQUARDT MODEL

	Hidden Layer 1 (%)				Hidden Layer 5 (%)				Hidden Layer 10 (%)			
Performances	*Class 1*	*Class 2*	*Class 3*	*Class 4*	*Class 1*	*Class 2*	*Class 3*	*Class 4*	*Class 1*	*Class 2*	*Class 3*	*Class 4*
Accuracy	98,2	96,6	100	88,9	98,3	96,6	100	100	100	96,7	100	100
Precision	96,3	92,9	100	78,8	95,8	92,0	100	100	100	92,0	100	100
Sensitivity	92,9	96,3	78,8	100	92,0	95,8	100	100	92,0	100	100	100
Specificity	96,8	93,8	100	81,1	97,1	94,4	100	100	100	94,6	100	100
F-Score	94,5	94,5	88,1	88,1	93,9	93,9	100	100	95,8	95,8	100	100

(a) (b) (c)

Fig. 3. Confusion matrix of GLCM trainbr (a) Hidden Layer 1, (b) Hidden Layer 5, (c) Hidden Layer 10

TABLE V. CLASSIFICATION RESULT OF BACKPROPAGATION BAYESIAN REGULARIZATION MODEL

Folds	Hidden Layer 1			Hidden Layer 5			Hidden Layer 10		
	Training	*Testing*	*Time*	*Training*	*Testing*	*Time*	*Training*	*Testing*	*Time*
1	79.30%	81.40%	0.00.00	96.80%	83.10%	0.00.00	99.40%	100%	0.00.05
2	77.90%	**86.40%**	0.00.00	96.30%	93.20%	0.00.00	98.30%	100%	0.04.19
3	78.70%	76.30%	0.00.00	96.30%	98.30%	0.00.00	98.70%	94.90%	0.00.05
4	79.30%	78.00%	0.00.00	97.20%	**100%**	0.00.00	98.90%	100%	0.00.05
5	**79.80%**	69.50%	0.00.00	**97.40%**	96.60%	0.00.00	99.10%	98.30%	0.00.05
6	78.90%	78.00%	0.01.30	97.00%	93.20%	0.01.30	99.10%	98.30%	0.00.05
7	79.10%	71.20%	0.00.01	96.30%	96.90%	0.00.01	98.10%	96.60%	0.00.05
8	78.70%	81.40%	0.00.01	95.10%	88.10%	0.00.01	98.90%	**100%**	0.00.00
9	77.80%	81.40%	0.00.01	95.50%	93.20%	0.00.00	**100%**	98.30%	0.00.00
10	78.30%	79.70%	0.00.00	95.00%	93.20%	0.00.00	98.30%	94.90%	0.00.05
Mean	78.78%	78.33%	0.00.09	96.29%	93.58%	0.00.09	98.88%	98.13%	0.00.29

TABLE VI. PERFORMANCE ANALYSIS OF BACKPROPAGATION BAYESIAN REGULARIZATION MODEL

	Hidden Layer 1 (%)				Hidden Layer 5 (%)				Hidden Layer 10 (%)			
Performances	*Class 1*	*Class 2*	*Class 3*	*Class 4*	*Class 1*	*Class 2*	*Class 3*	*Class 4*	*Class 1*	*Class 2*	*Class 3*	*Class 4*
Accuracy	96,2	92,7	100	96,2	100	98,5	100	100	100	100	100	100
Precision	90,9	83,3	100	90,9	100	96,4	100	100	100	100	100	100
Sensitivity	95,2	95,2	76,9	100	96,4	100	100	100	100	100	100	100
Specificity	93,9	88,6	100	93,9	100	97,4	100	100	100	100	100	100
F-Score	93,0	88,9	87,0	95,2	98,2	98,2	100	100	100	100	100	100

IV. Conclusion

The conclusions obtained in this study are gray level co-occurrence matrix (GLCM) and Multilayer Perceptron (MLP) can classify dental caries images. The best model according to analysis result is Lavenberg Marquard model with hidden layer 10 (Training: 99.20%, Testing: 98.30%). Based on Backpropagation Bayesian Regularization model, the best results are found in hidden layer 10 as well (Training: 100%, Testing: 100%). The result of the proposed algorithm is excellent. The future research develops the algorithm to be a system and test the validation.

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