A Computer-Aided Clinical Decision-Making System for Dental Diseases

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Abstract

Introduction: The CNN–Fuzzy approach is used in this article to create a computer-aided clinical decision-making system. According to the literature, dentists are inconsistent when it comes to diagnosing abscesses, fractures, impacted teeth, reversible and irreversible pulpitis. As a result, the objective of this research is to guide and assist dentists in more accurately diagnosing dental diseases. **Methods:** To address inaccurate and ambiguous dental radiograph values, as well as disease signs and symptoms, a robust algorithm based on CNN–Fuzzy logic has been developed. To initiate, the probability of diseases was calculated for each category using an independently designed CNN approach, which was then applied to a fuzzy knowledge base and the Mamdani inference, which contains 947 rules to diagnose diseases and make recommendations to the dentist. **Results and Discussion:** The CNN–Fuzzy approach's findings are compared to dentists' recommendations. With the help of five professional dentists, the accuracy, macro-averaged precision, recall, F1 score, and kappa value are calculated from 250 randomly generated sample cases. The CNN–Fuzzy approach has a 92.8% accuracy, which is 6.4% higher than specialist prediction. The proposed method yields result that are consistent with the dentists' diagnoses. **Conclusion:** The proposed computer-aided decision-making system for dental diseases boosts dentists' confidence in diagnosing abscesses, fractures, impacted teeth, reversible and irreversible pulpitis, and reduces false diagnoses caused by ambiguous values of dental radiograph, signs, and symptoms.

Keywords

Artificial Intelligence; Convolutional Neural Networks; Dental Diagnosis; Fuzzy Logic.

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Introduction

Oral disorders are the most common non-contagious disease, and it directly impacts people in a variety of ways throughout their lives. Diseases such as abscess, fracture, impacted tooth, reversible pulpitis, and irreversible pulpitis must be properly diagnosed. Pulpitis is an inflammatory condition that affects the dental pulp in the center of the tooth. One of the most common causes of pulpitis, according to a systematic review conducted in 2016 by Rechenberg et al. [1], is when bacteria irritate the dental pulp. Normally, such irritants cause reversible pulpitis initially. If the pulp continues to remain inflamed, pulpitis becomes irreversible, and the pulp may die. A traditional examination by a dentist can diagnose pulpitis based on a person's symptoms, an analysis of the teeth, and possibly a radiographic evaluation. Radiographs are the most conventional diagnostic tool, and as emerging technologies have evolved, computer-aided diagnosis has surpassed manual radiograph analysis, ranging from traditional techniques to artificial intelligence (AI)-based techniques for various types of radiographs for diagnosis.

Several studies have been conducted to exemplify image processing and artificial intelligence-based approaches for forecasting dental caries in various types of radiographs. Panoramic radiographs [2-4] and Periapical radiographs [5,6] are the most often used diagnostic tools for dental caries diagnosis, but a number of studies have picked Periapical radiographs for dental caries diagnosis.

An abscess is an accumulation of pus caused by an infection in the teeth, gums, or bone that retains the teeth in place. A fracture is a break in the tooth's outer layer. An impacted tooth is a situation in which a tooth does not fully emerge from the gums.

A literature review has been carried out on specified challenging diseases. Tuan et al. [7] and colleagues concentrated on five diseases: Missing, Cavities, Periodontitis, Hidden, and Cracked. They presume that dentists utilize their knowledge to scrutinize dental X-ray images to classify patients' symptoms for feasible disease diagnosis, which is purely focused on professional knowledge that differs from dental professional to dental professional. They proposed an integrated structure employing Clustering and Fuzzy Rule-based schemes to solve differences in the diagnosis of the aforementioned diseases. They used a clustering algorithm called Semi-Supervised Fuzzy Clustering-Fuzzy Satisficing and Mamdani-based Fuzzy Rule-based systems to diagnose dental problems. The proposed methodology employs 56 real dental case images of five diseases to achieve optimum performance with a mean average error of 0.087.

Prajapati et al. [8] and colleagues proposed an automated dental assistance framework for the diagnosis of three diseases: periodontitis, periapical infection, and dental caries. They discovered a major challenge in the lack of labelled dental diseases datasets, small datasets, and the efficiency of CNN on small datasets. To address these concerns, they enlisted the assistance of dentists and radiologists to categorise 251 RadioVisioGraphy (RVG) x-ray images from three different classes. They tested the performance of CNN on a small labelled dental dataset, and they used transfer learning on VGG-16 to enhance the accuracy. A small dataset of 251 x-ray images was divided into training, validation, and testing datasets, each with 180, 45, and 26 images. The proposed automated dental assistance system for the diagnosis of three diseases obtains an overall accuracy of 88.46%, which is very promising.

Son et al. [9] and colleagues worked on panoramic radiographs for the diagnosis of dental diseases and created a MATLAB-based graphical user interface. They claimed that automated dental diagnosis systems based on X-Ray images are of keen importance to clinicians for accurate decision making of potential diseases and treatments since sub-clinical disease seems to have no identifiable clinical features, so it is advisable to segment the dental x-ray image into clusters and then use computational intelligence methods to verify whether or not any disease is present within it. To complete the task, a unique framework called Dental Diagnosis System for dental diagnosis was developed, which is relied on a hybrid algorithm of segmentation, classification, and decision making. The best dental image segmentation technique called semi-supervised fuzzy clustering was used for the segmentation task, a unique graph-based clustering algorithm named APC+ has been used for classification, and a decision-making methodology was intended to assess the ultimate disease from a group of diseases observed from the segments. The suggested framework makes use of 87 dental images of five common diseases: periodontal bone resorption, missing teeth, root fracture, inclusion teeth and decay. The claimed model's accuracy is 3.07% higher than that of the fuzzy inference system and 2.73% higher than that of affinity propagation clustering.

