Classification of Caries X-Ray Images using Multilayer Perceptron Models Based Shape Features

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Abstract—**Dental caries is one of the diseases that are often experienced by society, one way to detect it by taking pictures using Computed Radiography technology. The aim of this study was to develop a method of classifying dental caries imagery with the Hu Moment Invariant (HMI) and Multilayer Perceptron (MLP) feature extraction methods as an alternative to facilitate the detection of dental caries. The dental caries image used is a dental caries image for grade 1, class 2, class 3, class 4, with a total of 220 images of which 90% are as training data and 10% data testing. Hu Moment Invariant is used as a method of feature extraction and image classification using the Multilayer Perceptron (MLP) method. Classification is carried out with 2 classifier models namely Levenberg-Marquardt (LM), and Bayesian Regularization (BR) with a ratio of 3 types of Hidden Layer (HL) namely Hidden Layer 1, 5, and 10. The results of the analysis showed that the classification of dental caries imagery using HMI feature extraction and MLP classification will be obtained the best results when using the LM Hidden Layer 10 Model with the best training and testing accuracy results with a value of 96.1% and 98.3% and an average computing time between 1 to 14 seconds.**

Keywords—Dental Caries, Feature Extraction, Hu Moment, GLCM, Classification, MLP

I. Introduction

Dental and oral health problems are quite common in everyone [1]. According to the Results of Basic Health Research in 2018 by the Ministry of Health stated that the largest proportion of dental problems in Indonesia is damaged / cavities / sick teeth as much as 45.3% [2]. One of the causes of the emergence of dental caries disease is caused by excessive sugar consumption. This is why children are susceptible to dental caries, which affects almost 50% of children worldwide. In addition, the lack of dental health care, and the difficulty of access to standard dental health services make the disease more widespread [2] [3] [4]. Dental caries disease if not treated in a timely manner will have an effect on difficulty in sharpening, speaking, or lowering the level of confidence in the environment [5].

Early detection of the disease is one of the important things in the application of imaging and diagnosis of dental caries disease [5]. X-ray imagery of teeth can provide a detailed evaluation of teeth and gums to the dentist, therefore dental X-ray becomes one of the diagnostic and disease prevention ways. quite popular dental caries [6] [7] [8]. X-ray is highly recommended because it will display the size, location and condition of the tooth and is also able to detect the presence of cavities before appearing on the surface of the tooth [5] [9] [10].

The diagnosis of dental caries disease is very dependent on reading the image by a dentist or related experts, so it is quite time-consuming to obtain the results of the diagnosis. The use of image processing for the detection of dental caries is very helpful for doctors in diagnosing early dental caries disease [1][11][12][13].

Multilayer Perceptron (MLP) is one of the best methods of classification and is often used in the classification of an image. The use of MLP as a classification method is carried out in studies related to classification with dental imagery described in [14] and [15]. M. Yang, A. Nayeem, and L. OrDonnell used MLP and Biogeography-based optimization (BBO) as optimization techniques, resulting in an accuracy of 83.75± 2.95%, 83.50± 5.16%, 84.00± 5.16%, and 84.75±3.43% for the incisor canine, premolar classes, and molar [14]. Another case with S. S. Bunyarit et al who use MLP as a classification method in his study is to do estimation age of Malaysian children aged 5-18 years based on teeth. The estimated accuracy was −0.05 ± 0.92 years for boys and −0.06 ± 1.11 years for girls [15].

In this study the MLP classification method will be combined with the Hu Moment Invariant feature extraction method. The Hu Moment Invariant extraction method has been used for detecting the shape and characteristic of an object [19]. In the study detection of dental caries, the Hu Moment Invariant method works very well in reading the forms of dental images. This method has been used in some studies such as those conducted by Y. Jusman et al [17] in cancer detection using leukaemia cell imagery and B. P. Sari and Y. Jusman [18] in early detection of cervical cancer.

Another study dental caries image classified using Gray Level Co-Occurrence Matrix (GLCM) and combine with Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) [16]. The result of this study revealed the highest accuracy generated by the Fine Gaussian SVM was 95.7%. In addition to MLP other classification methods are also developed in various studies of dental caries image cutting as studies have been conducted by [16], [9], [11], [10], [12], and [13].

