Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16


ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# A WAVELET BASED STATISTICAL TECHNIQUE FOR DENTAL CARIES SEVERITY CLASSIFICATION USING FUZZY FEATURE SELECTION

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**ABSTRACT**

Dental caries is a disease resulting in tooth decay due to bacterial infection in it. The caries can be classified into four severity types i.e., incipient, moderate, advanced and severe, depending on the depth or extent to which they affect the tooth. In this paper, we have classified the caries into different severity types using wavelet domain-based feature extraction methods followed by fuzzy feature selection. The input dental X-ray images of caries infected tooth are subjected to feature extraction using three statistical methods i.e., Wavelet Completed Local Binary Pattern (WCLBP), Wavelet Completed Local Binary Count (WCLBC) and Wavelet Completed Local Ternary Pattern (WCLTP). Since severity/extent of caries is subjective in nature, we further propose a fuzzy rule-based system for selecting important features from the extracted ones, suitable for severity classification. This also addresses the dimensionality problem faced by the above methods. The improved results of the proposed model, using fuzzy feature selection, prove its potency. This study justifies that WCLTP followed by fuzzy rule-based feature selection and Adaboost classification proves to be one of the most effective ways to identify and classify the dental caries based on the severity.

**Keywords:** *Dental Caries, Medical Imaging, Fuzzy Feature Selection, Severity Based Classification*

## 1. INTRODUCTION AND RELATED WORK

Dental Caries is an oral health disease that affects about 3.9 billon people worldwide [1]. It is caused by the bacteria present in the mouth which turns sugar and carbohydrates in one's food into acid. This acid softens the minerals present in the tooth enamel and removes them resulting in tooth decay [2]. It is noted that oral health affects children and considerably harms their quality of life [3, 4, 5, 6]. Severe early childhood caries (SECC) is a serious oral health problem prevalent in preschool toddlers. Studies show that a large percentage of children suffering from this problem were diagnosed as anaemic [7]. A study of Korean adults [8] showed that a large percentage of middle aged men and women suffering from severe/advanced dental caries also suffered from coronary heart disease.

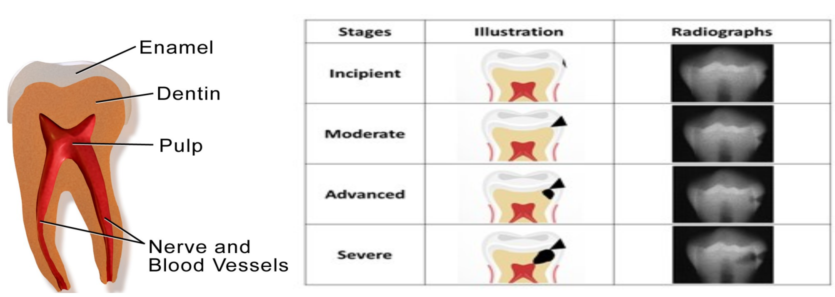


*Figure 1: (a) Tooth Taxonomy [Wikimedia Commons] (b) Dental Caries Severity Classes [Dentistryiq.com.2021]*

Hence, it is very important, not only to detect the caries at an early stage but also to diagnose the degree of their severity for better treatment and timely cure.

The interproximal caries can be classified according to their severity into the following classes depending on the extent of the enamel region and the dentin region involved in the caries [9]. Figure 1 (a) shows the tooth taxonomy and figure 1 (b) shows the classification of dental caries based on the severity.

- Incipient Caries: This dental caries extends only in the enamel portion less than midway.
- Moderate Caries: This dental caries spreads more than halfway through enamel but does not engage the dentin part.
- Advanced Caries: This dental caries covers through the dentin less than halfway.
- Severe Caries: This dental caries outspreads more than halfway through dentin and includes the pulp region.

Clinical examination of caries involves examining the colour and texture of the lesion physically [10] together with their associated microbial activity, which is determined from the biopsies of these lesions. However, visual and physical examinations are less sensitive due to their subjective nature. Nyvad et al. [11] proposed a method to assess the severity of caries based on the surface topography and the texture of a lesion examined clinically over a period of time. The International Caries Detection and Assessment System (ICDAS) [12] classifies the extent of dental caries into seven classes ranging from normal to extreme cavitation. Although, the ICDAS identifies different stages of carious lesions, there were problems in applying the system to epidemiological surveys [13, 14]. This led Ribeiro et al. [15] to propose a new caries detection instrument, termed Caries Assessment Spectrum and Treatment (CAST) where a severity score was assigned to the caries to classify it as mild, moderate or severe. However, as mentioned above, all these methods involved clinical examination of caries over a period of time. Now, the post COVID-19 period demands methods that are more aseptic and involve less human intrusion. Such methods would not only reduce the effort of the dentist and avert the disparity in the diagnosis but also support the dentists and patients in the post COVID period to sustain physical detaching and still detect the problem accurately.

