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Analysis of Image Enhancement Techniques for Dental Caries Detection Using Texture Analysis and Support Vector Machine

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Abstract: Different enhancement techniques are used to diagnose dental caries in dental X-ray images. The diagnostic performances of the enhancement methods for caries detection in digital radiographs are evaluated. The proposed method consists of pre-processing of dental X-ray images using Gaussian low pass filter in frequency domain, extraction of statistical features from enhanced image using Support Vector Machine (SVM) classifier. 105 images of normal and dental caries derived using digital radiography are used to evaluate the performance of the SVM classifier with 10-fold cross validation. The images are annotated by a dentist. The quantitative analysis is done after evaluating the performance parameters of SVM classifier. The findings show that the proposed method gives TP rate = 0.982, FP rate = 0.018, ROC area = 0.982, and PRC area = 0.973. By using 2-way ANOVA, the results are tested at significant level of 5%, show that the interaction of enhancement methods with dental images on performance parameter values are significant. The results suggest that the proposed framework is a promising approach for the automatic detection of dental caries in dental radiographs, can also be used for other dental applications. The performance of the system can be further improved by high quality and high quantity dataset and suitable segmentation technique.

Keywords: Digital radiography; computer assisted diagnosis; image enhancement; dental caries; image pre-processing; SVM.

1. Introduction

Dental caries causes bacterial damage to teeth and is the most common disease. Therefore, early diagnosis of the caries is important for maintaining dental health. At an early stage, caries may not be visible to human eye, if located in-between teeth. Existing caries detection systems are not fully accepted by the practicing dentists and results are not fully accurate. The main limitations of diagnostic caries monitor are false positive diagnosis due to accumulation of food debris and plaque, staining of tooth and hypo mineralization results in wrong diagnosis. Electrical Caries Monitor (ECM) gives high false positive result for stained teeth, limit its usage. The main demerit of Direct Image Fibre Optic Trans-illumination (DIFOTI) is dentists must interpret images and it uses expensive machinery. Quantitative Light-induced Fluorescence (QLF) uses a complex procedure and demerit of this is initially dentist must detect the caries by manual examination. Hidden caries cannot be identified in photographic images. Photography works only on the surface of the tooth enamel and it is unable to detect caries which are in between the tooth and depth of caries. Radiographs helps to find the location of caries which

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cannot be seen during visual examination. It uses relatively high dose of ionised radiation that are injurious to health. Moreover, dentist must interpret images to detect caries in conventional radiographs. The sensitivity of detection of dental caries in conventional radiographs varies between 0.4 and 0.6 [1].

Digital dental X-rays in dental procedures are widely used because the images are available immediately, the lower radiation dose, and the possibility of image enhancement. These are convenient because it helps in computer aided dental X-rays analysis. Despite advantages of digital images over conventional radiography, because of significantly lower resolution, diagnostic performance for caries detection in digital images is not better than conventional radiographs. Therefore, a suitable enhancement technique is essential for analysis of dental digital images.

Dental radiographs are divided into teeth areas, bone areas and background area. It is difficult to distinguish between teeth and bone areas as their intensities are alike in cases of uneven exposure. Dental X-ray analysis is a complex problem due to image noise, low contrast, and sampling artefacts; complicated topology; arbitrary teeth orientation; and lack of clear demarcation between regions of interest. Pre-processing of dental images help in increasing the contrast between image background and tooth and to sharpen the edges or boundaries of caries regions. Accuracy and precision-based caries detection is essential treatment of dental diseases.

The ‘artefact’ on X-ray image appear as light or dark spots, lines, fogging, specks etc. which are caused by motion, poor contact and so on. The quantum noise is dominant and results due to quantization of energy into photons which are Poisson distributed. To improve both contrast and intensity evenness simultaneously, computer aided image processing algorithms can be used [2].

P. L. Lin et al. proposed an enhancement method that combines homomorphic filtering, adaptive contrast stretching based homogeneity and adaptive morphological transformations. In this work binary support vector machine (SVM) is used to classify each tooth to molar or premolar. P. L. Lin et al. used top-/bottom-hat morphological transformation enhancement techniques for tooth isolation [3, 4]. Pedro H. M. Lira et al. also used the morphological operations for teeth segmentation [5].

