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G.V Black dental caries classification and preparation technique using optimal CNN-LSTM classifier

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Abstract
Dental caries is one of the oral diseases which are a major health problem for many people across the globe. It can lead to pain, discomfort, disfigurement, and even death in some cases. Dental caries is caused by the infection of the calcified tissue of the teeth. They can be prevented easily by early diagnosis and treated in the early stages. The development of a reliable model for the diagnosis and classification of dental caries can lead to effective and timely treatment. The G.V Black Classification system of dental caries is one of the systems which is widely accepted worldwide. It classifies caries into six classes based on the location of caries. This paper proposes a novel deep convolution layer network (CNN) with a Long Short-Term Memory (LSTM) model for the detection and diagnosis of dental caries on periapical dental images. The proposed model utilizes a convolutional neural network for extracting the features and Long Short term memory (LSTM) for conducting short-term and long-term dependencies. The main objective of this study is to detect dental caries and classify them into various classes based on G.V Black Classification. The periapical dental images are pre-processed and are fed as input to deep convolutional neural networks. The deep convolutional neural network classifies the input into various classes. The proposed algorithm is optimized using the Dragonfly optimization algorithm and gave an accuracy of 96%. Experiments are conducted to evaluate and compare the proposed model with the recent state-of-art deep learning models. This study justifies that a deep convolutional neural network is one of the most efficient ways to detect and classify dental caries into various G.V black classes. The achieved accuracy of the proposed optimal CNN-LSTM model for G.V black classification proves its efficacy as compared to the classification accuracy achieved by widely used pre-trained CNN models i.e. Alexnet (accuracy: 93%) and GoogleNet (accuracy: 94%) on the same database. The performance of the proposed CNN-LSTM model is further strengthened by comparing the results with the CNN model, 2 layer LSTM model and CNN-LSTM model without dragonfly optimization. The proposed optimal CNN-LSTM model shows the best performance with 96% accuracy and helps in dental image classification as the second opinion to the medical expert.

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Keywords G.V black Classification · Convolution neural network · Long short-term memory model · Dental caries

1 Introduction

One of the most prominent oral health diseases is dental caries or cavities that affect a majority of the population of young children to adults. It is a disease, which damages the tooth structure. Caries are primarily a result of the bacteria converting the carbohydrates and sugar in the food to acid, which in turn dissolves the minerals present in the enamel and destroys them, resulting in a damaged tooth [22]. The treatment of caries can be decided by obtaining information about the level of damage to the teeth. There are six basic classes of caries as proposed by G. V Black, illustrated in Fig. 1, which gives information about the damage caused to the structure of the teeth. These classes are discussed below [21]:

- Class I: The decay when diagnosed in the fissures and pits of the occlusal surfaces in the premolars and molars then the dental caries are classified into the first class [21].
- Class II: The decay when diagnosed in the proximal surfaces (distal or mesial) of the premolars and molars then the dental caries are classified into the second class [21]. This type of caries cannot be detected visually, hence a radiograph is utilized for the detection of dental caries. The restoration of these caries usually includes the occlusal surface and at times may include more than two surfaces.
- Class III: The decay when diagnosed in the proximal surfaces (distal or mesial) in the canines and incisors, then the dental caries are classified into the third class [21]. This is similar to the previous class with an exception of the inclusion of the anterior teeth.
- Class IV: The decay when diagnosed in the proximal surfaces (distal or mesial) of the canines and incisors, then the dental caries are classified into the fourth class [21]. The difference between class III and class IV is that the latter involved the angle or incisal edge of the tooth.
- Class V: The decay when diagnosed in the gingival third of the lingual or facial surfaces of the tooth, then the dental caries are classified into the fifth class [21]. It is also referred to as smooth surface decay. The dental material used for restoring the surface of the tooth depends on which tooth is affected.
- Class VI: The decay when diagnosed on the cusp tips of posterior teeth and the incisal edge of anterior teeth then, the dental caries are classified into the sixth class [21]. This type of decay is a result of defects and wears (abrasion).

Dental X-rays, or Radiography, an extensively used technique for the detection of lesions in the tooth, helps in the diagnosis of proximal as well as interproximal cavities. Even though it provides good diagnostic performance, this technique offers variations in the sensitivity level

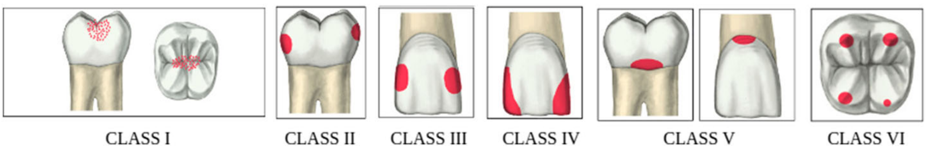


Fig. 1 G.V Black classification of dental caries [21]

of detecting the same carious lesions and also exposes the patients to high amounts of ionizing radiation. Enhanced visual systems have likewise been used for recognizing dental caries, which include light or laser fluorescence, fiber-optic trans-illumination, advanced radiography, and electrical obstruction [10].

Although the frameworks referenced above permit the visualization of the demineralization, which cannot be analyzed visually, the low execution of these frameworks attracted the experts to look for better detection systems for improving their diagnosis. Therefore, an automatic technique for the detection and classification of caries becomes necessary for a more accurate prediction [3]. Hence the motivation behind our research can be stated as follows:

The diagnosis of dental disease is a challenging task. The dental Image classification system is desired in the field of dentistry due to the increased demand for dental health care. With the help of a reliable dental image classification system, the medical student and budding dentist can classify the dental X-ray image into one of six G.V Black classes. Depending on the accurate classification of dental X-ray images, correct and timely treatment can be given to the patients. Highly accurate dental image classification systems are required for the medical students and dentists as it directly affects the suitable treatment plan and treatment priorities. With the help of reliable dental image classification system, the work of the dentist can be greatly reduced and also prevent the variation in the diagnosis. This motivated us to propose an automatic and reliable algorithm for G.V Black classification of dental caries.