Medical diagnosis is basically a pattern classification phenomenon, in which an expert reaches a conclusion based on the knowledge and input provided by the patient. Image Processing plays a vital role in medical diagnosis [16, 17]. Processing of dental X-ray images plays a key role in diagnosis of dental diseases. The detection of dental caries can be done with help of radiography, an imaging technique using X-rays. These radiographs can be enhanced before caries detection [18]. After enhancement, they can be used for the detection of proximal and interproximal caries. The latest tools to detect caries include fiber optics trans-illumination, light or laser fluorescence, advanced radiography and electrical obstruction [19]. The statistical features used for dental X-ray image classification include correlation, local homogeneity, entropy, average etc. [20]. These features have low computation burden and they are easy to implement [21]. Other such feature detection methods include Local Binary Pattern (LBP), Local Ternary Pattern (LTP), Complete Local Binary Pattern (CLBP), Complete Local Binary Count (CLBC) and Complete Local Ternary Pattern (CLTP). The LBP [22] is associated with the difference between the gray level value of the center pixel and its circular neighborhood pixels. It is one of the most widely used method for detecting statistical features in medical images because of its simple implementation and fast performance. However, LBP also has many limitations. It may classify different patterns falsely to same class. They are not invariant to rotations. They are sensitive to noise and illumination changes. Many variants of LBP that are rotation invariant, have been used to make the classification performance more accurate. Local Ternary Pattern (LTP) [23] is an extension of LBP. The LTP encodes the neighborhood pixels into 3 values by using a threshold value. Another variant of LBP is Completed Local Binary Pattern (CLBP) [24]. In this, the features that are extracted contain information related to sign (CLBP_S), magnitude (CLBP_M) and center components (CLBP_C). Similar to CLBP, the completed local binary count (CLBC) [25] extracts the features i.e. CLBC_S, CLBC_M and CLBC_C. Since CLBP and CLBC are sensitive to noise, so to overcome this, another variant Completed Local ternary Pattern (CLTP) was proposed. The main features detected by CLTP are CLTP_S which is a sign component, CLTP_M which is a magnitude component and CLTP_C which is the center component. The above descriptors for texture classification give good results but they are unable to classify noisy and rotational textures correctly. Hence, a new feature extraction method, Wavelet Complete Local Ternary Pattern (WCLTP) [27] was developed to enhance the CLTP performance. In WCLTP, the image is first transformed from spatial domain to wavelet domain using the Redundant Discrete Wavelet Transform (RDWT). RDWT decomposes the image into the four sub-bands. These sub-bands are of equal size, so relevant textures in the image would be at same location of each sub-band. The CLTP operators are then computed using the LL sub band. Hence, local textures can be measured accurately. The WCLTP feature extraction thus increases the classification accuracy due to its shift invariant property. Although the classification accuracy increases considerably, the high dimensionality of CLTP as well as WCLTP lead to increase in computation time and requirement of large memory space. Hence, in this paper, we propose a fuzzy rule-based feature selection method to select relevant features after WCLTP feature extraction method to reduce its dimensionality. Feature selection chooses a relevant subset of the available features and eliminates those that have little or no predictive information. This leads to an increase in the classification accuracy and a decrease in the computation time. Various methods have been proposed in literature for feature selection. One of the most popular method for feature selection based on fuzzy logic was proposed by Xiang et al. [28]. It uses human expertise in the form of fuzzy rules to select relevant features from a large feature set. In this paper we have proposed a machine learning method that uses fuzzy feature selection for dental X-ray image classification. The motivation behind this research is the increasing demand of an efficient dental X-ray classification system to assist dentists in classifying input dental X-ray images into different severity classes. This would help in providing the right treatment at the correct time to the patients. This can reduce the work of the dentist and can help in accurate and timely diagnosis. The existing work in the proposed area of research on dental images has been discussed further.

