Machine Learnings of Dental Caries Images based on Hu Moment Invariants Features

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***Abstract*— Dental caries generally occurs due to consuming foods containing carbohydrates, such as sucrose, and rarely brushing teeth, thus causing gradual damage to the layers and structures of the teeth. This study aims to build a dental caries level classification system using image processing and machine learning methods. The first step was to analyze and discover the extraction results from Hu's moment invariants. After successfully extracting the features, the classification was carried out using a Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). This 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.**

Keywords—caries images, X-ray images, Hu's moment invariants, classification, analysis.

I. INTRODUCTION

Oral and dental health is always essential to be maintained. There are several organs in the mouth, such as teeth and tongue; each has different functions. For example, the tongue functions as a sense of taste and helps swallow food, while the teeth serve as a food processor to soften food. Thus, when food enters the digestive system, it can be adequately digested by other organs such as the stomach and intestines. Teeth have three types and functions, covering incisors that function to cut food, molars that serve to grind and chew food, and canines, which function to tear food because these teeth are the sharpest.

Curvature of the teeth often occur due to the lack of dental care, causing them to not be optimal in processing food. Moreover, teeth can also be a nest of dirt that causes plaque and erodes the teeth, thus causing cavities or caries in the teeth. Dental caries generally occurs due to consuming foods containing carbohydrates, such as sucrose, and rarely brushing teeth, thereby gradually damaging the layers and structures of the teeth [2].

The Ministry of Health of the Republic of Indonesia published on its website, www.kemkes.go.id that in 2016, the global burden of disease study stated that dental and oral health problems, especially dental caries, were one of the diseases experienced by almost half of the world's population, totaling 3.58 billion people. In addition, gum disease is the 11th most common disease in the world. The basic health research also declared that 45.3% of dental problems in Indonesia in 2018 were damaged or perforated teeth. All doctors in Indonesia establish the diagnosis of dental caries using radiographs or X-Ray rays. However, sometimes the results of radiographs or X-Ray rays are unclear and cause obstacles to diagnosing dental caries. Therefore, all doctors must follow the protocol in reading the results of radiographs or X-Ray rays. Hence, the examination of the patient's teeth can detect whether he has caries on the teeth or not [3].

Patric Kiel Navarro et al. conducted a study on dental images detected using the SVM method, and the decision tree image was processed with Histogram Equalization and augmented to 10x10. The results obtained 84% and 78% accuracy [1]. A new segmentation method based on level set (LS) was proposed in two phases: IC generation using morphological information of image and intelligent level set segmentation utilizing motion filtering and backpropagation neural network. The segmentation results were efficient and accurate as compared to other studies [2].

Surveys of segmentation in dental X-ray images for diagnosis of dental caries were conducted [3], [4]. Benchmark for comparison of dental radiography analysis algorithms were carried out based on several research groups [5], [6], [7], [8], [9]. Some deep learning research on caries levels has been presented [10], [11], [12]. Tooth recognition in dental radiographs by Hu's moment invariants was discussed [13], and other studies using Hu's moment were explained [14], [15], [16], [17], [18], [19], [20].

Based on the implementation of hu moments invariant is limited for caries images. Meanwhile, the shape features is the important features to differentiate the caries levels. Thus, in this study, the authors performed hu moment invariant and artificial intelligence methods to detect dental caries correctly. The hu moment invariant as features extraction method for dental images extracted the shape features. Then the classification process was carried out by the Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) to obtain dental image results diagnosed according to each class of dental caries.

II. METHODOLOGY

This study implemented various stages, which started with inputting dental caries images, and then the pre-processing stage was carried out by varying the number of images. The next stage was the feature extraction process by

Hu's moment, and the feature extraction results were continued to the classification process by the SVM and KNN. These various stages were processed using the hardware of Intel Core i5 9400f, 16.00 GB memory, and 6 GB Nvidia RTX 2060 graphics. The stages in this study are presented in Figure 1.

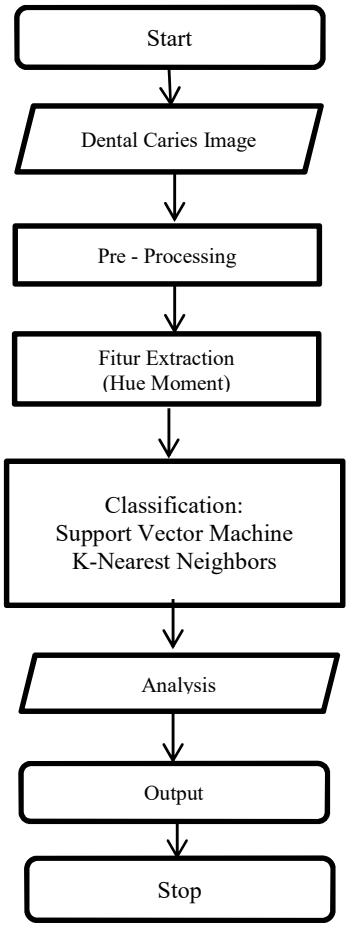

Fig. 1. Research flow chart

A. Data and Tools

This study utilized radiographic results of four classes of dental caries images, namely Class 1, 2, 3, and 4. Class 1 consisted of 81 images, Class 2 comprised 63 images, Class 3 contained 36 images, and Class 4 involved 18 images. The radiographic results of dental caries images were obtained from the Dental and Oral Hospital (RSGM) of Universitas Muhammadiyah Yogyakarta. The hardware specifications are displayed in Table 1.