Siti Arpah Ahmad et al. given qualitative and quantitative comparison between original images and four image enhancement techniques namely adaptive histogram equalization (AHE), contrast adaptive histogram equalization (CLAHE), median adaptive histogram equalization (MAHE) and sharp contrast adaptive histogram equalization (SCLAHE) applied to dental X-ray images. The quality of the images and the diagnostic ability of the periapical pathology is observed, and quantitative analysis are done using contrast improvement index, signal to Noise Ratio (SNR) and root mean square error (RMSE) [6].

Soma Datta et al. specified a method for detection of dental caries for optical images in which image enhancement is done using wiener filter [7]. S. A. Ahmad et al. studied about the effectiveness of various contrast enhancement methods for dental radiograph images and shown that Sharp Contrast Adaptive Histogram Equalization (SCLAHE) slightly improve the appearance of dental abnormities over original image than Sharp Adaptive Histogram Equalization (SAHE) and Sharp Median Adaptive Histogram Equalization (SMAHE) [8]. Aisyatur Radhiyah et al. used Gaussian filtering and Histogram equalization for enhancement of dental radiographs for labelling dental radiographs [9]. Veena Divya et al. used contrast adjustment and Histogram equalization enhancement techniques for characterization of dental pathologies for Digital Panoramic X-ray images [10, 11].

Veska M. Georgieva et al. used homomorphic wavelet filter to remove noise components and to eliminate non-uniformity luminance distribution for dental X-ray images. The comparison of this work with contrast improvement by limited adaptive histogram equalization (CLAHE) and morphological processing is done in terms of PSNR and Effectiveness of filtration [12]. Wei Li et al. presented clinical X-ray image-based tooth decay diagnosis using

SVM and GLCM without enhancement technique [13]. Manuella DFB et al., has given opinion to use sharpen filter to improve the diagnostic performance of dental caries [14].

Now a days, despite available highly reliable diagnostic tools, dental probe and digital radiography are widely used for screening and final diagnosis of dental caries. Dentist inspect caries on tooth surfaces by observation of texture and discoloration using visual tactile method [15]. This method is highly subjective, based on dentist's expertise [16-18]. Hence it is necessary to implement an efficient, fully automatic and accurate dental caries detection algorithm.

Computer aided systems are much more reliable, improve quality of diagnostic decisions and reduce variance among physician's decision. By combining visualization, image processing and machine learning for decision making it is possible to develop an efficient computer assisted dental caries diagnostic system. This paper proposes an algorithm for detection of dental caries in digital radiographs. This would help doctors for as an add on approach for identification and analysis.

2. Materials and Methods

Development of dental caries identification system involves identification of suitable enhancement technique, extraction of textural features in the enhanced image and training and validating SVM classifier. The algorithms are evaluated using WEKA tool. Figure 1 shows the proposed methodology for identification of dental caries.

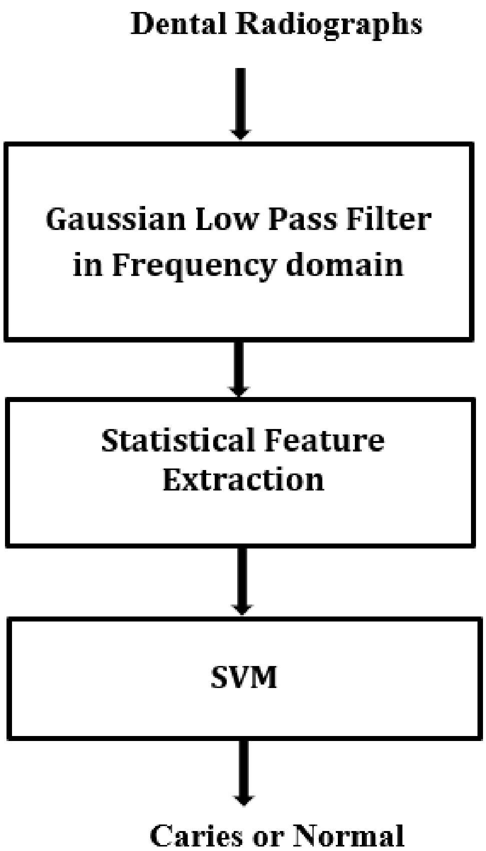

Figure 1. Proposed methodology.