Fuzzy based systems have been proposed in dental care as well. Tran et al. [29] proposed a novel fuzzy based decision making method for medical diagnosis from dental X-ray images. Le Hoang et al. [30, 31] proposed a novel system called Dental Diagnosis System (DDS) for dental problems. It used novel semi-supervised fuzzy clustering to group all similar dental diseases from a database. Prem Kumar et al. [32] proposed an automated caries detection system in which dental X-ray images were pre-processed, segmented by K-means clustering. The features were extracted using gray level co-occurrence matrix (GLCM). Finally, the images were classified as cavitated and non cavitated using SVM. Tuan et al. [33] proposed a fuzzy rule-based system for classification of dental problems. The dataset of 56 dental images were classified into 5 diseases i.e. cracked, hidden, cavities, missing and periodontics. The accuracy of the system was 91%. Prajapati et al. [34] used a Convolutional Neural Network (CNN) to classify dental X-ray images of three different dental diseases (caries, periapical infection., periodontitis) into their respective classes with an average accuracy of about 88%, but did not mention about the severity of caries. Vicky et al [35] used neural network approach in diagnosis of Gingvits disease. Charvat et al [36] used diffuse reflectance spectrometry to determine the quality of dental tissue of datasets recorded by a spectrometric system. This measurement of quality classifies the dental tissue into two classes ie, healthy tissue and unhealthy tissue, which further assists in diagnosing various dental diseases. Some recent work is also done regarding application of different segmentation techniques to dental images to detect the presence of caries [37, 38]. Researchers have also used deep neural network approaches to classify dental images as normal or caries infected [39, 40, 41] but none of these measure the caries severity. Prados et al [42] presented a systematic review of a number of neural network based approaches for dental caries diagnosis. Each method uses a different deep neural network but they mostly deal with detection of caries rather than their severity.

While most of the existing work focusses on detection of caries, very little work exists regarding classification of caries into different types. The caries can be classified based on G V Black classification or severity based classification. The former classifies caries into six classes depending on the location of the caries on the tooth it affects [43, 44, 45]. The latter, which is the focus of this paper, classifies caries into four classes depending on the degree of severity or the extent of damage that it does to the tooth. Bhan et al [46] performed morphological operations to extract caries from dental images and graded their severity based on the cavity area. However, the accuracy of grading is low as the model doesn’t consider the depth of the caries under consideration.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

In this paper, we have proposed severity based classification of dental X-ray images. We have done feature extraction using three techniques i.e., WCLTP, WCLBP and WCLBC and followed each by fuzzy feature selection. Then various classifiers are used for classifying these images into the various severity types. We have also presented comparative results of all the techniques with and without our proposed fuzzy feature selection method. The aim of this paper is to classify dental X-ray images of patients into four severity classes i.e. the incipient caries, the moderate caries, the advance caries and the severe caries. The main contribution of the research paper is as follows:

- This is an innovative effort to classify dental caries according to their severity using fuzzy logic.
- The work augments the wavelet-based feature extraction method with the proposed fuzzy rule-based feature selection to select the features that can accurately facilitate the required classification.
- The proposed system has high accuracy and will prove to be a boon in dentistry especially in the post COVID era.

The rest of the paper is organized as follows: section 2 presents the proposed fuzzy methodology for classification of caries infected dental X-ray images into different severity types, section 3 discusses the results. Finally, Section 4 concludes the paper.