A detailed literature survey in the next section enumerates various proposed techniques for caries detection. To the best of our knowledge, not much work has been done in the area of automatic G.V Black classification of dental caries. In recent years, deep learning has been used for a lot of real-world applications and problems. One of the most widely used deep learning techniques is Convolution Neural Network (CNN) and Long Short-Term Memory (LSTM) [4]. The main objective of this study is to contribute to the classification of dental images according to G.V Black Classification using these deep learning techniques. The main reason for using these techniques on dental images for the Black's Classification is because of the capability of the LSTM model to capture the sequence information and CNN extract the important features of the images. The proposed model contains the benefits of both the deep learning techniques and hence improves the performance of the classification of dental images.

A CNN-LSTM model with dragonfly optimization is proposed which classifies the dental images into six classes and further predicts the treatment to be carried out for each class of caries. The main advantage of using a CNN-LSTM is the high precision with which they classify the images. LSTM gives better classification accuracy as compared to CNN. Long term dependencies can be memorized by LSTM i.e. they can remember the pattern for a long duration of time. One advantage of using the LSTM model over the CNN model is that they contain both feed-forward and feed backward connection [1]. The first choice for image classification is CNN as they learn the components of the image, whereas the LSTM learns to recognize image features across time. For optimization, the dragonfly algorithm is used since it can enhance the random population of the given problem and converge towards the global optimum. The input images are preprocessed using the median filtering technique and segmented with the help of a binary segmentation technique. Finally, these images are fed to the classifier for the process of classifying them into different G.V black classes of dental caries. To the best of our knowledge, it is the first and novel attempt to classify the dental x-ray images into G.V Black classes using our proposed method i.e. the capability of both the CNN and LSTM layers. We have also assessed our proposed model with existing pre-trained deep learning models i.e. Alexnet and GoogleNet for classification of dental images. The rest of the paper is organized as follows, Section II contains the literature review, section III contains the proposed methodology and section IV discusses the results and comparisons. Section V summarizes the conclusion section.

2 Literature review

The state of dental caries has been portrayed in the literature under various terms. It is a multifactorial sickness that is described by limited and dynamic demineralization of the inorganic bits of the tooth and the resulting weakening of its natural part. [2].

Datta et al. [3] developed an optical image technique to detect dental caries. They developed an optical image-based monitoring system to monitor the size of caries. It was observed from the results that the accuracy of the system was 93% but it failed in detecting the conditions where a tooth is broken. Also, it was unsuccessful in detecting the depth of caries. Naebi et al. [17] developed an image processing approach along with particle swarm optimization (PSO) algorithm for detecting dental caries. The developed technique could be applied to 2D as well as 3D images. The fitness of the PSO was enhanced by the use of some mathematical relationships. From the results, it was observed that this technique along with improving the accuracy also reduced the time required for the detection of caries.

Prerna et al. [22] developed an automatic caries detection model based on Discrete Cosine Transformation (DCT) and Radon Transformation (RT). The low-frequency details of each image were captured by performing RT on all the x-ray images. 2-D DCT was applied to these images to obtain the coefficients of the features that are further subjected to PCA (Principal Component Analysis) for feature extraction. The features are finally applied to different classifiers. From the results, it was observed that of all the classifiers that were tested, random forest classifier gives the highest accuracy of 86%. The main limitation of this technique was that it was designed to classify only non-cavitated and cavitated teeth. A lot of research is done using machine learning methods in the field of dentistry. Deep learning was introduced in the dentistry field since 2016 [6]. The accuracy of the deep learning model in the medical field is closer to the human expertise and it can be used as the first choice for diagnosis of the medical problems for better accuracy. Prajapati et al. [18] attempted to precisely classify the small labeled dataset which comprised 251 Radiovisiography (RVG) X-ray images of three distinct classes using the CNN model. They used transfer learning to improve accuracy. The accuracy achieved was 88%. Miki et al. [13] investigated the use of Deep CNN for the classification of the different types of the tooth on dental cone-beam CT (computed tomography) images. They proposed a model for classifying the tooth into 7 different types that can be used for automatically filling dental charts for forensic identification. They achieved an accuracy of 88.8% with an augmented dataset. One of the drawbacks of this technique was the amount of data considered for evaluation was small.

Lee et al. [11] assessed the effectiveness of a deep CNN algorithm for detecting and diagnosing the dental cavities. 3000 periapical radiographic images were considered of which 80% were for training data and the remaining 20% as test data. A pretrained GoogleNet Inception v3 CNN was used for the detection of dental caries. The accuracy of the model was 91%. Even though the obtained efficiency and accuracy was considerably good, there are some drawbacks. This technique was not designed to differentiate between the proximal, early, and root caries. A technique that combined deep CNN and optical coherence tomography