Based on the background of the implementation of the MLP and Hu Moment Invariant methods in these studies, it is known that the use of MLP and Hu Moment Invariant methods in the classification of dental caries imagery is very limited. Therefore, the authors developed a dental caries disease detection system using the MLP classification method and extraction of the Hu Moment Invariant feature. As an early detection system for dental caries disease.

II. METHODE

A. Data and Tools

The dental caries image data used in this study are X-ray computed radiographic type image, with total data of 220 dental caries images. In this study, GV Black dental caries classification is used for X ray dental images. The images of dental caries defined by medical expert in dentistry consisted of into 4 types of classes, namely class 1, class 2, class 3 and class 4. A total of 90 caries images for class 1, 70 caries images of class 2, 40 imagery of class 3, and 20 images of class 4. The image is proceeded the preprocessing algorithm with the process of cropping and resize. The dental caries image taking in collaboration with dental and oral nurseries Hospital (RSGM) Universitas of Muhammadiyah Yogyakarta.

B. System Design

This research went through several steps, starting with the capture of dental caries image data which was then carried out the pre-processing process. The next step is the extraction of the feature using the Hu Moment invariant method, followed by the classification stage using the Multilayer Perception (MLP) method. This entire step is displayed on the Figure 1.

C. Pre-processing

In this pre-processing step, the augmentation process is carried out using a 180°degree rotation and horizontal flip as presented in Figure 2. This process aims to multiply the image of dental caries. The software used in this study is MATLAB software version R2018b. The specifications of the computer that was built during the image processing process are shown in Table 1.

TABLE I. HARDWARE SPECIFICATION

Hardware	Characteristic
Processor	Intel® Core i5 9400f
Memory RAM	16GB
Graphics	Nvidia RTX 2060 6GB

D. Feature Extraction

The features extraction in this study used the Hu Moment Invariant (HMI) method. Hu Moment Invariants is a feature extraction method used to define 7 moments (features) that represent an object. The extraction stage of this feature is carried out after preprocessing imagery. There are seven feature results from the calculation of seven extracted features is labeled phi 1, phi 2, phi 3, phi 4, phi 5, phi 6, and phi 7. In this method the first moment until fourth moment have resistance to scale, translation, and rotation. The 5th to the 7th moments are the deviations from the 2nd and 3rd moments [19].