2.1 Input images

The dental radiographs are of three categories namely Panaramic, Bitewing and Periapical. Periapical radiographs show the entire view of the specific teeth, including crowns and roots, and has few teeth in which between and inside the tooth can be observed. Hence periapical images are considered for analysis. Digital radiographs of periapical bmp images were used as a database for designing caries identification system. The dataset used for training and testing consists of 55 normal images and 55 caries images. The images used in this work are obtained from Conservative Dentistry and Endodontics department of SJM Dental College, Chitradurga, INDIA. The images are taken using intra oral Gendex X-ray machine with RVG sensor. The images were analysed by the clinician for caries. Caries was detected by interpreting the radiodensity of the images. In normal tooth the dentin and enamel appear as radiopaque. Caries results in the loss of mineralization of these structures and hence appears as radiolucent.

2.2 Enhancement

The image size is reduced to 256 x 256 and fed to the enhancement stage. The input image is enhanced using Gaussian low pass filter in frequency domain. The transfer function of Gaussian low pass filter is given by

$$H(u, v) = e^{-D^2(u,v)/2\sigma^2} \tag{1}$$

where D(u,v) is the distance from the origin of Fourier transform, σ is the measure of spread/dispersion of the Gaussian curve. Larger the value of σ, larger is the cut off frequency and the filter is milder. This type of filters can be used in the situations where no artefacts are desirable. They have smooth transition between pass band to stop band as the cut off frequency increases, and hence does not introduces any ringing in the output image. It is generally used as a pre-processing step before an automatic recognition. It is also used to reduce noise in the images.

2.3 Feature Extraction

The enhanced image is passed through the feature extraction section. 16 statistical features and 4 area features of the image are extracted and stored in the database. The sixteen statistical features extracted are Contrast, Correlation, Energy, Homogeneity, Mean, Standard Deviation, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM and four area features are area, centroid and bounding box. These features are fed to SVM classifier.

2.4 Classification

SVM is an extensively used classifier for data analytics and pattern recognition. SVM handles both separable and non-separable problems of simple, linear as well as complex nonlinear classification tasks. Binary SVM classifier creates a hyperplane to define decision boundaries, which separates the data points. It maps the input space data points into high dimensional feature space using suitable kernel, to simplify the problem. Then the optimal hyperplane separating the two classes is chosen.

Binary support vector machine is used to classify each enhancement technique into check caries or normal dental images. The performance of the classifier is evaluated using 10-fold cross validation. Cross validation is one of the techniques used to test the effectiveness of a machine learning models, to evaluate a model if we have a limited data sample. The dataset is randomly partitioned into k equal sized subsamples, a single subsample is retained for testing the model, and the k-1 subsamples are used as training data. The aim of this work is to compare the diagnostic ability of different types of enhanced techniques in terms of quantitative measurements like TP rate, FP rate, Precision, Recall, F-measure, MCC, ROC area and PRC area.

3. Results and Discussion

Dentist opinion for the true presence/absence of caries in 110 dental radiographs are used as a reference for estimating absolute performance numbers (true positive, true negative, true false positive and false negative) and performance parameters TP rate, FP rate, Precision, Recall, F-measure, MCC, ROC area and PRC area. These parameters of the proposed enhancement technique (Frequency domain Gaussian low pass filter) are compared with other enhancement techniques in Table 1 with statistical feature extraction and SVM classifier. Figure 2 shows original and enhanced images. The PSNR value of the enhanced image is 32.054 indicates that ensures no loss of information in the image but noise level of the image is reduced after enhancement.

(a) (b)

Figure 2. (a) original image (b) enhanced image using frequency domain Gaussian low pass filter.

The TP rate and ROC area of the different enhancement techniques are indicated in the form of bar chart in Figure 3. The results indicates that the frequency domain Gaussian low pass filter gives higher values of performance measure as compared with other enhancement techniques with TP rate = 0.982, FP rate of 0.018, precision of 0.982, recall = 0.982, F measure = 0.982, MCC = 0.964, ROC area = 0.982 and PRC area = 0.973. If the images are not enhanced, the TP rate is 0.836. Table 2 shows significant differences observed in the ANOVA test ($p<.05$) for performance parameters for different enhancement methods.