(OCT) imaging modality, for detecting the occlusal cavity lesions, was developed by Salehi et al. (2019) [20]. They collected 51 permanent teeth of humans that were extracted and grouped them into caries which extend to the enamel, dentin, and non-carious teeth. The specificity and sensitivity of differentiating among the non-carious and carious lesions were 100% and 98% respectively. Srivastava et al. [24] developed a deep fully convolutional network (DCNN) consisting of 100 + layers for the detection of dental caries using bitewing dental images. The recall, precision, and F1 score were 80%, 61%, and 70% respectively. Prerna et al. [23] proposed a CNN model for the classification of dental images into various G.V Black classes using periapical dental images. The models used were pretrained Alexnet and GoogleNet. The dataset consisted of 1500 images. Of these, 1200 were used for training and 300 for testing. The classification accuracy for Alexnet was 93% and GoogleNet was 94%. Imangaliyev et al. [7] proposed a deep learning model for the classification of dental plaque images. The numbers of dental images used for training were 427. The automated dental red autofluorescence plaque image classification is based on Convolutional Neural Network (CNN). The FI score of the model was 0.75. Karimian et al. [9] designed a deep learning classifier with optical coherence tomography images for early dental caries detection. The number of training dataset consisted of 5 optical coherence tomography (OCT) images. The sensitivity of the proposed method was 97% and specificity was 100%. Lee et al. [11] proposed diagnosis and prediction of periodontally compromised teeth (PCT) using deep learning-based convolutional neural network algorithm. The pre-trained deep CNN architecture VGG-19 was used for diagnosing of PCT. The training dataset consists of 1044 dental periapical radiograph. The accuracy of the classifier was 82.8% for premolars and 73.4% for molars. It can be observed that all the techniques discussed above have been used only in the process of detecting and classifying dental caries, most of them having a further scope for improving the accuracy of classification. Researchers have been using the CNN-LSTM model for image classification in the recent past. Murata et al. [15] proposed a deep learning model to automate diagnostic imaging. They used CNN and RNN (Recurrent Neural Network). The RNN model used was LSTM. The dataset used for the experiment was 704 dental images. The accuracy of the model was 65.7%. Liu et al. [12] proposed the CNN-LSTM model for detecting defects in the Co_2 welding molten pool. The accuracy of the model was 94%. Murtaza et al. [16] developed a classification model called Biopsy Microscopic Image Cancer Network (BMIC_Net). This model was used to classify breast cancer into eight distinct subtype through deep learning (DL) and hierarchical classification approach. The BMIC_Net outperformed the existing machine learning models and obtained the highest accuracy of 95% for first level classifier and 94% and 92% for second-level classifier. Guo et al. [5] developed a high-performance network- based on CNN-RNN paradigm which outperforms the CNN (ResNet) for image classification. The CNN-RNN can use the coarse labeled training data to improve the classification of fine categories. The widely available ImageNet 2012 dataset was used for the image classification. Ioannis et al. [8] developed a reliable CNN-LSTM model for gold price prediction and movement. The accuracy of the CNN-LSTM model for gold price prediction was 55%.The work done in the field of computer vision techniques for dentistry is mostly related to caries detection, tooth detection, dental plaque, peridontium, osteoporosis, and others. Hence this paper develops a novel CNN-LSTM model along with a dragonfly optimization technique for improved accuracy of the classification and also this model is developed such that once the classification is done it may foretell dentists about the treatment required for each class of dental caries.

3 Proposed methodology

The contribution of this work is the development of the model for the classification of dental X-ray images based on G.V Black's Classification by utilizing the advantages of deep learning techniques. Convolutional layers are used for extracting the important features and learn the internal representation of the dental X-ray images and the LSTM layers are responsible for long-term and short-term dependencies. This section starts with the description of the convolutional layer, LSTM layers, and Dragonfly optimization followed by the proposed framework,

3.1 Convolution layers

CNN architecture comprises of a set of hidden layers along with the input and output layer. These hidden layers consist of a number of convolution layers. Convolution Layers consists of a set of kernels. These layers convolve with the input with the help of kernels and pass the convolved matrix to the next layer. The result obtained from the convolution layers is the feature map of the image. The convolution layers possess certain attributes or hyper-parameters such as the size of the kernels and the number of input and output channels. The convolution layer is followed by the rectified linear unit called Relu function, pooling layers and fully connected layers. Relu layer uses a rectified linear activation function which is the piecewise linear function. The pooling layer takes the value of the convolved layer as the input and further produces a lower dimension matrix as output. Finally, the fully connected layer uses the results of the pooling layer to classify the image.

3.2 LSTM layers

LSTM layer is a type of a recurrent neural network (RNNs) that has the ability to learn the long term dependencies by the utilization of feedback connections. An LSTM layer is a combination of a memory cell and three main gates: input, output and forget. With the help of this architecture, the LSTM can decide which information to "forget" and which information to "remember" in order to maintain long-term dependencies. The various equations showing the input gate, memory state, forget gate, output gate are shown in Eqs. (1)-(6) [8]. Here, i_t is the input gate and c_t^* is the new gate that controls new information stored in the memory state c_t at time t. f_t is the forget gate which manages the past information. o_t is the output gate that manages which information should be utilized for the output of the memory cell. The h_t is the hidden state which calculates the output of the memory cell.

$$i_t = \sigma(U_i x_t + W_i h_{t-1} + b_i), \tag{1}$$

$$f_t = \sigma\left(U_f x_t + W_f h_{t-1} + b_f\right), \tag{2}$$

$$c_t^* = tanh(U_c x_t + W_c h_{t-1} + b_c), \tag{3}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t^*, \tag{4}$$

$$o_t = \sigma(U_O x_t + W_o h_{t-1} + b_o), \tag{5}$$

$$h_t = o_t \odot \tanh(\mathrm{c_t}) \tag{6}$$

where x_t is the input of the LSTM layer, W and U are the weight matrices with subscript representing the gate. i, f, o are input gate, forget gate, cell activation vectors, and output gate respectively., b_* are the vector of bias term,σ is the sigmoid function and $\odot$ is the component multiplication. The memory state c_t and the hidden state $h_t$of the LSTM layer is the input of the next LSTM layer.