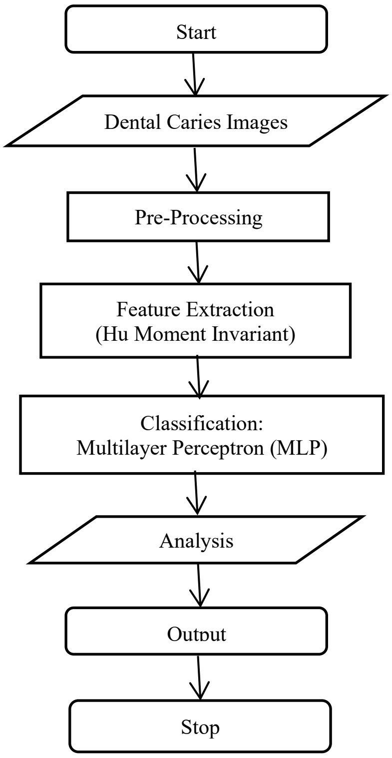


Fig. 1. System Design Flow Chart

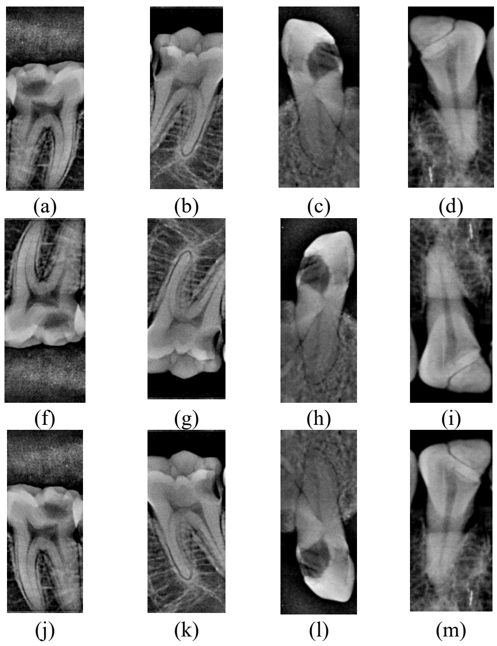


Fig. 2. Pre-processing Result Image *(a,b,c,d original image class 1-4, f,g,h,i, 180° rotation image class1-4, j,k,l,m, horizontal flip image class1-4)*

E. Classification

The data that has been extracted (features) is then classified using the Multilayer Perceptron (MLP) method. In this study, two classifier models were used, namely Levenberg- Marquardt (LM), and Bayesian Regularization (BR). The LM is method solves the least squares problems, by the two algorithms (gradient descent method and the gauss–newton method) [20]. BR is method corrects the weight and refraction, by minimizes the combination of error squares and weights, then determine the correct combination to produce a good network [21].

Each model was then tested with a comparison of 3 types of Hidden Layer (HL) namely Hidden Layer 1, 5, and 10 in each feature extraction. Differences in model, hidden layer and extraction of features used will provide a difference in accuracy value after the classification process is carried out. The calcification results are analyzed based on training computing time, training accuracy and testing accuracy. The results will then be displayed on the Receiver Operating Characteristic (ROC) chart.

III. Result and Discussion

A. Feature Extraction Result

Feature extraction is performed using Hu Moment Invariant (HMI). There are seven feature results of the extraction. The results are displayed in Table 2. Table 2 shows the results of the calculation of the average ± standard deviation phi in each class of feature extraction results from the image of dental caries.

B. Classification Result

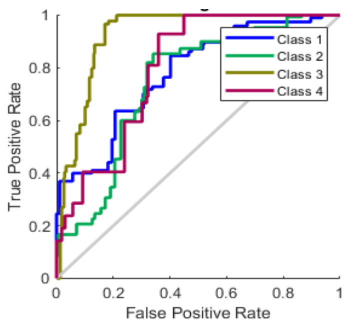
All classification results are carried out using the Multilayer Perceptron (MLP) method, with 2 base models namely Levenberg-Marquardt (LM) and Bayesian Regularization (BR). Each of these models was tested with 3 variations, namely Hidden Layer (HL) 1, 5, and 10 on each feature extraction. The results of training, testing and training times are shown in Table 3 and Table 4. The results of the Receiver Operating Characteristic (ROC) chart of LM and BR models displayed on Figure 3 and Figure 4, respectively.

From Table 3, you can see the results of classification using the LM Model with Hidden Layer 1 resulting in the best training accuracy on the eighth run with a value of 59.2%, the best test accuracy result is on the second run with a value of 66.1%. Classification using Hidden Layer 5 produces the best accuracy training on the third run with a value of 80.9%, the result of testing accuracy in the ninth run, namely with a value of 76.3%.

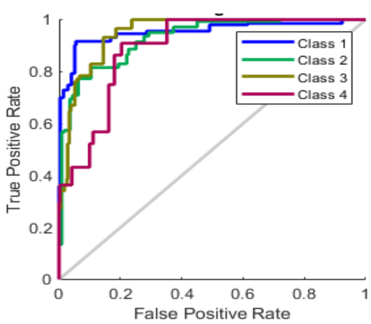
Classification using model BR is displayed on Table 4. The result for Hidden Layer 1 of this model produced the best accuracy on the fifth run with a score of 58.7%, the best result of testing accuracy is on the fourth run with 61% value with an average computing time of 1 second.

The results of this classification are also shown in the form of an ROC graph displayed in the Figure 3 and Figure 4. The reading of the ROC chart visually can be seen from the true positive rate value, which is close to 1, and the ratio is to the false positive rate.