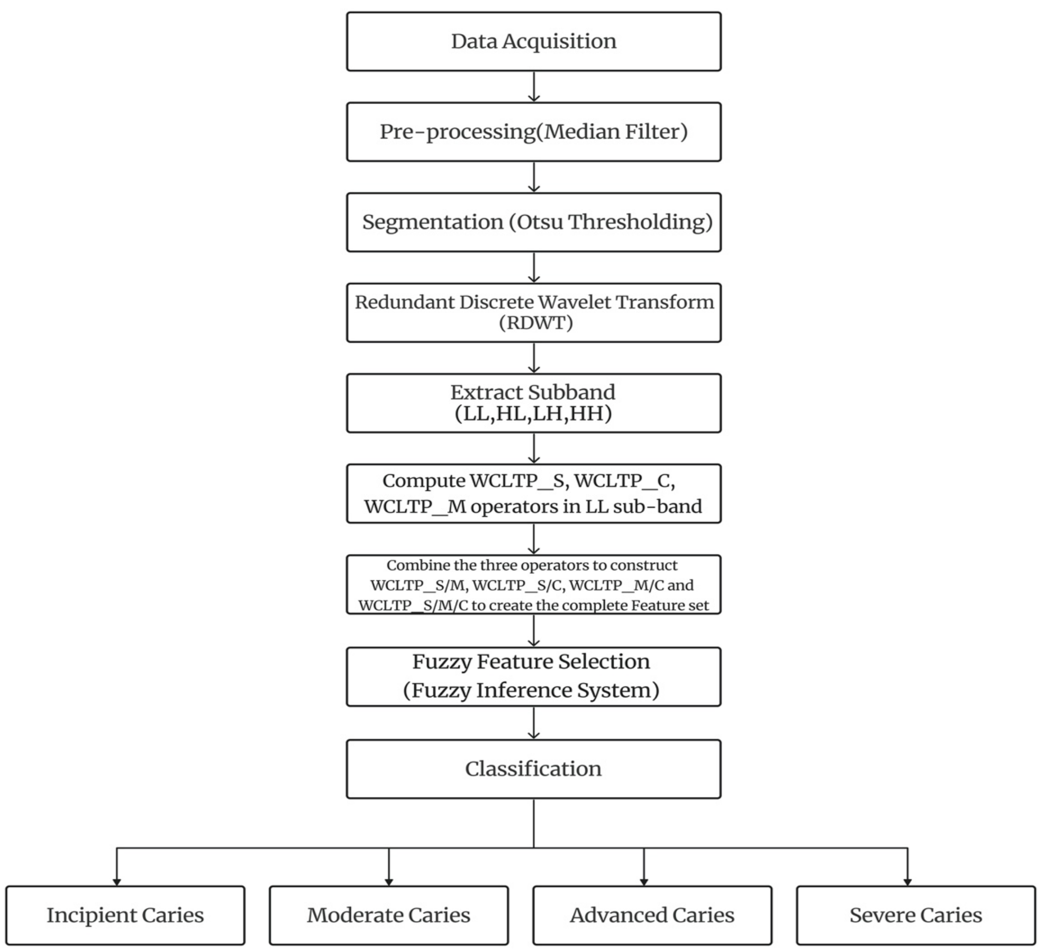



*Figure 2: Proposed Model*

## 2. METHOD

This section presents in detail the steps of the proposed methodology for detecting and classifying dental caries based on the severity. The flowgraph is shown in figure 2 and explained in detail below.

### 2.1. Data Acquisition

More than 1000 periapical dental X-ray images were gathered from the two prominent dental clinics in New Delhi, India. This dataset was balanced i.e., it consisted of equal number of images for each severity class. The digital radiography system used for taking these dental X-ray images was Kodak RVG 5200. The RVG format X-ray images obtained were transformed to JPG format before they were subjected to further processing.

### 2.2. Image Processing Using Median Filtering

The images collected from the clinics showing overlapped teeth were discarded in this step. They were then processed for noise removal using the median filter. The median filter is used because it is a non-linear filter and has an ability to reduce the impulse noise. [47]. The SNR of images considered for filtering was between 25 DB and 35 DB.

### 2.3. Image Segmentation

Segmentation is the process of dividing the input images into many parts in order to make them easy to analyze. This step uses Otsu thresholding [48] for image segmentation. It is based on global thresholding method. It minimizes intra class variance and maximizes inter class variance.

### 2.4. Feature Extraction

In the proposed approach, the feature extraction is based on Wavelet Complete Local Ternary Pattern (WCLTP). The WCLTP method first uses the Redundant Discrete Wavelet Transform (RDWT) [49], and then the Complete Local Ternary Pattern (CLTP) to extract the features from the dental images. The RDWT divides the input dental image into four sub- bands (LL, LH, HL and HH). LH represent the horizontal, HL represent the vertical and HH represent the diagonal details. The four sub-bands are of same size as the original image unlike the ones obtained after the Discrete Wavelet Transform (DWT) in which sub-bands are smaller than the original image. Thus, in RDWT, the important features are at the same spatial location in each sub-band. Further, the RDWT exhibits the shift-invariant property. The LL sub-band contains the significant information of the image, so it is used to extract the features WCLTP_M, WCLTP_S and WCLTP_C. WCLTP_M denotes the features of the magnitude component. WCLTP_S represents the feature of sign component. WCLTP_C denotes the features of the center components. Firstly, the lower and the upper component of WCLTP_S, WCLTP_M and WCLTP_C are calculated. Each component of WCLTP_S, WCLTP_M and WCLTP_C is built by concatenating the lower and upper components [27]. In order to improve the classification accuracy, the proposed WCLTP components are combined into joint as well as hybrid distributions (WCLTP_S/M, WCLTP_S/C, WCLTP_M/C, WCLTP_S/M/C) as shown in figure 1, to build the final operator histogram. Since the obtained histogram is very large in size, thereby the size of the feature set is very large. Similarly feature extraction can be done using Wavelet Complete Local Binary Pattern (WCLBP and Wavelet Complete Local Binary Count (WCLBC). The effectiveness of WCLTP is shown in the next section by comparing it with WCLBP and WCLBC approaches. The WCLBP consists of RDWT integrated with CLBP. The WCLBC consists of RDWT integrated with CLBC. The comparison of the three feature extraction methods reveals that feature set obtained by WCLTP method gives better results in terms of classifying the dental X-ray images based on the severity of the caries.