Table 1. Performance parameters for the different enhancement techniques for caries diagnosis.

Sl. No.	Enhancement	TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area
1	Laplacian	0.964	0.036	0.966	0.964	0.964	0.93	0.964	0.948
2	Weiner filter	0.882	0.118	0.883	0.882	0.882	0.765	0.882	0.837
3	Unsharp masking	0.845	0.155	0.855	0.845	0.844	0.7	0.845	0.795
4	Power law transformation	0.855	0.145	0.855	0.855	0.854	0.71	0.855	0.803
5	Morphological operations	0.855	0.145	0.859	0.855	0.854	0.713	0.855	0.804
6	Median filter	0.845	0.155	0.846	0.845	0.845	0.691	0.845	0.792
7	Mean filter	0.873	0.127	0.873	0.873	0.873	0.745	0.873	0.825
8	Homomorphic filter	0.527	0.473	0.529	0.527	0.522	0.056	0.527	0.514
9	Histogram equalization	0.864	0.136	0.864	0.864	0.864	0.727	0.864	0.814
10	High boost filter	0.827	0.173	0.833	0.827	0.827	0.66	0.827	0.773
11	Bilateral filter	0.891	0.109	0.891	0.891	0.891	0.782	0.891	0.848
12	Anisotropic diffusion	0.891	0.109	0.891	0.891	0.891	0.782	0.891	0.848
13	Adaptive median filter	0.827	0.173	0.827	0.827	0.827	0.655	0.827	0.771
14	Gaussian filter	0.855	0.145	0.856	0.855	0.854	0.711	0.855	0.804
15	CLAHE	0.855	0.145	0.855	0.855	0.855	0.709	0.855	0.803
16	Laplacian + CLAHE	0.936	0.064	0.944	0.936	0.936	0.88	0.936	0.912
17	Laplacian + HE	0.909	0.091	0.91	0.909	0.909	0.819	0.909	0.872
18	Frequency domain ideal low pass filter	0.973	0.027	0.973	0.973	0.973	0.946	0.973	0.96
19	**Frequency domain Gaussian low pass filter**	**0.982**	**0.018**	**0.982**	**0.982**	**0.982**	**0.964**	**0.982**	**0.973**
20	Frequency domain Gaussian high pass filter	0.9	0.1	0.9	0.9	0.9	0.8	0.9	0.86
21	Frequency domain ideal high pass filter	0.909	0.091	0.909	0.909	0.909	0.818	0.909	0.872
22	Without enhancement	0.836	0.164	0.837	0.836	0.836	0.673	0.836	0.781