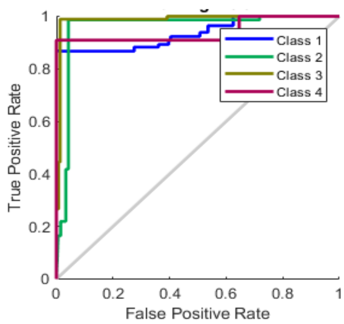
Based on the graph shown in Figure 3 and Figure 4, it can be seen that result classification with Hidden Layer 10 get the best ROC value compared to Hidden Layer 1 and Hidden Layer 5. The comparison of each model's classification (LM and BR) with 3 difference Hidden Layer are displayed in the Figure 5.



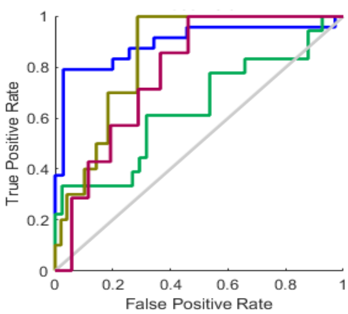
(a) Hidden Layer 1 Training ROC



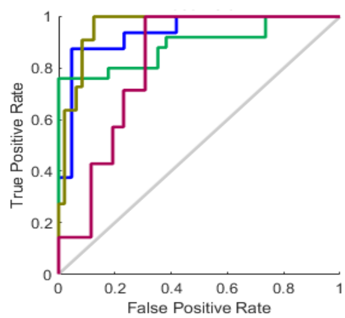
(b) Hidden Layer 5 Training ROC



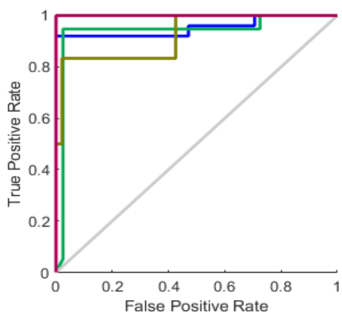
(c) Hidden Layer 10 Training ROC



(d) Hidden Layer 1 Testing ROC

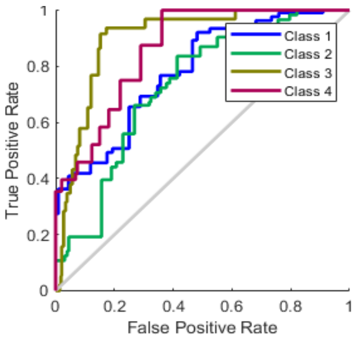


(e) Hidden Layer 5 Testing ROC

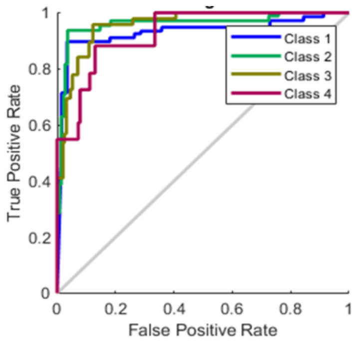


(f) Hidden Layer 10 Testing ROC

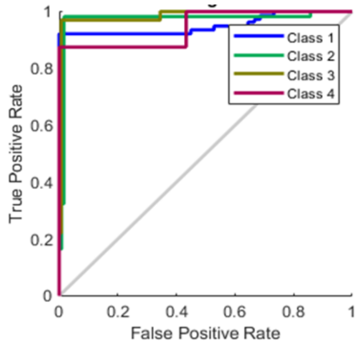
Fig. 3. ROC with Model Levenberg-Marquardt