### 2.5. Fuzzy Feature Selection

The WCLTP method of feature extraction described in the previous subsection gives better accuracy in classifying dental images but it suffers from the high dimensionality problem resulting in increased computational time and increased requirement of memory space. Feature selection not only reduces dimensionality, it also reduces overfitting, improves classification accuracy and reduces training time. As explained in the previous subsection, the three feature set components WCLTP_M, WCLTP_S and WCLTP_C were extracted and combined to form 7 feature set components namely WCLTP_M, WCLTP_S, WCLTP_C, WCLTP_S/M, WCLTP_S/C, WCLTP_M/C, WCLTP_S/M/C to create the complete feature set. The proposed fuzzy inference system calculates the parameters: within_class_variance, cross_class_variance, rank and augmented variance ratio for this feature set comprising of 7 components. These variables are explained in Table 1. Fuzzy Rules are created for

Journal of Theoretical and Applied Information Technology
31st August 2023. Vol.101. No 16

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

these input variables. Figure 3 shows the block diagram of the fuzzy inference system. The output of the fuzzy inference system is a rank which is either low, medium or high. Further, a feature is selected on the basis of the rank and augmented variance ratio (AVR). Figure 4(a-d) shows the triangular membership functions used for all the four variables. Eighteen fuzzy rules were designed for selecting a particular feature in the LL sub-band. Rules (1-9) and Rules (10-18) are divided into two stages as show in Table 2. Table 3 lists the various variables and linguistic terms used for various range of their values.

*Table 1: Description of the variables of the fuzzy inference system*

| Variables | Description |
|---|---|
| Within_class_variance | It is defined as the variance of the feature within the class. It should be minimum |
| Cross_class_ variance | It is defined as the variance of the feature among the classes. It should be maximum |
| Rank | Rank is selected based on the value of within_class_variance and cross_class_variance, high rank is given to feature with high cross_class_variance and low within_class_variance |
| Augmented Variance Ratio | AVR is a ratio of cross_class _variance and within_class _variance. It should be high for the feature to be selected. |

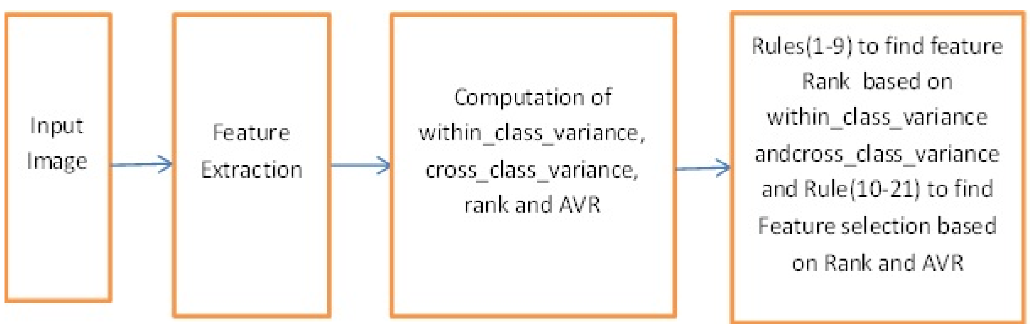
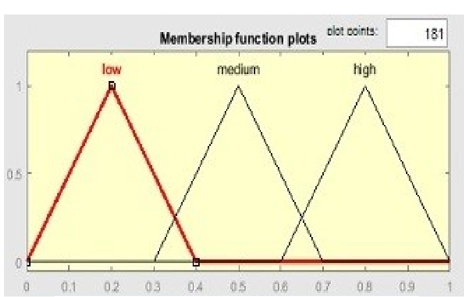
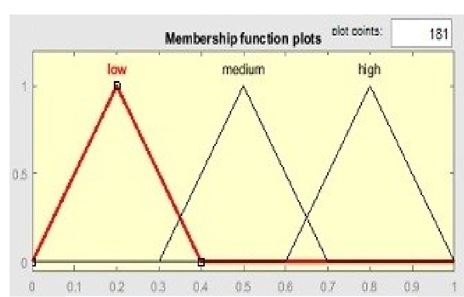



*Figure 3: Proposed Model of Fuzzy Inference System*




input variable: Within_class_variance
(a)




input variable: Cross_class_variance
(b)

Journal of Theoretical and Applied Information Technology
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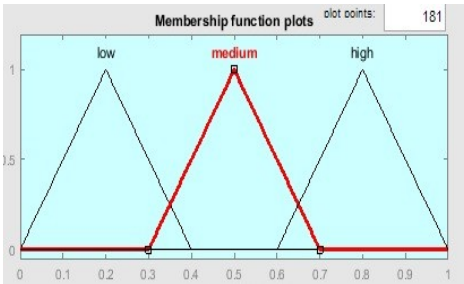
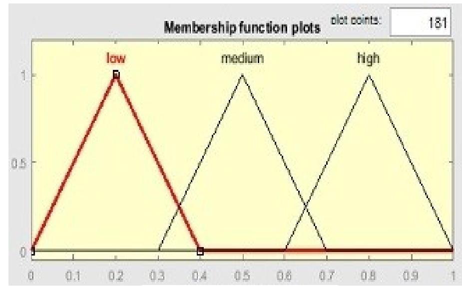
ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



output variable: Rank
(c)



input variable: AVR
(d)