Mago et al. [16] and colleagues developed a GUI-based decision-making system that is based on Mamdani's fuzzy inference framework. They discovered a challenge from the literature that there is a lack of coherence between dental professionals in selecting treatment plans. As a result, they developed a decision-making system to assist the dental professional in choosing treatment plans for the broken tooth. A decision-making system accepts inaccurate and ambiguous values for dental signs and symptoms associated with a broken tooth, has a knowledge base of 60 rules, and employs the Mamdani inference algorithm to select one or more treatments. The claimed system's results are compared to the dentists' recommendations, and it is discovered that the system's findings are consistent with the treatment plan suggested by the dental professionals. The Chi-square assessment of uniformity is performed, and the result is 3.843565, which is less than the significance level of 12.592. The evaluation of the proposed decision support system for the treatment of broken teeth rises dentists' confidence when making treatment plan decisions. Above studies attempt to diagnose all diseases using a single AI-based approach and neither study focus on deciding whether dental Pulpitis is reversible or irreversible.

Our research question is how to accurately diagnose dental symptoms from radiographs because the grey-scale value difference in the disease region is extremely small, making dental disease classification complicated. To respond, we utilized CNN techniques to classify dental symptoms and Fuzzy-based frameworks to combine symptoms with CNN results for dental diagnosis.

The objective of this article is to eliminate or reduce inappropriate diagnoses and provide a second opinion by using a novel Convolutional Neural Network (CNN)-Fuzzy based approach that is more accurate than a traditional approach to diagnosing a dental abscess, fracture, impacted, reversible and irreversible pulpitis. The majority of research, according to the literature, focuses only on image-based diagnosis, which means that it lags behind patients' symptoms-based diagnosis, which is crucial for an accurate diagnosis. In the traditional clinical approach, an expert makes a diagnosis based on a combination of results from image-based symptoms and symptoms felt by the patient. The beauty of this approach is that it emphasises patient symptoms and image-based diagnosis. It also aids in aligning symptoms' vagueness values with a mathematical formula that is described in depth in the method section. To the best of our knowledge, we genuinely think we are the first group to work on a novel CNN-Fuzzy based approach for a computer-aided clinical decision-making system for abscess, fracture, impacted, reversible, and irreversible pulpitis.

Methods

This section is divided into three parts: data sets and pre-processing, CNN, and the fuzzy approach. The first part of this section describes the initial step of transforming raw image data into understandable image data. Once transformed, the image will be used in the second part, where pixel data will be processed to extract disease features from the image using an own designed convolutional neural network (CNN). These image-based symptoms and sign symptoms provided by the patient are used in the final section where a fuzzy approach resolves the uncertainty and imprecision associated with symptoms for diagnosing abscesses, fractures, impacted teeth, reversible pulpitis, and irreversible pulpitis.

Dataset and Pre-Processing

The dataset used for training and validation of our CNN-based dental x-ray symptoms prediction model consists of 570 of 1070 periapical x-ray images, with each class (named as apical radiolucency, crack tooth, embedded tooth, deep caries and shallow caries) containing 114 periapical x-ray images and was evaluated and labelled by three dental surgeons. The proposed method was tested using the remaining x-ray images. The fuzzy approach was implemented in

MATLAB, and the convolutional neural network model was created in Python using the Keras library. We used data augmentation to optimize our CNN model and minimize bias and generalization errors due to the limitations of the limited training dataset. To aid model convergence, images were rescaled to 224x224-pixel resolutions and normalized for the mean.

Convolutional Neural Network

CNNs have emerged in recent years as prominent deep learning algorithms for image-based dental diagnosis [10-12] due to their capability to uphold complex features while examining input images. Figure 1 illustrates the overall system architecture.

A set of filters makes up the convolution layer. It is an operation in which we move a small number matrix (known as the kernel) over our image, transform it based on the kernel values, that retrieve features by forming a fresh layer. Each fresh layer represents one or more of the input image's important features. Succeeding feature map merit is computed using below mathematical formula [13], where I represent input image, F represents our kernel and rows and columns of the fresh matrix are denoted by x and y, correspondingly.

$$\mathrm{M}[x,y] = (I * F)[x,y] = \sum_{\mathrm{p}} \sum_{\mathrm{q}} F[p,\mathrm{q}] I[x-\mathrm{p}, y-\mathrm{q}] \quad (1)$$