3.3 Dragonfly optimization (DA)

Dragonfly algorithm is a swarm optimization technique proposed first by Mirjalili [14]. The main inspiration of the DA algorithm originates from the static and dynamic behaviors of dragonflies in nature. The two important phases of optimization algorithm are exploration and exploitation. In our proposed approach, Dragonfly algorithm (DA), optimizes the weights of the CNN and improves the classification accuracy. The dragonfly algorithm is based on five different principles. The first principle is the principle of separation. The principle of separation states the avoidance of collision of a dragonfly with the other dragonflies. The second principle is the principle of alignment, which is the matching of a velocity of a dragonfly with other dragonflies. The third principle is the principle of cohesion that states the dragonfly tendency towards the center of the space that contains the other dragonflies. The fourth principle states the principle of food attraction. The fifth principle is the principle of enemy distraction in which all the dragonflies move away from the enemies to survive. The v-shaped transfer function [19] is used which takes the velocity input and returns the number between 0 and 1. The function makes quick changes in particles with high velocity. The best cost evaluation procedure is calculated. The best cost of each dragonfly is calculated based on the two important measures i.e. the accuracy and error rate. The dragonfly algorithm in our architecture is implemented in the fully connected layer for weight optimization. The weights of each connection between the neuron in the fully connected layer are used to enhance the accuracy of the classification. The food source and the enemy in the dragonfly algorithm are chosen from the best and the worst solution found. This leads to the convergence of the most promising results. The Dragonfly optimization will stop when the maximum number of iteration or an optimal cost value has been reached.

The proposed model is shown in Fig. 2 and is detailed below.

3.4 Data acquisition

The first stage is data acquisition. The dataset consisting of dental X-ray periapical images have been collected from two dental clinics in New Delhi, India. The resolution of dental X-ray images is 256 pixels × 256 pixels. For this study, 1500 images of teeth for six different classes are considered. For each class, 250 images are considered. The dental X-ray images are taken from Kodak RVG 5200 Digital Radiography system. The sensor used in the machine is Super CMOS with fiber optics. The power supply is an AC 200V/110V. The scan time is 10–12 sec. The patient's position while taking the image can be standing or in the wheelchair. The

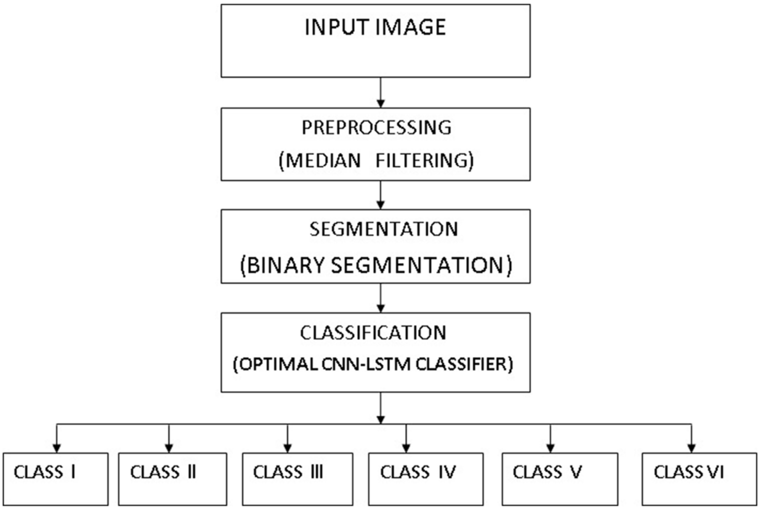


Fig. 2 Proposed model

periapical dental image consists of the whole tooth of either the upper jaw or the lower jaw. Periapical dental images are important since any change in the root and surrounding bone structure can be detected through these images. They visualize the structures of both anterior and posterior teeth. Since the teeth in periapical dental images can be diversely rotated, that is why it is very challenging to do image processing on periapical dental images. The dental X-ray images have been obtained without the patient's information, for e.g. name, gender, address, phone number, age, etc. The dental X-ray images acquired from the dental clinics were in RVG format. They were converted to the "JPG" format for further processing. The 1500 dental X-ray images were divided into two datasets, the training dataset which consists of 1200 dental X-ray images and the testing dataset which consists of 300 dental X-ray images.

3.5 Image preprocessing

Image preprocessing is the basic step of image processing. Its main operations are noise removal, contrast enhancement, and illumination equalization. A linear or a non-linear filter can be used for the removal of noises in an image. The median filter is a non-linear filter, which is widely being used in image processing because of its ability to reduce impulse noise [25, 26]. The acquired images collected from the clinics, that showed the overlapping teeth and had signal to noise ratio (SNR) of less than or equal 10 dB were quite distorted and were not considered for the dental image classification. The rest of the images were filtered using a median filter for noise removal. SNR of most of the images that were considered for filtering was between 25 dB to 35dB.

3.6 Image segmentation

Segmentation is the process of segregating a digital image into many segments (set of pixels) to simplify the image representation such that it is easy to analyze. This study uses a binary segmentation technique for segregating the filtered image into various sets of pixels.