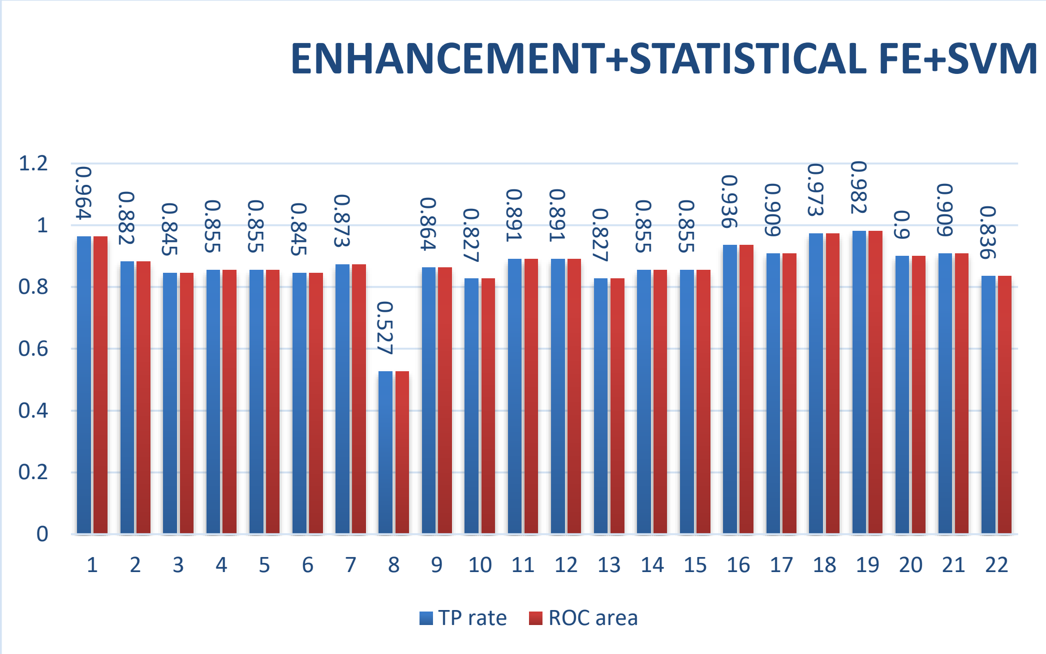

Figure 3. TP rate and ROC area of SVM classifier for different enhancement technique.

Table 2. Results of ANOVA test for performance indices of SVM classifier for different enhancement techniques shown in Table 1.

Source	SS	df	MS	F	Prob>F
Columns	10.0843	7	0.44061	260.28	1.81232e-79
Rows	1.0244	21	0.04878	8.81	3.78269e-17
Error	0.8136	147	0.00553		
Total	11.9223	175			

SS =Sum of Squares df = Degrees of Freedom MS = Mean Squares
F = F value Prob= Probability

The Table 3 shows comparison of different textural features with the proposed method. Figure 4 indicates the TP rate and ROC area of statistical feature extraction are of higher value as compared to glcm, gldm and LBP features. Table 4 shows the result of two-way ANOVA test for performance indices of SVM classifier for different feature extraction techniques shown in Table 3. Significant differences observed in the ANOVA test ($p<.05$) for the different textural features.

Table 3. Performance parameters for the different textural features for caries diagnosis.

Sl.No.	Textural Features	TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area
1	glcm	0.927	0.073	0.928	0.927	0.927	0.855	0.927	0.896
2	gldm	0.9	0.1	0.901	0.9	0.9	0.801	0.9	0.86
3	**statistical**	**0.982**	**0.018**	**0.982**	**0.982**	**0.982**	**0.964**	**0.982**	**0.973**
4	LBP	0.927	0.073	0.93	0.927	0.927	0.857	0.927	0.897

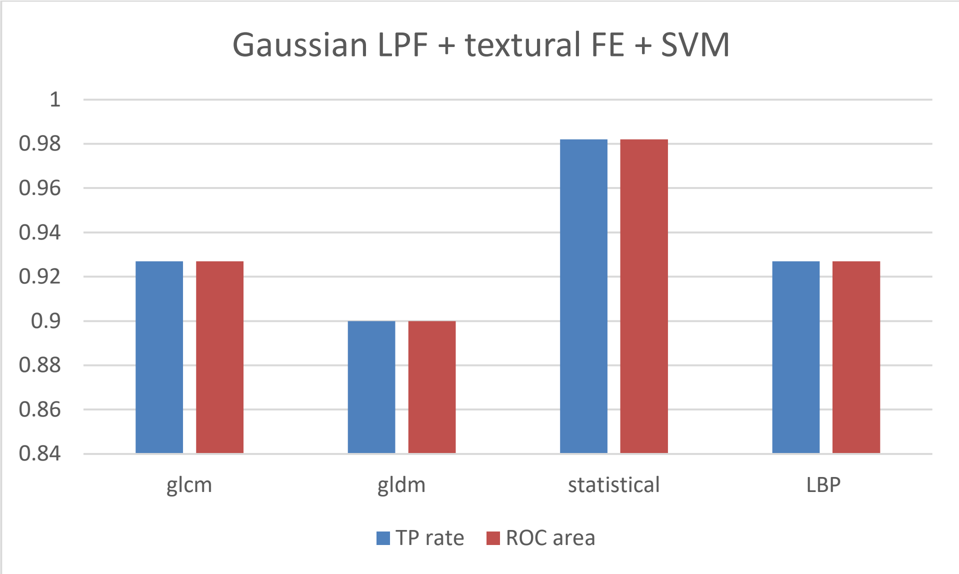

Figure 4. TP rate and ROC area of SVM classifier for different feature extraction technique.

Table 4. Results of ANOVA test for performance indices of SVM classifier for different feature extraction techniques shown in Table 3.