This CNN architecture has ten convolution layers and takes as input a 244x244 dental image tensor. The very first convolution layer then hires 5x5 filters with stride 1x1 for 32 filters. The output of the first layer is then normalized. The second layer obtains the output of the foremost layer, uses 64 filters, and its output is normalized before being applied to a max-pooling matrix with a stride of 2x2, minimizing the input to 50% of its original dimension 112x112. The result of the pooling layer is forwarded along with the ReLU activation for all layers. An obtained nonlinear output is fed within two similar type convolution layers having 128 filters, 3x3x64 dimension, and stride value of 1x1. The resulted output is passed through the 2x2 strides of a max-pooling layer, lowering the input to a size of 56x56. After activating the ReLU, the output is diverted to the fifth through seventh convolution layers, each having 256 filters and 3x3x128 of kernel size, with a 1x1 stride. An obtained output is fed through a max-pooling layer, yielding a tensor of 28x28. The output is fed into ReLU activation before being fed into the eighth to tenth convolution layer, which has 512 filters, a kernel size of 3x3x256, and the same stride of 1x1. The output of the tenth convolution is max-pooled, resulting in a tensor with the shape 14x14x512 and a flattened tensor with 1,00,352 neurons. Neuron weighed values resemble apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries symptoms. A dropout rate of 0.2 is used here to control network overfitting. The fully connected layer converts the 1,00,352-neuron tensor into the number of dental image categories. This method achieved an accuracy of 82.80%, which is approximately 9.93% higher than the traditional VGG16, VGG19, ResNet50, Xception, and InceptionV3 approaches.

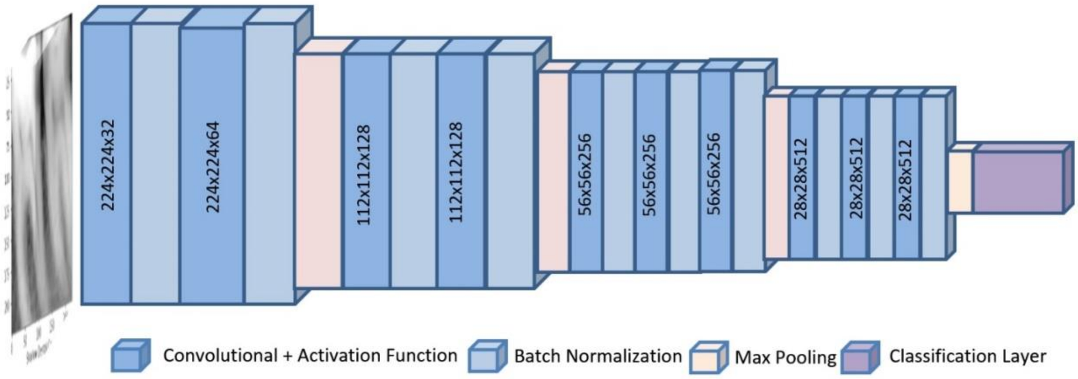


Figure 1. *Proposed CNN architecture for classifying dental diseases.*

Proposed Fuzzy Based System

We present a novel framework for dental decision-making based on a CNN-Fuzzy system in this study, intending to facilitate the dentist in diagnosing an abscess, fracture, impacted, reversible pulpitis, and irreversible pulpitis. The system receives noticeable signs and symptoms of dental diseases as observed by the dentist along with verbal descriptions provided by the patient, and the proposed CNN network's predicted possibility of apical radiolucency, crack tooth, embedded tooth, deep caries or shallow caries is instantly provided to the dentist for next phases of fuzzy-based prediction. As the vagueness of information associated with the image had been solved during the learning phase of the CNN but the diagnosis result of our approach is based on a combination of image-based symptoms and symptoms felt by the patient. Verbal descriptions of the signs and symptoms felt by the patient can contain a significant amount of ambiguity. For example, continuous pain may be mild, moderate, or severe, and its value or verbal descriptions differ from patient to patient. This challenge requires a robust algorithm, which fuzzy logic has.

A fuzzy logic-based technique has been formed and widely adopted in medical fields [14-16]. The term "fuzzy logic" first arose in the development of professor Lotfi A. Zadeh's theory called fuzzy sets in the years 1965 and 1988. In contrast to traditional bi-valued logic, an artificial intelligence-based fuzzy logic employs fuzzy rules and membership functions. The Fuzzifier, Rule Applier, Inference Engine, and De-fuzzifier are the major core elements of the Fuzzy Logic-based intelligent system. The knowledge base used by the inference engine is made up of if-then rules.

Fuzzification and Fuzzy Membership Function Development for Input-Output Variables

The process of defining membership functions for linguistic expressions is known as fuzzification. The membership functions for the linguistic expressions used as input and output variables in this learning are shown in Table 1.

Table 1. *Linguistic Expressions for Input-Output Variables*

Variables for Input	**Linguistic Expressions**
Apical Radiolucency	Probability: Low, Medium, High
Crack Tooth	Probability: Low, Medium, High
Embedded Tooth	Probability: Low, Medium, High
Deep Caries	Probability: Low, Medium, High
Shallow Caries	Probability: Low, Medium, High
Continuous Pain	Mild, Moderate, Severe
Pus Discharge	Mild, Moderate, Severe
Swelling Around Tooth and Gums	Mild, Moderate, Severe
Mastication Pain	Yes, No
Sensitivity to Hot	Mild Hot, Extreme Hot
Sensitivity to Cold	Normal Cold, Extreme Cold
Output Variables	**Linguistic Expressions**
Abscess	Yes, No
Fracture	Yes, No
Impacted	Yes, No
Reversible Pulpitis	Yes, No
Irreversible Pulpitis	Yes, No