3.7 Dental image classification

Dental image classification is a complex process and requires consideration of many factors. The major step of image classification is finding a suitable classification system, selection of training sample, image preprocessing, and assessment of accuracy. One of the widely used image classifiers is CNN. Some of the CNN based architecture for image classification is LeNet, AlexNet, VGG, and GoogleNet. Lots of work is done by the researchers in the field of dentistry in the last few years by exploiting the two pre-trained model Alexnet and Googlenet [6]. This is the reason for choosing these two models for comparison with our proposed model which has the novel CNN-LSTM architecture. The proposed optimal CNN-LSTM combines the advantages of both the deep learning techniques. The challenges faced during the development of this architecture for dental image classification are as following:

- The pre-defined dataset is not available. For proper learning huge dataset is required. However, due to a lot of confidential information in medical data, obtaining dental images was a challenging task.
- The verification of the architecture was difficult since the proposed G.V Black classification is one of its kind.
- The performance or accuracy is directly influenced by the hyper-parameter selection. Therefore the selection of hyper-parameter was the major challenge in designing the model. The combination of CNN and LSTM was done in order to increase the robustness on different categories of images and in order to improve generalization. Hyper-parameter tuning was the challenging job and the use of the Dragonfly algorithm to optimize the hyper-parameter was a difficult job.

The basic architecture consists of the novel optimal CNN-LSTM classifier employed for G.V Black classification of dental images is depicted in Fig. 3. The dental X-ray image is used as an input to CNN. The features are extracted with the help of convolution and pooling layers. The features that are extracted by the convolution layer consist of extraneous information, extracted by the kernel. In case if we want to extract deeper image features and improve the accuracy of the model we can add more convolutional layers, max- pooling layers, and convolutional kernels. This may lead to a more complex network and lead to increase the computation cost. It may also increase the risk of over fitting. In order to avoid the above problem, we can add the RNN network namely, LSTM. LSTM can filter the redundant data. It can also filter the extraneous information extracted by the multiple kernels. It uses the advantages of both CNN and LSTM. We have used the CNN-LSTM framework to classify the dental images into six G.V Black classes. This model has significantly improved the classification accuracy. For this model, a dental X-ray image of size 256×256 pixels is given as input to a single convolution layer. The number of kernel is 23, kernel size of the convolutional layer is 8×8, value of the stride is 4 and padding is 1. The output image size of the convolutional layer is $64 \times 64 \times 23$. The convolution layer is followed by the Relu and normalization layer. The output of the convolution layer is given to the maxpool layer with filter size 3*3, the value of stride as 2, and no padding. The output image size of the max-pooling layer is $32 \times 32 \times 23$. This layer is followed by the LSTM (Long Short term Memory) layer. The LSTM basically aids in the learning of long term dependencies among the time steps. The LSTM comprises special units, which are referred to as memory blocks. Two LSTM layers with 92 and 50 neuron size are considered in the proposed model. Each memory block consists of memory cells along with

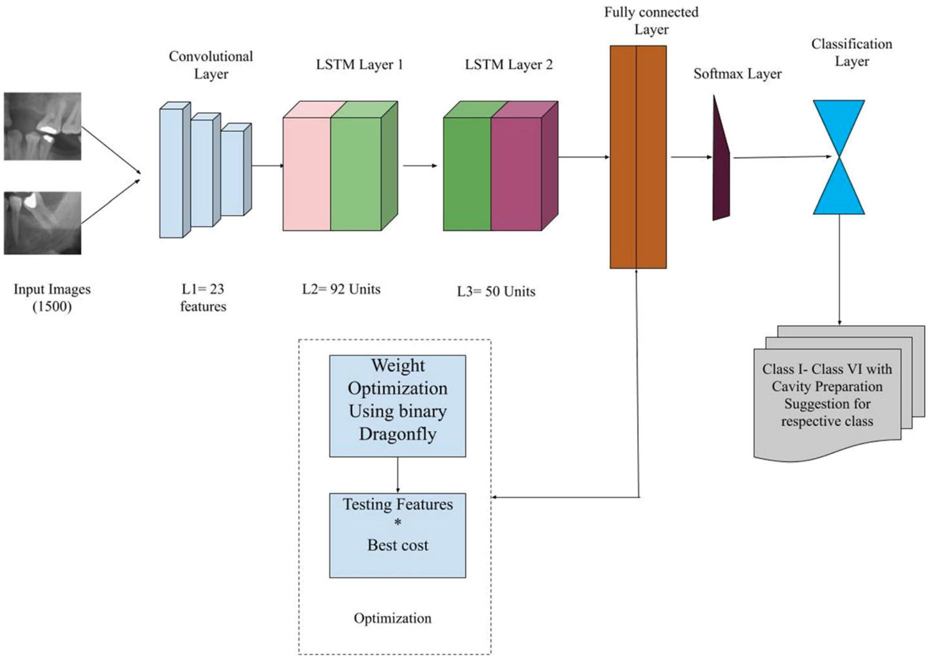


Fig. 3 Dental image classification architecture (optimal CNN-LSTM classifier)

the multiplicative units referred to as gates for controlling the information flow. There are two gates input and output gate. The input gate controls the flow of input activations into the memory cell while the function of the output gate is to control flow of the cell activations into the remaining part of the network. The LSTM layer is followed by the fully connected layer where the weights are optimized by the application of the Dragonfly optimization algorithm. The output of the fully connected layer is the input of the softmax layer that shows the classification result according to the six G.V Black classes (Table 1).