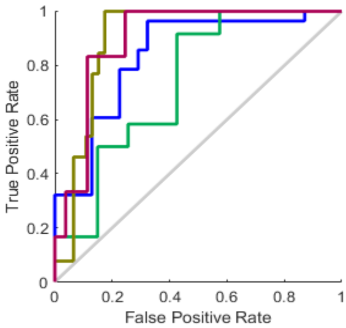
(a) Hidden Layer 1 Training ROC



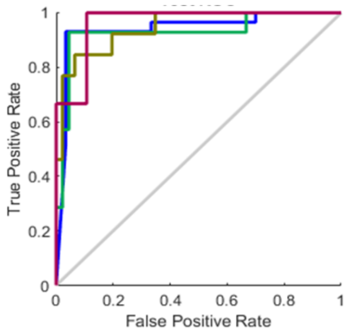
(b) Hidden Layer 5 Training ROC



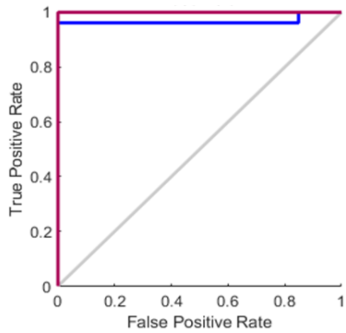
(c) Hidden Layer 10 Training ROC



(d) Hidden Layer 1 Testing ROC



(e) Hidden Layer 5 Testing ROC



(f) Hidden Layer 10 Testing ROC

Fig. 4. ROC with Model Bayesian Regularization

TABLE II. MEAN AND STANDARD DEVIATION OF FEATURE EXTRACTION RESULTS

Hu Moment Features	**Dental Caries level Classes**			
	Class 1	***Class 2***	***Class 3***	***Class 4***
phi 1	1.86E-03± 2.89E-04	1.74E-03± 2.09E-04	1.81E-03± 2.8E-04	1.85E-03± 4.47E-04
phi 2	4.73E-07± 2.11E-07	1.7E-07± 8.36E-08	7.26E-08± 3.88E-08	9.09E-08± 7.77E-08
phi 3	3.22E-11± 6.97E-11	3.95E-12± 4.46E-12	1.11E-11± 1.17E-11	9.49E-12± 1.22E-11
phi 4	3.17E-11± 6.61E-11	4.17E-12± 4.74E-12	1.24E-11± 1.45E-11	1.79E-11± 2.71E-11
phi 5	5.14E-21± 3.87E-20	2.89E-23± 1.12E-22	3.03E-22± 6.48E-22	6.66E-22 ± 1.30E-21
phi 6	-1.5E-14± 3.82E-14	-1.6E-15± 1.73E-15	-3.4E-15± 5.64E-15	-7.1E-15± 1.323E-14
phi 7	5.07E-23 ± 1.47E-21	-7E-25± 8.61E-24	-2.2E-24± 9.46E-23	-2.1E-23 ± 2.15E-22

TABLE III. ACCURACY RESULTS OF CLASSIFATION WITH LEVENBERG-MARQUARDT MODEL

Model Levenberg-Marquardt									
RUN	**Hidden Layer 1**			**Hidden Layer 5**			**Hidden Layer 10**		
	Training	***Testing***	***Time***	***Training***	***Testing***	***Time***	***Training***	***Testing***	***Time***
1	53.40%	55.90%	00.00	77.50%	69.50%	00.00	91.30%	**91.50%**	00.00
2	53.80%	**66.10%**	00.00	72.70%	71.20%	00.00	80.70%	78.00%	00.00
3	51.70%	52.50%	00.00	**80.90%**	74.60%	00.00	60.50%	66.10%	00.00
4	51.90%	44.10%	00.00	75.00%	72.90%	00.00	**92.60%**	83.10%	00.00
5	54.60%	54.20%	00.00	69.30%	72.90%	00.00	75.40%	69.50%	00.00
6	51.10%	57.60%	00.00	69.30%	62.70%	00.00	71.80%	64.40%	00.00
7	52.50%	54.20%	00.00	63.90%	66.10%	00.00	72.90%	72.90%	00.00
8	**59.20%**	62.70%	00.00	71.00%	66.10%	00.00	66.80%	64.40%	00.00
9	58.80%	47.50%	00.00	63.70%	**76.30%**	00.00	84.90%	86.40%	00.00
10	50.20%	52.50%	00.00	76.10%	74.50%	00.00	72.90%	71.20%	00.00
Mean ± STD	53.72% ± 3%	54.73% ± 6%	0.00 ± 0.00	71.94% ± 5%	70.68% ± 4%	0.00 ± 0.00	76.98% ± 10%	74.75% ± 9%	0.00 ± 0.00