TABLE I. HARDWARE SPECIFICATIONS

Hadware Memory	**Characteristic**
Processor	16 Gb
Graphics	Intel Core i5-9400 CPU @ 2.90 GHz
Hadware	GeForce GTX 970 4Gb

B. Pre–Processing Stage

In the pre-processing stage, there was an augmentation process aiming to vary the number of images. This augmentation process consisted of rotating 180 degrees and flipping horizontally to the original image. These processes were chosen because the possible direction of the teeth is only vertical. Total of images used after preprocessing are 396 images. Training data is 90% of total images then the rest is the testing data. The image resolution used was 445 x 1169 pixels. The results of pre-processing are demonstrated in Fig. 2. The rotated 180 degrees results are presented in Fig. 2b, and the horizontal flip results are presented in Fig. 3c.

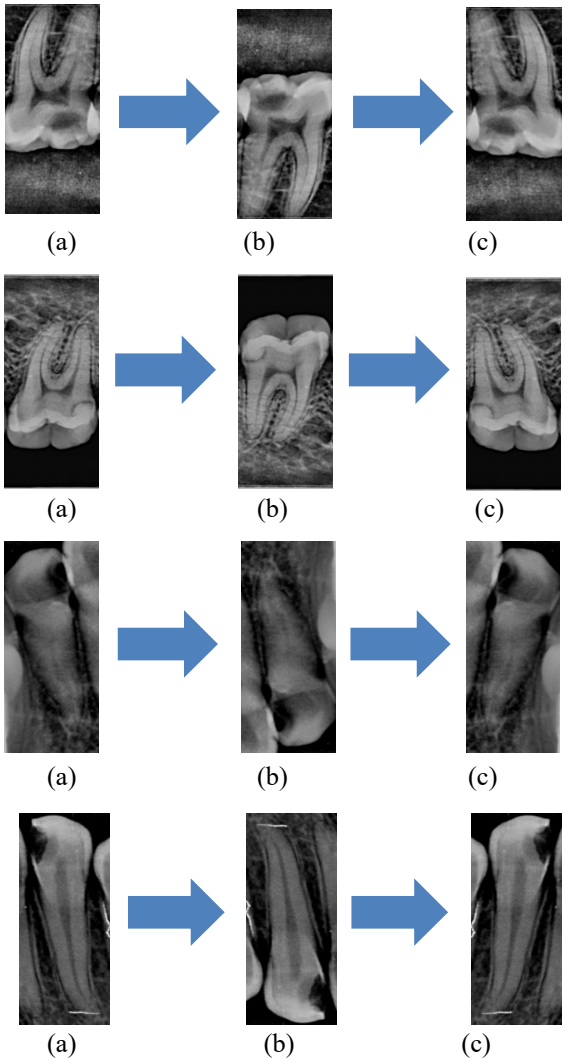

Fig. 2. (a) Initial condition of the image before processing b) Image result after being rotated 180 degrees (c) Image result after the horizontal flip.

C. Feature Extraction Stage with Hu's Moment

The Hu's moment was applied as the feature extraction method in this study. The pre-processing process was carried out first, followed by the extraction with Hu's moment, resulting in seven features in each extracted image.

D. Classification and Analysis Processes

The feature extraction results obtained were classified using the SVM. This SVM method aimed to discover the best hyperplane functioning as a separator of two data groups in the input space. The first step in the SVM algorithm process was to input the dataset, proceed with the calculation process with the SVM kernel function, and then was followed by the SVM training process. The SVM process

was the testing process on the dataset or image. Finally, the last stage was the classification evaluation. The following is an explanation of the SVM algorithm process flow. The KNN also was used to train and test to show the accuracy results.

III. RESULTS AND DISCUSSIONS

This study applied two processes, features extraction and classification, to process four classes of dental caries images. The feature extraction process with Hu's moment produced feature values owned by each image. Hence, the feature extraction results could be presented in a table and used for the classification process. This classification process utilized three SVM models and two KNN models: Cubic SVM, Quadratic SVM, and Fine Gaussian SVM, Fine KNN, and Weight KNN to produce accuracy values.