4 Results and discussion

The experimental classification of the images of dental caries into six GV black classes is conducted on the processor Intel (R) Core (TM) i3 Lenovo platform with 3 GHz main a processor

Table 1 Detailed description of proposed CNN architecture

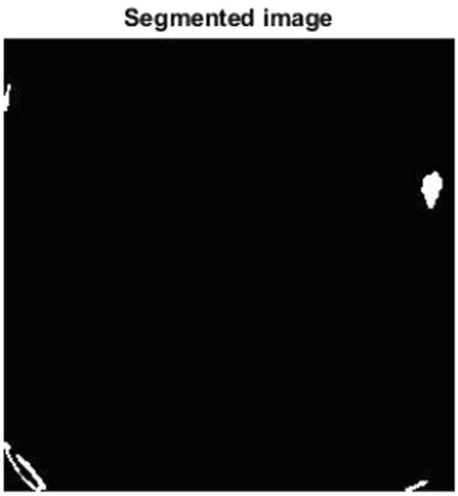
Layers	Input Image size	Output Image size	No. of filters	Filter size	Stride	Padding
Convolution Layer + Relu + Normalization	256*256	64*64*23	23	8*8	4	1
Max Pooling	64*64*23	32*32*23		3*3	2	0
LSTM Layer 1	32*32*23	29*29*92	92			
LSTM Layer 2	29*29*92	15*15*50	50			
Fully Connected Layer		512				
Softmax Layer		6				

Fig. 4 Filtered image

speed and 8 GB memory. The proposed system is developed in Matlab 2018a. A total of 1500 dental images are considered for 6 classes with 250 images for each class. Out of 1500 dental images, 1200 dental images are used as the training data and 300 dental images are used as the testing data. These dental X-ray images were resized to 256*256 pixels for better visualization. The resized image is then converted to a gray scale image. The pre-processed dental X-ray images are input to the optimal CNN-LSTM model as shown in Fig. 3. The median filtering technique is applied to the dental X-ray image to remove unwanted noise in the image.

This filtered image after removal of the unwanted noise is shown in Fig. 4. The image after applying the median filter is segmented using a binary segmentation technique. Figure 5 shows the segmented image. The segmented image is fed to the CNN-LSTM classifier in order to classify the dental X-ray image. The results of the classification process using the CNN-LSTM classifier with optimization are presented below. The performance analysis of the proposed model is evaluated by the following methods:

Fig. 5 Segmented image



- convergence curve.
- Evaluation of Loss function.
- Performance metrics.
- Comparison with other state-of-art models.

4.1 Convergence curve

The convergence speed is the crucial factor for all the iterative methods. Figure 6 illustrate the convergence curve for the proposed model. The convergence curve calculates the plot between the best cost/solution and the number of iterations. The convergence curve is plotted on a testing dataset, which consists of 300 dental x-ray images. It clearly shows the curve decreases at 50 iterations and decreases rapidly at 300 iterations. This indicates the high convergence speed of our proposed model.

4.2 Evaluation of loss function

Figure 7 shows the performance of the loss function of the optimal CNN-LSTM model. The training dataset consists of 1200 dental X-ray images that are divided into 2 sets and 2 complete iterations complete one epoch. In this model, we have train the model for 250 epochs. The validation dataset consists of 300 dental X-ray images The loss function used in the model is categorical cross-entropy. The model shows a good result on both the training dataset and the validation dataset. This can be analyzed by the plot in Fig. 7 where validation loss is more than the training loss. Both the training loss and validation loss decrease and stabilize at the same point (50 epochs). The loss curve of the proposed curve is also compared