Source	SS	df	MS	F	Prob>F
Columns	2.57366	7	0.36767	428.94	0
Rows	0.024	3	0.008	9.33	0.0004
Error	0.018	21	0.00086		
Total	2.61566	31			

SS =Sum of Squares df = Degrees of Freedom MS = Mean Squares
F = F value Prob= Probability

Extracted features are applied to SVM classifier and the performance measures for different kernels are evaluated. Table 5 shows the performance measures for the SVM classifier with different kernels. Here, the polykernel yielded high results as compared to other kernels. Figure 5 shows TP rate and ROC area of SVM classifier for different kernels. Table 6 shows results of ANOVA test for performance indices of SVM classifier for different kernels shown in Table 5 at significant level of 5%. It indicates that the interaction of the kernels on performance measures is significant.

Table 5. Performance parameters for the different kernels of SVM classifiers for caries detection.

Sl. No.	SVM kernels	TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area
1	Normalized polykernel	0.973	0.027	0.974	0.973	0.973	0.947	0.973	0.961
2	PUK	0.945	0.055	0.948	0.945	0.945	0.893	0.945	0.922
3	Ploykernel	0.982	0.018	0.982	0.982	0.982	0.964	0.982	0.973
4	RBF	0.945	0.055	0.951	0.945	0.945	0.896	0.945	0.924

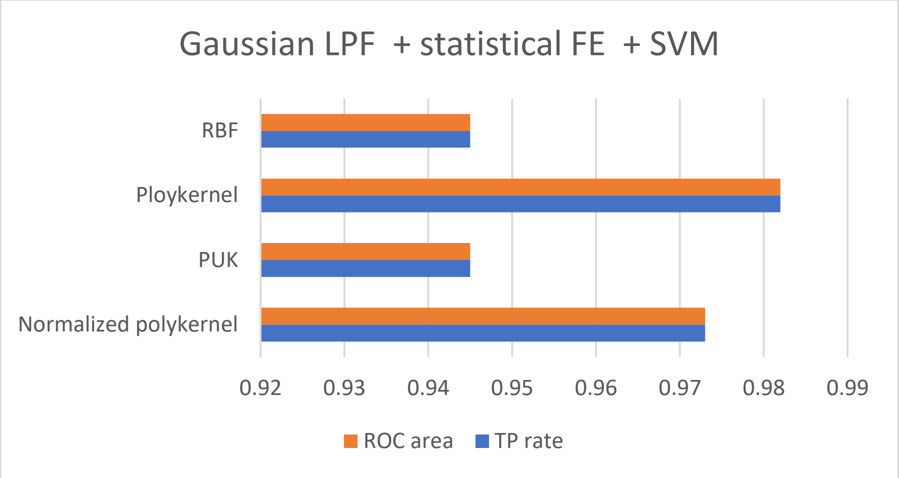

Figure 5. TP rate and ROC area of SVM classifier for different kernels.

Table 6. Results of ANOVA test for performance indices of SVM classifier for different kernels shown in Table 5.

Source	SS	df	MS	F	Prob>F
Columns	2.93748	7	0.41964	1668.27	0
Rows	0.00693	3	0.00231	9.18	0.0004
Error	0.00528	21	0.00025		
Total	2.9497	31			

SS =Sum of Squares df = Degrees of Freedom MS = Mean Squares
F = F value Prob= Probability

Table 7 gives the performance measures for Multilayer perceptron, Naive Bayes, SVM Random forest, J48 and KNN classifiers. The SVM is giving higher performance values for TP rate, FP rate, precision, Recall, F measure and MCC as compared to other classifiers. But PRC area and ROC area are slightly lower than multilayer perceptron and random forest classifiers. Figure 6 shows comparison of TP rate and ROC area for the classifiers.

Table 7. Comparison of Performance parameters of SVM classifier with other different classifiers.