Typically, the membership function is obtained from metadata or probability distribution functions. However, in our context, the deficiency of dental metadata makes the use of computerized algorithms difficult. As a result, we were successful in obtaining the assistance of our experts in developing the membership functions along with specifying the reference frame for all parameters. The reference frame was decided to be between [0, 1]. Initially, we had considered a triangular membership function for all variables, but we were unable to reach an agreement with the specialists, so we depend on their advice and elected Gaussian membership functions, S-mf and Z-mf, as they are more suitable for this model. The following is a summary of various input and output variables, and membership functions associated with them, that were used in this study:

Apical Radiolucency, Crack Tooth, Embedded Tooth, Deep Caries and Shallow Caries: Understanding the nature of dental diseases, such as whether caries is deep or shallow, is critical, and this can be accomplished by determining the level of caries from X-rays using the proposed CNN-based approach. Let y represent apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries, respectively. As a result, the membership function for linguistic expressions (Low Probability, Medium Probability, High Probability) will be considered, as shown in Eq. (2 to 4).

$$\boldsymbol{f}_{\textbf{Low Probability}}(\boldsymbol{y}) = \begin{cases} \boldsymbol{0}, & \boldsymbol{y} \leq -\boldsymbol{0.1} \\ \frac{\boldsymbol{y}+\boldsymbol{0.1}}{\boldsymbol{0.1}}, & -\boldsymbol{0.1} \leq \boldsymbol{y} \leq \boldsymbol{0} \\ \frac{\boldsymbol{0.4}-\boldsymbol{y}}{\boldsymbol{0.4}}, & \boldsymbol{0} \leq \boldsymbol{y} \leq \boldsymbol{0.4} \\ \boldsymbol{0}, & \boldsymbol{0.4} \leq \boldsymbol{y} \end{cases} \tag{2}$$

$$f_{Medium\,Probability}(y) = \begin{cases} 0, & y \leq 0.3 \\ \frac{y-0.3}{0.2}, & 0.3 \leq y \leq 0.5 \\ \frac{0.7-y}{0.2}, & 0.5 \leq y \leq 0.7 \\ 0, & 0.7 \leq y \end{cases} \tag{3}$$

$$f_{\text{High Probability}}(y) = \begin{cases} 0, & y \leq 0.6 \\ \frac{y-0.6}{0.2}, & 0.6 \leq y \leq 0.8 \\ \frac{1-y}{0.2}, & 0.8 \leq y \leq 1 \\ 0, & 1 \leq y \end{cases} \tag{4}$$

Continuous Pain, Pus Discharge and Swelling Around Tooth/Gums: The continuous pain, pus discharge, and swelling around the tooth and gums can be mild, moderate, or severe. Experts use Gaussian membership functions for these variables. Assume that in fuzzy membership functions, y is the variable. Eqs. (5–7) give Gaussian membership functions for continuous pain, whereas Eqs. (8–10) give Gaussian membership functions for Pus discharge and swelling around the tooth and gums.

$$f_{\text{Mild Pain}}(y) = e^{\frac{-(y-0.2)^2}{0.08}} \tag{5}$$

$$f_{\text{Moderate Pain}}(y) = e^{\frac{-(y-0.6)^2}{0.02}} \tag{6}$$

$$f_{\text{Severe Pain}}(y) = e^{\frac{-(y-0.9)^2}{0.02}} \tag{7}$$

$$f_{\text{Mild}}(y) = e^{\frac{-(y-0.1)^2}{0.02}} \tag{8}$$

$$f_{\text{Moderate}}(y) = e^{\frac{-(y-0.4)^2}{0.02}} \tag{9}$$

$$f_{\text{Severe}}(y) = e^{\frac{-(y-0.8)^2}{0.08}} \tag{10}$$

Mastication Pain, Sensitivity to Hot or Cold, Abscess, Fracture, Impacted, Reversible and Irreversible Pulpitis: Extreme hot, mild hot, normal cold and extreme cold are the different levels of heat and cold sensitivity. Mastication pain, abscess, fracture, impacted, reversible and irreversible pulpitis, on the other hand, can be divided into two linguistic categories: Yes and No. Let y symbolize the value of mastication pain, hot and cold sensitivity, abscess, fracture, impacted, reversible and irreversible pulpitis. The Z-mf specified in Eq. (11) governs fuzzy set for the terms Mild Hot, Normal Cold, and No, while the S-mf specified in Eq. (12) governs fuzzy set for the terms Extreme Hot, Extreme Cold, and Yes.

$$f_{\text{zmf}}(y) = \begin{cases} 1, & y \leq 0.45 \\ 1-2(\frac{y-0.45}{0.10})^2, & 0.45 \leq y \leq 0.50 \\ 2(\frac{y-0.55}{0.10})^2, & 0.50 \leq y \leq 0.55 \\ 0, & y \geq 0.55 \end{cases} \tag{11}$$

$$f_{\text{smf}}(y) = \begin{cases} 0, & y \leq 0.45 \\ 2(\frac{y-0.45}{0.10})^2, & 0.45 \leq y \leq 0.50 \\ 1-2(\frac{y-0.55}{0.10})^2, & 0.50 \leq y \leq 0.55 \\ 1, & y \geq 0.55 \end{cases} \tag{12}$$