*Figure 4:. Triangular membership function for (a) within_class_variance (b) cross_class_variance (c) Rank (d) AVR*

*Table 2: Fuzzy Rules for Ranking the features*

| |
|---|
| Rule 1: IF (within_class_variance is min) AND (cross_class_variance is min) THEN (rank is medium)<br>Rule 2: IF (within_class_variance is min) AND (cross_class_variance is medium) THEN (rank is high)<br>Rule 3: IF (within_class_variance is min) AND (cross_class_variance is high) THEN (rank is high)<br>Rule 4: IF (within_class_variance is medium) AND (cross_class_variance is min) THEN (rank is low)<br>Rule 5: IF (within_class_variance is medium) AND (cross_class_variance is medium) THEN (rank is low)<br>Rule 6: IF (within_class_variance is medium) AND (cross_class_variance is high) THEN (rank is high)<br>Rule 7: IF (within_class_variance is high) AND (cross_class_variance is min) THEN (rank is low)<br>Rule 8: IF (within_class_variance is high) AND (cross_class_variance is medium) THEN (rank is low)<br>Rule 9: IF (within_class_variance is high) AND (cross_class_variance is high) THEN (rank is medium) |
| Rule 10: IF (rank is low) AND (AVR is low) THEN (feature selected is no).<br>Rule 11: IF (rank is low) AND (AVR is medium) THEN (feature selected is no).<br>Rule 12: IF (rank is low) AND (AVR is high) THEN (feature selected is no).<br>Rule 13: IF (rank is medium) AND (AVR is low) THEN (feature selected is no).<br>Rule 14: IF (rank is medium) AND (AVR is medium) THEN (feature selected is no).<br>Rule 15: IF (rank is medium) AND (AVR is high) THEN (feature selected is yes).<br>Rule 16: IF (rank is high) AND (AVR is low) THEN (feature selected is no).<br>Rule 17: IF (rank is high) AND (AVR is medium) THEN (feature selected is yes).<br>Rule 18: IF (rank is high) AND (AVR is high) THEN (feature selected is yes). |

*Table 3: Values and terms for the fuzzy variables*

| Variables | Terms | Value Range |
|---|---|---|
| Within_class_variance | Low | 0-0.4 |
| | Medium | 0.3-0.7 |
| | High | 0.6-1 |
| Cross_class_variance | Low | 0-0.4 |
| | Medium | 0.3-0.7 |
| | High | 0.6-1 |
| Rank | Low | 0-0.4 |
| | Medium | 0.3-0.7 |
| | High | 0.6-1 |
| Augmented Variance Ratio | Low | 0-0.4 |
| | Medium | 0.3-0.7 |
| | High | 0.6-1 |

### 2.6. Classification

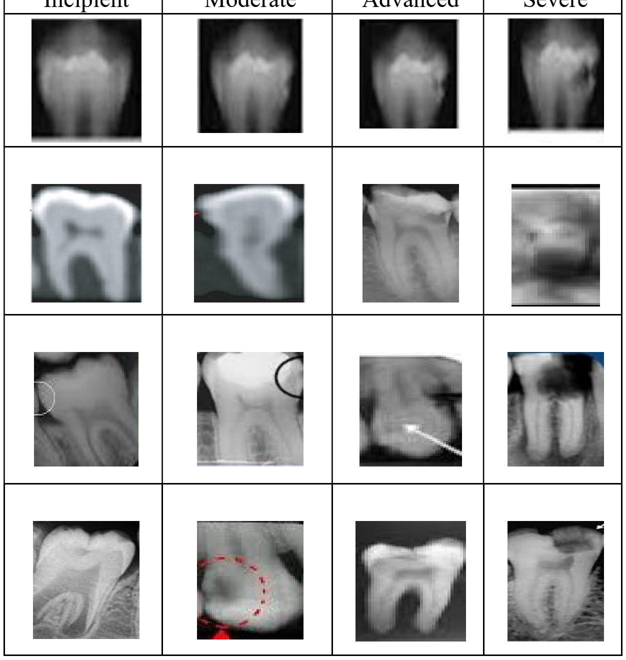
In order to develop the automated detection system, classification is a very important process. The significant features selected on the basis of the above fuzzy rule-based system, are subjected to various state-of-art classifiers for classifying their corresponding dental images into various types depending on the severity i.e. the incipient caries, the moderate caries, the advanced caries and severe caries. Various classifiers have been used for analysis, i.e., Naïve Bayes, Neural Network, Random Forest, Adaboost, Decision Stumps, K-nearest neighbor (KNN), Decision tree, Sequential Minimal Optimization, Radial Basis Function, and Support Vector Machine (SVM) [51].