A. Feature Extraction Results

The feature extraction process using Hu's moment invariants produced seven features. The resulting feature extraction values were used to distinguish one image from another. Thus, each image had a feature extraction value. Table 2 exhibits feature extraction results, the average value, and standard deviation of each class, namely Class 1, 2, 3, and 4. Hence, the system could distinguish each dental caries image based on its class.

B. Classification Results

The classification process employed the three SVM models and two KKN models: Cubic SVM, Quadratic SVM, Fine Gaussian SVM Fine KNN, and Weight KNN, to obtain an accuracy value by running ten times. Table 3 depicts the accuracy values and classification times.

Based on Table 3, the highest accuracy value is in the Fine Gaussian SVM model, obtaining an accuracy value of 77.6% with a time of 5.7 s. In contrast, the lowest accuracy value is discovered in the Cubic SVM model with a value of 57.4% and a time of 40.98 s. Meanwhile, the highest accuracy by using KNN is 100% of accuracy using Fine and Weighted KNN models. The averages of duration times are 1.92 and 1.7 seconds for fine and weighted KNN models, respectively. Based on the Table 2, the feature values are significantly different, so it can be grouped the images data features well. Thus, the basic theory for KNN classification is realized in this case. Because of that, the KNN accuracy values can achieved higher than SVM for this study.

TABLE II. FEATURE EXTRACTION RESULTS

Hu's Moment Feature	**Average ± Standard Deviation**			
	Class 1	Class 2	Class 3	Class 4
Hue 1	0.0018 ± 0.000297	0.0017 ± 0.00019	0.0018 ± 0.00026	0.0018 ± 0.00042
Hue 2	2.89E-07 ± 2.13E-07	1.7E-12 ± 8.38E-08	7.26E-08 ± 3.45E-08	8.81E-08 ± 7.45E-08
Hue 3	2.21E-11 ± 6.95E-11	3.95E-12 ± 4.03E-12	1.11E-11 ± 1.15E-11	9.28E-12 ± 1.2E-11
Hue 4	1.9E-11 ± 6.6E-11	4.17E-12 ± 3.93E-12	1.24E-11 ± 1.35E-11	1.77E-11 ± 2.62E-11
Hue 5	4.83E-21 ± 3.87E-20	2.89E-23 ± 5.78E-23	3.03E-22 ± 5.75E-22	6.62E-22 ± 1.25E-21
Hue 6	-1.1E-14 ± 4.08E-14	-1.6E-15 ± 1.57E-15	-3.4E-15 ± 4.52E-15	-6.9E-15 ± 1.24E-14
Hue 7	-3.7E-22 ± 9.29E-21	6.67E-25 ± 2.07E-23	-2.2E-23 ± 1.66E-22	1.07E-23 ± 2.49E-22

TABLE III. SUPPORT VECTOR MACHINE (SVM) AND K-NEAREST NEIGHBORS (KNN) CLASSIFICATION RESULTS

	Average ± Standard Deviation SVM						**Average ± Standard Deviation KNN**			
	Cubic SVM (%)	**Time (s)**	**Quadratic SVM (%)**	**Time (s)**	**Fine Gaussian SVM (%)**	**Time (s)**	**Fine KNN (%)**	**Time (s)**	**Weighted KNN (%)**	**Time (s)**
1	61	44.99	65	9.5	77.6	5.7	100	6.4	100	5.6
2	58.9	46.49	65.2	4.5	75.9	1.5	99	0.8	99.5	0.4
3	59.8	42.49	66.2	5.5	75.9	1.5	99	0.8	98.5	0.9
4	60.8	45.99	66	5.5	75.6	2.0	99.5	0.8	99.8	0.9
5	62.5	3.99	65.8	5.5	75.6	1.5	99	1.1	99	1.3
6	59.9	44.52	64.6	6.5	77.1	2.1	100	4.8	100	3.8
7	58.8	45.99	64.8	7.5	74.7	1.5	99	0.8	99.5	0.4
8	59.9	42.99	66.8	7.0	77.6	2.0	99	0.8	98.5	1.0
9	59.4	46.53	64.8	4.0	73.7	1.5	99.5	1.2	99.8	0.9
10	57.4	40.98	66.8	4.0	77.4	1.5	99	1.1	99	1.1
Average	59.9	40.50	65.6	5.9	76.1	2.1	99.30	1.92	99.36	1.7

IV. CONCLUSIONS

Machine learnings of dental caries images using Hu moment invariant features could be developed using Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). The features of the hu moment invariant algorithm have significantly value to differentiate the caries levels. The SVM classification method revealed the highest accuracy value generated by the Fine Gaussian SVM model was 77.6%. Conversely, the lowest accuracy value generated was 57.4%, derived from the Cubic SVM model. Meanwhile, the highest accuracy by using KNN is 100% of accuracy using Fine and Weighted KNN models. The averages of fine and weighted KNN models are 99.30 and 99.36% of accuracy values and duration times are shorter than the SVM models results. The KNN classification results are higher than the SVM results.

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