Designing Fuzzy Rules

The proposed system made a decision based on fuzzy if-then rules. We chose eleven input variables: apical radiolucency, crack tooth, embedded tooth, deep cavity, shallow cavity, continuous pain, pus discharge, swelling around tooth and gums, mastication pain, sensitivity to hot and sensitivity to cold. Table 1 shows the linguistic variables for these parameters. The entire system is administered by 947 rules. The following are a few examples of the rule that have been comprised to the rule base of the fuzzy system:

Rule 1: If (Apical Radiolucency is Low Probability) **and** (Crack Tooth is Low Probability) **and** (Embeded Tooth is Low Probability) **and** (Shallow Cavity is Medium Probability) **and** (Deep Cavity is Low Probability) **and** (Continuous Pain is Moderate) **and** (Pus Discharge is Mild) **and** (Swelling Around Tooth and Gums is Mild) **and** (Mastication Pain is No) **and** (Sensitivity to Cold is Normal Cold) **and** (Sensitivity to Hot is Mild Hot) **then** (Abscess is No)(Fracture is No)(Impacted is No)(Reversible Pulpitis is Yes)(Irreversible Pulpitis is No).

Rule 751: If (Apical Radiolucency is Medium Probability) **and** (Crack Tooth is Low Probability) **and** (Embeded Tooth is Low Probability) **and** (Shallow Cavity is Low Probability) **and** (Deep Cavity is Low Probability) **and** (Continuous Pain is Mild) **and** (Pus Discharge is Mild) **and** (Swelling Around Tooth and Gums is Mild) **and** (Mastication Pain is No) **and** (Sensitivity to Cold is Extreme Cold) **and** (Sensitivity to Hot is Extreme Hot) **then** (Abscess is Yes)(Fracture is No)(Impacted is No)(Reversible Pulpitis is No)(Irreversible Pulpitis is No).

Rule 924: If (Apical Radiolucency is Low Probability) **and** (Crack Tooth is Low Probability) **and** (Embeded Tooth is Medium Probability) **and** (Shallow Cavity is Low Probability) **and** (Deep Cavity is Low Probability) **and** (Continuous Pain is Mild) **and** (Pus Discharge is Mild) **and** (Swelling Around Tooth and Gums is Mild) **and** (Mastication Pain is Yes) **and** (Sensitivity to Cold is Normal Cold) **and** (Sensitivity to Hot is Mild Hot) **then** (Abscess is No)(Fracture is No)(Impacted is Yes)(Reversible Pulpitis is No)(Irreversible Pulpitis is No).

Fuzzy Inference Mechanism and De-fuzzification

The Mamdani and Takagi–Sugeno–Kang models are the most popularly used fuzzy rule-based models. We chose the Mamdani because it can resolve fuzzy sets in if-then rules' antecedent and consequent segments. Table 1 shows eleven antecedent variables and five subsequent variables used for this study.

The Centroid method was used to de-fuzzify the system output in order to offer the dentist a standard predictive value for all classes of diseases. The de-fuzzified output Ycentroid of the centroid method is given in Eq. (13):

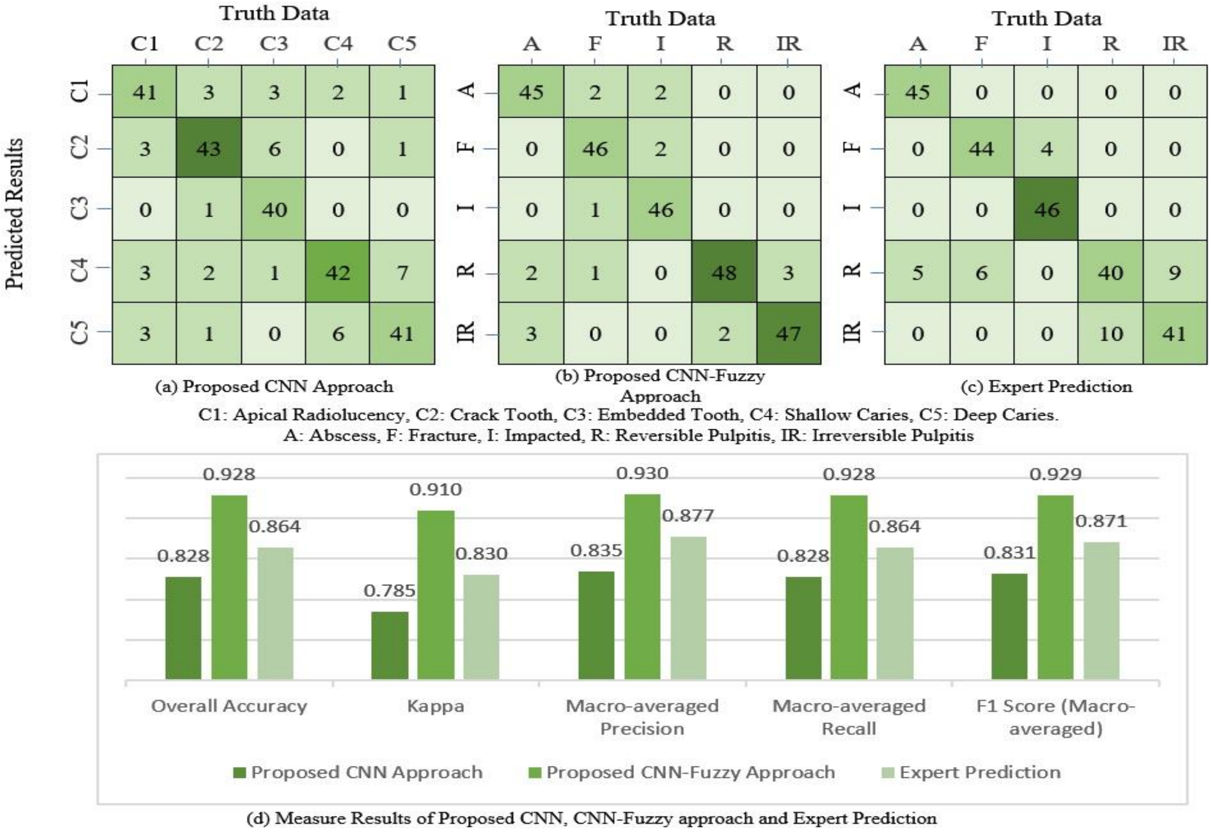
$$Y_{\text{centroid}} = \frac{\int \mu(Y).YdY}{\int \mu(Y)dY} \tag{13}$$