Sl.No.	Gaussian LPF + Statistical FE + Classifiers	TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area
1	Multilayer Perceptron	0.973	0.027	0.973	0.973	0.973	0.946	0.999	0.999
2	Naive Bayes	0.945	0.055	0.951	0.945	0.945	0.896	0.976	0.976
3	**SVM**	**0.982**	**0.018**	**0.982**	**0.982**	**0.982**	**0.964**	**0.982**	**0.973**
4	Random Forest	0.955	0.045	0.955	0.955	0.955	0.909	0.996	0.996
5	J48	0.945	0.055	0.946	0.945	0.945	0.881	0.959	0.946
6	KNN	0.936	0.064	0.938	0.936	0.936	0.874	0.936	0.909

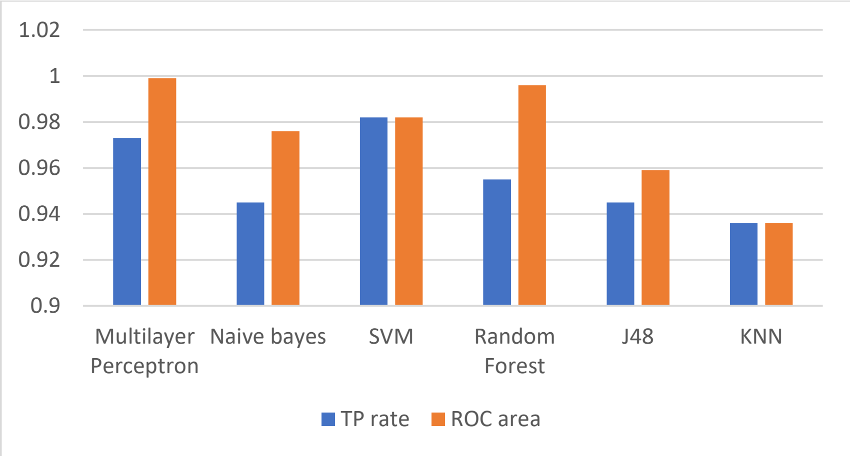

Figure 6. TP rate and ROC area for different classifiers for caries diagnosis.

3.1 Comparison with Other Published Works

Singh et al. proposed a caries detection based on Radon Transformation and DCT using dental X-ray images [19]. Selected features are extracted using PCA technique, applied to Random Forest classifier and obtained accuracy of 86%. Ainas et al. presented Dental X-ray based tooth caries detection system using Histogram of Oriented Gradient and BPNN and have got an accuracy of 64.91% [20]. Wei Li et al. developed caries detection system using SVM and obtained 86.15% accuracy for training dataset and 77.34% accuracy for test dataset [13]. Tooth decay diagnosis developed by Yang Yu et al. using BPNN [21]. The authors achieved an accuracy of 94.2% with 10 hidden layers. Shreyansh et al. developed Convolutional Neural Network (CNN) based classification of major dental diseases and got an accuracy of 87.5% for detection of dental caries [22]. Joe-Hong Lee et al. evaluated the deep CNN algorithm for detection of dental caries on periapical radiographs and obtained diagnostic accuracy of 89.0% for premolars [23]. Solmaz Valizadeh et al.developed diagnostic computer software designed for evaluation of caries on digital radiographic images and computer program diagnosed 97% of caries in posterior teeth [24].

Table 8 shows the comparison of proposed work with other published work. The experimental results for the proposed method show that caries and normal X-ray images could be distinguished accurately by the diagnostic system. Hence the proposed method is concluded as giving higher accuracy than other previously published work.

Table 8. Comparison of caries identification in dental images proposed work with other published methods.

Published work	**Accuracy**
Shreyansh et al. [22]	87.5 %
Jay-Hong Lee et al. [23]	89%
Ainas A ALbahbah et al. [20]	64.9 %
Wei Li et al. [13]	77.34 %
Yang Yu et al. [21]	94.2 %
Solmaz Valizadeh et al. [24]	97%
Singh et al. [19]	86 %
Proposed work	**98.2 %**

4. Conclusion

Gaussian Low pass filter in frequency domain method of enhancement is giving best performance-related indices for SVM classifier to detect dental caries. The work shows that statistical and area features, SVM with poly kernel improve the diagnostic performance of dental caries. The proposed method gives TP rate = 0.982, FP rate = 0.018, ROC area = 0.982, and PRC area = 0.973. The research work is useful for the dentists as it is independent of the human skills and subjectivity diagnosis. It will relieve the dentists from physical observation and detection. For future work, better segmentation solution to distinguish each tooth for caries identification is expected.

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