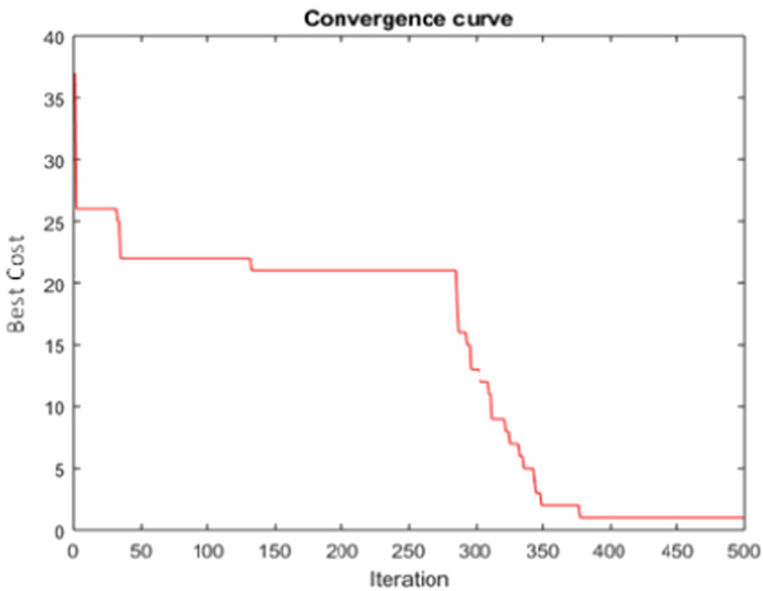


Fig. 6 Convergence curve

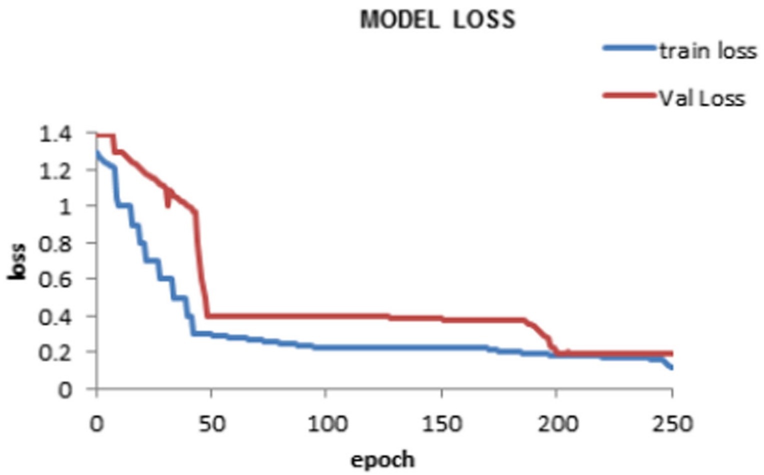


Fig. 7 Loss curve for optimal CNN-LSTM Model

with the loss curves of the CNN model, LSTM model, and CNN-LSTM without dragonfly optimization. Figure 8 shows the performance of the loss function of the 2 Layer LSTM model. The model is trained for 250 epochs. The validation loss is more than the training loss as depicted in the figure but after 160 epochs the training loss gets slightly more than the validation loss and both the losses stabilizes after 200 epochs. Figure 9 shows the performance of the loss function of the CNN architecture. The model is trained for 250 epochs for the training and the validation dataset. As shown in Fig. 9, the training loss of the CNN architecture is more than validation loss and both the loss stabilizes after 160 epochs. The proposed optimal CNN-LSTM model has lesser loss as compared to the 2 layer LSTM model and the CNN model which clearly justifies the model for the classification.

4.3 Performance metrics

Various performance metrics have been used to evaluate the proposed model. Figure 10 illustrates the Receiver Operating characteristic (ROC) curve of the CNN-LSTM classifier using the test dataset. Table 2 shows the confusion matrix of the proposed CNN-LSTM

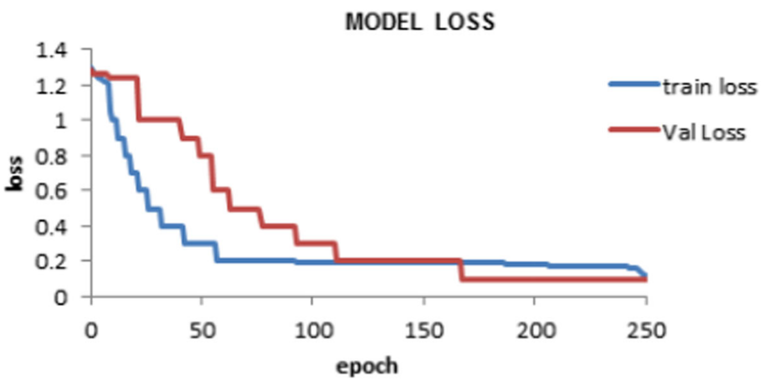


Fig. 8 Loss curve for LSTM model

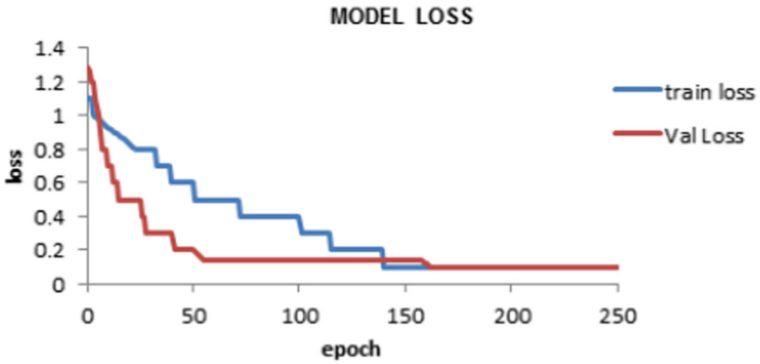


Fig. 9 Loss curve for CNN model

classifier. The area under the curve for Class I, Class II, Class III, Class IV, Class V, and Class VI of dental caries is 0.96, 1.0, 0.88, 1, 0.92, and 1 respectively. ROC curve shows that the proposed model classifies the dental images quite well based on the G.V Black classification. The proposed CNN-LSTM model as shown in Table 2 has a better trade-off between the true-positive and true-negative rate. Table 3 tabulates other performance metrics of the proposed model namely accuracy, sensitivity, specificity, precision, F-measure, and G-mean. High values of sensitivity and specificity indicate that the proposed model correctly identify true positives and true negatives. A high value of precision signifies more number of true positives identified. The high value of the F-measure of the proposed model indicates good accuracy in