To determine the diseases, we look at Ycentroid. If Ycentroid > 0.5, the result is Yes; otherwise, the result is No. This is applied to all the class of diseases.

Results

This section focuses on the CNN-Fuzzy model's outcome. The proposed CNN models' results were first focused on, and then the CNN-Fuzzy models' diagnosis results were compared to a group of doctors' diagnosis results. Clinical practitioners are skilled in fusing radiographic symptoms with those described by patients or felt by them. It is advised to compare the results of its diagnosis with those of a group of physicians' diagnoses because our approach tries to develop a diagnosis using a sophisticated algorithm and mathematical formula that functions similarly to the traditional clinical approach and since there isn't a single model that can be utilized for both types of symptom-based diagnosis.

The proposed CNN architecture for classifying apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries is shown in Figure 1. To begin, the efficiency of this architecture is compared to that of the VGG16, VGG19, ResNet50, Xception, and InceptionV3 models, which are extensively addressed in the discussion section. This architecture achieved 82.80% accuracy (Figure 2 a and d), which is approximately 9.93% higher than the traditional VGG16, VGG19, ResNet50, Xception, and InceptionV3 approaches; as a result, this model is suitable for CNN-Fuzzy approaches. We tested this model with 50 images of each disease due to the limited dataset. Figure



3 (a-d) shows the predicted probability of apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries for a sample of 250 images from the testing dataset.

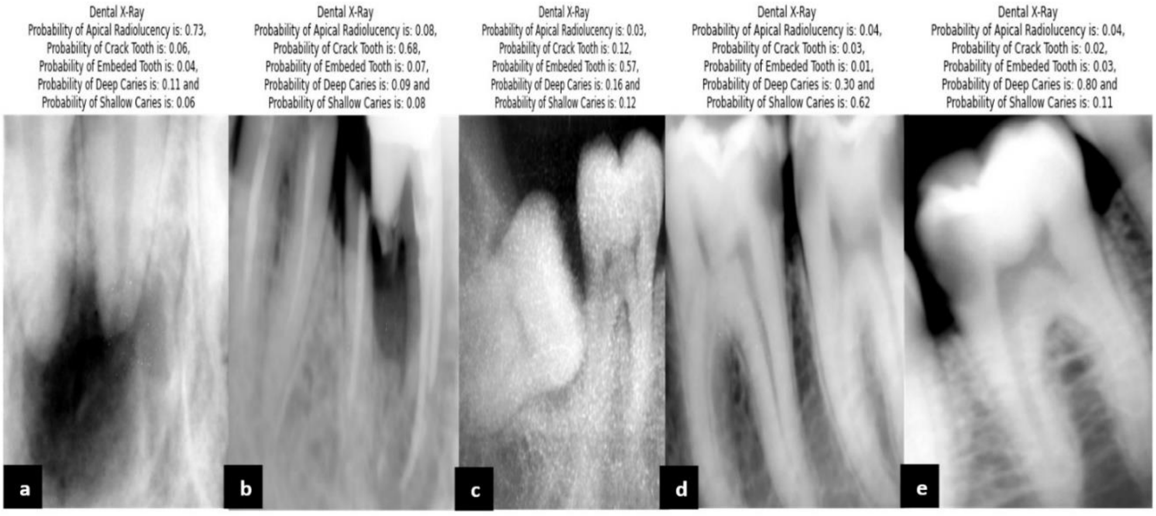
Figure 2. *Results and comparison of Proposed CNN, CNN-Fuzzy approach and Expert prediction.*

Our presented CNN model calculates the probability of apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries, which is then passed to a Fuzzy model, which merges the predicted probability of an image-based symptom with the symptoms given by the subject, which are listed in Table 1, to evaluate whether the disease is an abscess, fracture, impacted, reversible, or irreversible pulpitis. We used a completely fresh dataset of 250 images, 50 images from each class of diseases, to diagnose each dental disease, and it was unknown to both our proposed model and the group of five dentists. Figure 2 (b) shows the proposed CNN-Fuzzy model's results for disease diagnosis, whereas Figure 2 (c) shows the results provided by a group of doctors in terms of a confusion matrix. Figure 2 (d) characterizes the confusion matrixes of both by correlating the quantified results of macro-averaged precision, F1 score, overall accuracy, kappa value and macro-averaged recall. The CNN-Fuzzy approach has an accuracy of 92.8%, which is 6.4% higher than expert prediction. The highly accurate novel CNN-Fuzzy approach has proved its potential for computer-assisted diagnosis of dental diseases called an abscess, fracture, impacted, reversible and irreversible pulpitis.