TABLE IV. ACCURACY RESULTS OF CLASSIFATION WITH BAYESIAN REGULARIZATION MODEL

Model Bayesian Regularization									
RUN	**Hidden Layer 1**			**Hidden Layer 5**			**Hidden Layer 10**		
	Training	***Testing***	***Time***	***Training***	***Testing***	***Time***	***Training***	***Testing***	***Time***
1	54.40%	50.80%	00.01	78.30%	78%	00.02	94.60%	98.30%	00.04
2	54.40%	61%	00.01	87.10%	84.70%	02.07	94.40%	84.70%	00.04
3	51.60%	50.80%	00.01	85.80%	86.40%	00.02	92.50%	86.40%	00.04
4	55.00%	61.00%	00.01	78.50%	61%	00.02	93.60%	86.40%	00.04
5	58.70%	52.50%	00.01	81.50%	69.50%	00.02	92.90%	98.30%	00.04
6	52.30%	49.20%	00.01	78.50%	86.40%	00.02	94.40%	94.90%	00.04
7	55.10%	54.20%	00.00	79.60%	81.40%	00.02	96.10%	94.90%	00.14
8	58.70%	47.50%	00.01	76.10%	72.90%	00.02	93.80%	94.90%	00.14
9	52.90%	54.20%	00.01	79.40%	72.90%	00.02	94.60%	93.20%	00.04
10	54.40%	50.80%	00.01	78.30%	78%	00.02	94.60%	98.30%	00.04
Mean ± STD	54.75% ± 2%	53.20% ± 4%	0.009 ± 0.003	80.31% ± 3%	77.12% ± 8%	0.225 ± 0.615	94.15% ± 1%	93.03% ± 5%	0.06 ± 0.04

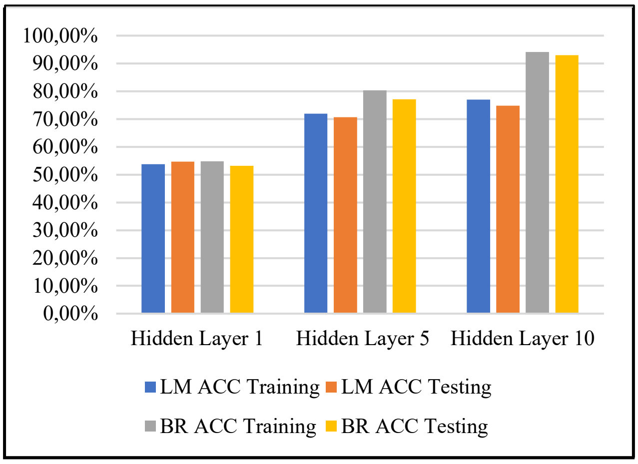


Fig. 5. Comparison of Classification Accuracy

IV. CONCLUSION

The Multilayer Perceptron (MLP) classification method and the Hu Moment Invariant (HMI) feature can be developed in aiding the classification of dental caries disease. In the classification of dental caries using Multilayer Perceptron (MLP) with the Levenberg-Marquardt Model (LM) produces the best accuracy and testing accuracy in Hidden Layer 1 of 59.2%, and 66.1%. Hidden Layer 5 produces the best accuracy of training and testing with a value of 80.9%, and 76.3%. Hidden Layer 10 produces the best accuracy of training and testing with a value of 92.6%, and 91.5% classification using the LM Model takes less than 1 second. Classification using the Bayesian Regularization (BR) Model produces the best accuracy and testing accuracy on Hidden Layer 1 with values of 58.7%, and 61%. Hidden Layer 5 produces the best accuracy of training and testing with values of 87.1% and 84.6%. Hidden Layer 10 produces the best accuracy of training and testing with a score of 96.1% and 98.3% and an average computing time between 1 to 14 seconds. Based on the results of the analysis of this study, it can be concluded that the classification of dental caries imagery using HMI feature extraction and MLP classification is obtained the best results. when using the LM Model with Hidden Layer 10. For further research testing using other feature extraction methods needs to be done to enrich the reference as a comparison.

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