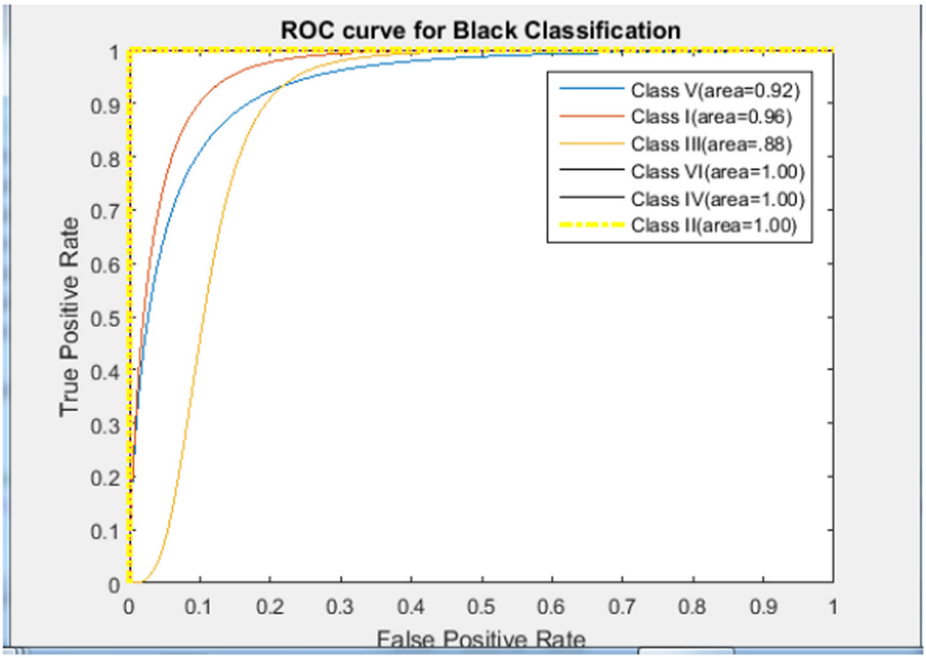


Fig. 10 ROC curve for black classification

Table 2 Confusion matrix for G.V Black classes for the test dataset

	Class I	Class II	Class III	Class IV	Class V	Class VI
Class I	48	0	1	0	1	0
Class II	0	50	0	0	0	0
Class III	6	0	44	0	0	0
Class IV	0	0	0	50	0	0
Class V	0	0	0	4	46	0
Class VI	0	0	0	0	0	50

terms of precision and recall. The good balance between true positive and true negative cases classified by the proposed classifier is depicted by the G-Mean metric. The area under Curve of the proposed model is 0.96 i.e. close to 1 which justifies the performance of the classifier. State of art model which clearly proves the high performance of the proposed model in dental image classification. The CNN-LSTM has good overall performance in terms of accuracy and balance between true-positive rate and true-negative rate. Favorable values of the performance metrics in Table 3 prove that our proposed CNN-LSTM model is highly reliable in the dental image classification based on the six classes of G.V Black.

4.4 Comparison with other state-of-art models

A lot of work is done by the researchers in the field of dentistry in the last few years by exploiting the two pre-trained model Alexnet and Googlenet. This is the reason for choosing these two models for comparison with our proposed model which has the novel optimal CNN-LSTM architecture. The accuracy of the pretrained CNN Model (Alexnet and GoogLeNet) on 1500 dental X-ray images gave an accuracy of 93% and 94% respectively [23]. The same dataset on the proposed model using the CNN-LSTM model has a better accuracy of 96%. This clearly proves that the optimal CNN-LSTM model yield better overall performance for Black classification as compared to the pre-trained model Alexnet and Googlenet. The proposed CNN-LSTM model clearly out-performed the state of art pretrained models as described in Table 3 presents the best accuracy. Other performance metrics (Sensitivity, specificity, precision, F-measure, G-mean, and Area under the curve) shown in Table 3 also show that the proposed model performs better than pre-trained models. The optimal CNN-LSTM architecture is also compared with the CNN architecture, 2- layer LSTM model, and CNN-LSTM model without optimization in Table 3. The results clearly show that the

Table 3 Performance metrics

Parameter	Optimal CNN LSTM	GoogleNet	Alexnet	CNN	LSTM(2 Layers)	Without Dragonfly Optimization
Accuracy (ACC)	96%	94%	93%	90%	92%	88%
Sensitivity	96%	94%	93%	89%	90%	86%
Specificity	93%	92%	91%	82%	89%	82%
Precision	95%	93%	92%	88%	90%	80%
F-measure	95%	92%	91%	88%	90%	81%
G-mean	94%	92%	91%	89%	89%	85%
Area under the curve (AUC)	0.96	0.94	0.93	0.90	0.92	0.88

```
composite resigns...1
silver amalgam, composite resins, or crown using gold or procelain inlay...2
composite resigns...3
procelain crown...4
If posterior teeth, silver amalgam is used and if anterior composite resin...5
Composite resins or silver amalgam...6
```

Fig. 11 Final classifier output

proposed model is more accurate, consistent, and reliable in the classification of dental images as compared to CNN, LSTM, and CNN-LSTM without optimization.

Once the images are classified into the respective classes this classifier will also suggest the treatments required for that class of caries. The final output is shown in Fig. 11. If the image is classified into class I the suggestion is to treat it with composite resin since the decay is confined to a small area. When the image is classified into the class- II then the tooth can be treated using composite resins or silver amalgam but in case of extensive decay, it is treated by placing a crown made of porcelain or gold inlay. The image classified into class III will require a treatment using composite resins while the one classified to class IV will need a porcelain crown. For the images classified into class V, the treatment required will be using silver amalgam for posterior teeth and composite resin in case of an anterior tooth. The images that come under class VI will require the treatment using composite resin or silver amalgam.

5 Conclusions

This study developed automatic dental image classification architecture for classification of dental caries into six G.V Black classes using an optimal CNN-LSTM classifier with dragonfly optimization. The classifier also predicted the treatment that is required for each class of caries. The CNN extracts the features and the LSTM processes the features extracted by CNN. The ability of CNN to extract the features is very strong and the long-term dependency ability of the LSTM network is stronger than that of the convolutional layer. The proposed optimal CNN-LSTM classifier with dragonfly optimization classified the images with an accuracy of 96%. Performance metrics prove the efficacy of the proposed model with the only limitation that less number of dental images was available due to the confidentiality of the patient and the medical data. The proposed model yields the results that are as promising as the diagnosis by the expert level dentist and dental radiologist. The model can be used by the medical students, dentist, and radiologists for accurate diagnosis of dental caries and classifying them into the various classes so that the right treatment can be given according to the type of caries identified. In order to improve the diagnosis in the future, the proposed optimal CNN-LSTM model is a very powerful tool. The system give the recommendation to the dentists based on the past data stored and is of great scientific contribution. Though the tool is very useful and makes predictions and recommendations based on past information though it is used as a second opinion and cannot replace the medical expert. The generalizability of the proposed work depends on the number of factors such as the number of parameters used for the various layers and the applicability of the proposed model on the larger dataset. Our future work will be to exploit the above factors to further strengthen our proposed model and heightens the generalizability.

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