Discussion

Our research question is how to accurately diagnose dental diseases because pixels in the disease region of radiographs have extremely small grey-scale value differences, creating dental disease classification challenging, and the implementation of the traditional Boolean approach in human intellectual may result in an inefficacy to estimate the severity of a symptom and radiographs when trying to diagnose dental disease. This is due to the fuzziness and ambiguity inherent in the dental diagnostic strategy. We used the CNN-Fuzzy approach to respond, which offers a mathematical approach for characterizing such vague information for disease diagnosis by connecting symptoms with radiographs.

Because of the small value differences of Gray-scale in radiographs, we require a robust classifier. Figure 1 demonstrates a highly tuned CNN-based classifier for dental diseases. We used two approaches to tune the proposed CNN's hyperparameters: Visualization of Feature Maps and Gradient-Weighted Class Activation Map (Grad-CAM). The feature maps also referred to as



activation maps, track the data that is used with filters such as image pixels. The main objective of visualizing a feature map for a specific input image is to evaluate which attributes in the feature maps are identified or preserved, which helps to tune CNN filter parameters. Figure 4 (a-e) represents a sample of the model's activation maps for proposed diseases.

Figure 3. *Result of predicted probability for* ***(a)*** *apical radiolucency,* ***(b)*** *crack tooth,* ***(c)*** *embedded tooth,* ***(d)*** *deep caries, and* ***(e)*** *shallow caries using the proposed CNN approach.*

Figure 4. *Activation maps of Convolutional Layer 1 for **(a)** apical radiolucency, **(b)** crack tooth, **(c)** embedded tooth, **(d)** deep caries and **(e)** shallow caries.*

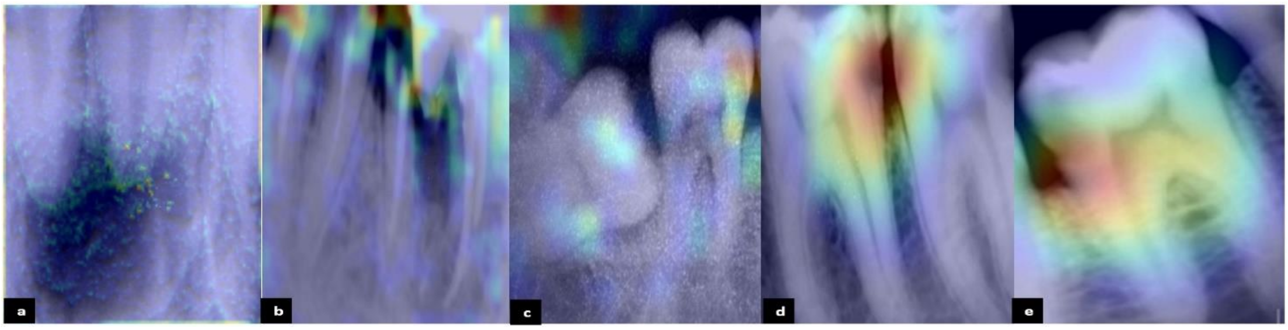
Grad-CAM, created by Selvaraju et al. [17], is a method that offers a graphic view of deep learning methods. Grad-CAM creates a graphic summary for deep CNN, which guides for model selection when performing classification or prediction tasks. The presented model is used to detect dental diseases on an x-ray image. Grad-CAM was computed for class X classification as a weighted summation of each feature map produced by the CNN's final convolution layer [18].

$$\mathrm{Grad\_Z}_X(\mathrm{p},\mathrm{q}) = \mathrm{ReLU}\left(\sum\nolimits_{\mathrm{k}} \alpha_{\mathrm{k}}^{X}\, \mathrm{f_k}(\mathrm{p},\mathrm{q})\right) \tag{14}$$

Grad-CAM is defined for class X as ZX, where α_k^X is the weight gained by calculating the gradient of a prediction score concerning the kth feature map and f_k(p, q) is the activation at the spatial element (p, q) in kth feature map.