## 3. RESULTS AND DISCUSSION

The proposed system is developed in Matlab 2018a. 1000 dental X-ray images were classified into 4 classes depending upon the severity. The dataset consists of 250 dental X-ray images for each class. Some sample images belonging to each of the four classes are shown in Table 4. The training dataset consists of 700 dental X-ray images and the testing dataset consists of 300 dental X-ray images. The actual size of the image was 55*46 pixels. The dental X-ray image were resized to 256*256 pixels. The steps of the proposed model are performed on these resized images. Figure 5 (a) shows the median filtered image and figure 5 (b) shows the segmented image. The segmented image is subjected to RDWT in order to divide the image into various sub-bands. The sub-bands formed after applying RDWT are LL, LH, HL and HH. The result of applying RDWT is shown in Figure 6. Since LL sub-band is the approximate sub-band so it is selected for feature extraction. Complete Local Ternary Pattern is used to extract the feature components WCLTP_S, WCLTP_M and WCLTP_C, which are further combined to form 7 feature set components as explained in previous section.

*Table 4: Dental Caries infected X-ray Images of different severity types*

| Incipient | Moderate | Advanced | Severe |
|---|---|---|---|



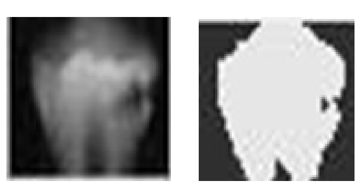


*Figure 5: (a) Filtered Image (b) Segmented Image*

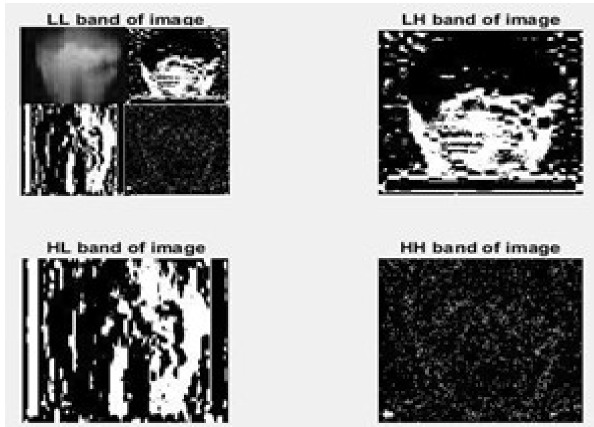


*Figure 6: Feature Extraction using RDWT and WCLTP*

These features are used to classify the dental images using various classification techniques into four classes based on severity. The results of the classification process without and with the proposed fuzzy feature selection method are presented in Table 5 and 6 respectively. The performance analysis of the proposed model is done as follows:

(i) Performing feature extraction using three different methods, i.e., WCLTP, WCLBC and WCLBP, followed by the classification with different state-of-art classifiers. In this case, fuzzy feature selection was not performed after feature extraction. The classification accuracy, sensitivity and specificity obtained for each classification technique with respect to each feature extraction method mentioned above, is presented in Table 5. Here, best results are obtained with WCLTP feature extraction method.

(ii) Performing feature extraction using three different methods, i.e., WCLTP, WCLBC and WCLBP, followed by the proposed rule based fuzzy feature selection and then using the selected features to perform the classification with different state-of-art classifiers. The corresponding classification accuracy, sensitivity and specificity obtained in this approach, is presented in Table 6. Here also, best results are obtained with WCLTP feature extraction method. The best classification accuracy of the proposed model using fuzzy inference system for feature selection is given by Adaboost as 93%. The Adaboost classifier is able to distinguish between the various classes almost perfectly.

A comparative analysis of the results shown in Table 5 (without fuzzy feature selection) and Table 6 (with fuzzy feature selection) clearly proves that the performance of state-of-art classifiers used in our experiments to classify the dental images into the various severity types is significantly improved by using the proposed fuzzy based feature selection method. It can be seen in Table 5, that the Adaboost classifier shows an accuracy of 88% without the fuzzy feature selection and with fuzzy based feature selection the accuracy increases to 93% (Table 6). The results of the classification process with and without fuzzy based feature selection methods are presented in the ROC curves in Figure 7 and Figure 8 respectively.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 5: Results of severity-based classification of dental images using various classifiers without fuzzy feature selection*

| | WCLBP | | | WCLBC | | | WCLTP | | |
|---|---|---|---|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity |
| Decision Tree | 72 | 70 | 70 | 68 | 70 | 71 | 82 | 80 | 84 |
| Random Forest | 77 | 75 | 72 | 75 | 76 | 73 | 84 | 86 | 82 |
| Naïve Bayes | 75 | 70 | 71 | 71 | 72 | 73 | 80 | 78 | 77 |
| SMO | 71 | 72 | 70 | 76 | 73 | 72 | 80 | 82 | 79 |
| Neural Network | 72 | 83 | 77 | 70 | 69 | 60 | 82 | 80 | 82 |
| Radial Basis Function | 74 | 72 | 71 | 70 | 71 | 68 | 78 | 75 | 74 |
| **Adaboost** | 73 | 70 | 72 | 82 | 76 | 74 | **88** | **86** | **82** |
| Decision Stump | 74 | 71 | 70 | 76 | 74 | 72 | 80 | 78 | 75 |
| SVM | 75 | 72 | 73 | 73 | 70 | 72 | 82 | 84 | 80 |
| KNN | 78 | 75 | 74 | 72 | 72 | 70 | 78 | 74 | 70 |

*Table 6: Results of severity-based classification of dental images using various classifiers after fuzzy feature selection*

| | WCLBP | | | WCLBC | | | WCLTP | | |
|---|---|---|---|---|---|---|---|---|---|
| | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity |
| Decision Tree | 78 | 80 | 74 | 74 | 76 | 72 | 89 | 96 | 85 |
| Random Forest | 83 | 87 | 78 | 80 | 77 | 72 | 90 | 92 | 86 |
| Naïve Bayes | 80 | 85 | 77 | 78 | 75 | 77 | 88 | 89 | 90 |
| SMO | 75 | 80 | 82 | 82 | 80 | 83 | 87 | 85 | 82 |
| Neural Network | 80 | 83 | 77 | 77 | 72 | 77 | 89 | 90 | 87 |
| Radial Basis Function | 75 | 77 | 70 | 72 | 76 | 75 | 85 | 84 | 88 |
| **Adaboost** | 80 | 82 | 79 | 85 | 82 | 83 | **93** | **94** | **93** |
| Decision Stump | 78 | 75 | 74 | 81 | 80 | 82 | 87 | 92 | 85 |
| SVM | 80 | 82 | 80 | 76 | 74 | 78 | 89 | 90 | 88 |
| KNN | 82 | 78 | 77 | 78 | 74 | 72 | 86 | 84 | 88 |

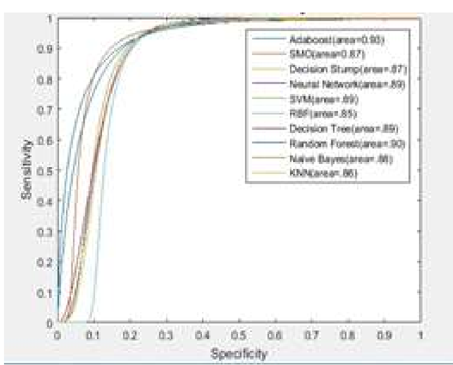



*Figure 7: ROC Curve with fuzzy feature selection*

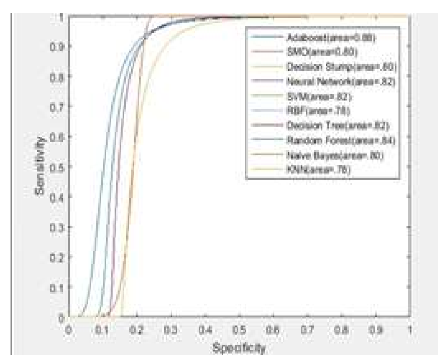



*Figure 8: ROC Curve without fuzzy feature selection*

## 4. CONCLUSION

In this paper, we proposed the classification of caries infected dental X-ray images into different severity types. The proposed method performs feature extraction from preprocessed dental X-ray images in the wavelet domain, using three statistical operators WCLBP, WCLBC and WCLTP. This is followed by rule-based fuzzy feature selection of important features in order to classify the dental images using state-of-art classifiers. It was observed that best results were given by Adaboost classifier with an accuracy of 93%, sensitivity 94% and specificity of 93% for the WCLTP feature extraction method using fuzzy feature selection. The comparative results of classification with the proposed approach and the approach without using fuzzy feature selection, prove the effectiveness of fuzzy feature selection for dental image classification based on severity. The results obtained from the proposed method ensure an accurate severity grading of the caries, equivalent to that of a doctor or a radiologist. This

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

model can be used by dentists for accurate classification of the dental caries into various types of severity after they are diagnosed. Our future work will be to use more fuzzy variables to further strengthen our model.

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