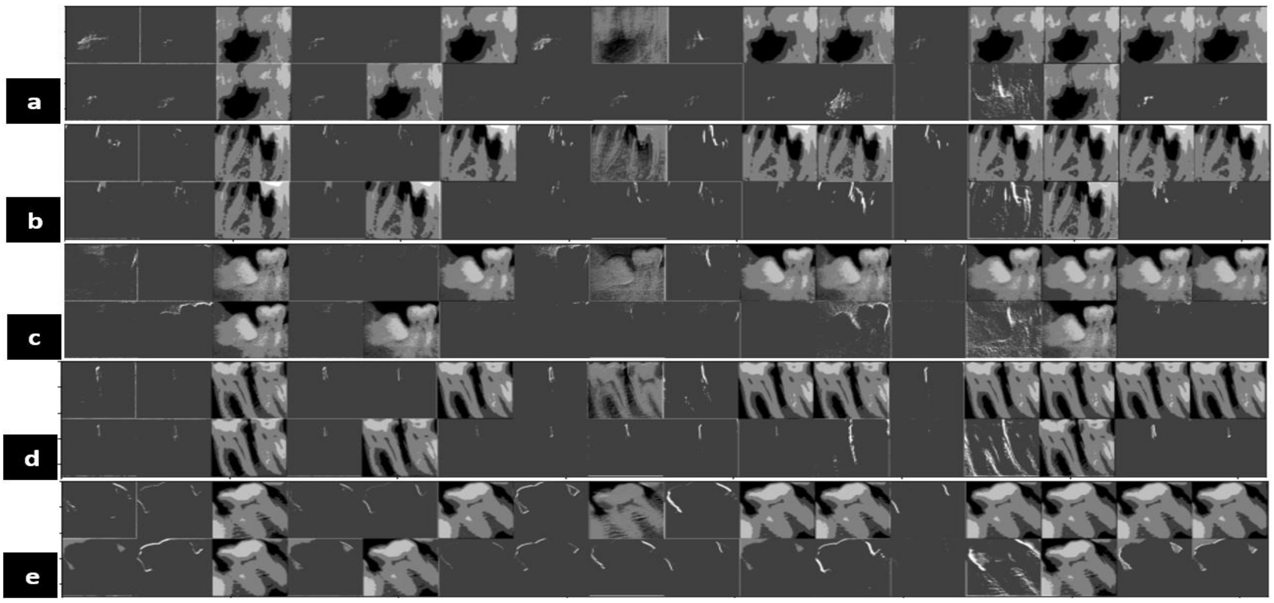
Grad-CAM is applied to all layers of the proposed network after the model quantifies the predicted label. Figures 5(a-e) depict Grad-CAM-based visualizations of diseases from the proposed model.

Figure 5. *Grad-CAM visualisations of for **(a)** apical radiolucency, **(b)** crack tooth, **(c)** embedded tooth, **(d)***



*deep caries and **(e)** shallow caries.*

Both approaches, Visualization of Feature Maps and Grad-CAM, aid in fine-tuning the CNN model hyperparameters shown in Figure 1. We compared the accuracy shown in Table 2 of our model to the results of standard models such as VGG16, VGG19, ResNet50, Xception, and InceptionV3 after



fine-tuning the hyperparameters of the proposed CNN model.

Table 2. *CNN Based Models' Accuracy.*

Model	Accuracy (in %)
VGG-16	70.43
VGG-19	71.57
ResNet50	70.59
Xception	72.87
InceptionV3	72.36
Proposed Approach	82.80

Our method achieved an accuracy of 82.80%, which is about 9.93% higher than traditional methods.

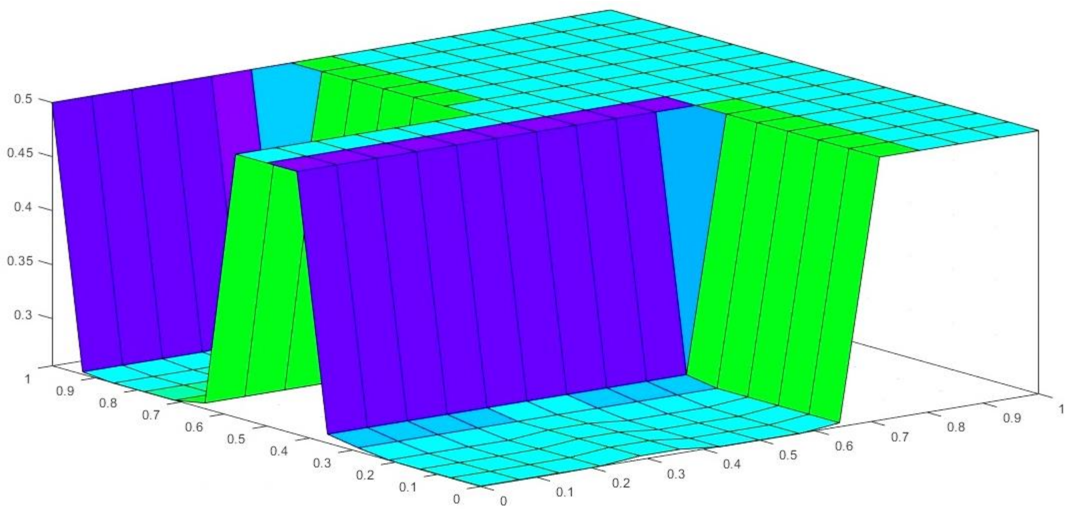
Once our CNN predicted the probability of an apical radiolucency, crack tooth, embedded tooth, deep caries, and shallow caries, we combined it with symptoms associated with them and used it as an input variable in our CNN-Fuzzy model, which is governed by 947 rules. Figure 6 shows a surface view of all dental disease diagnosis rules. The CNN-Fuzzy approach has a 92.8% accuracy, which is 6.4% higher than an expert prediction, demonstrating its potential for a computer-aided clinical decision-making system for dental diseases. According to the literature, the majority of research focuses solely on image-based diagnosis, and there isn't a single model that provides a diagnosis based on both types of symptoms. However, a limited set of literature has worked on diseases that are similar to our proposed diseases, and table 3 compares their accuracy to our approach. It demonstrates that the CNN-Fuzzy approach outperforms the literature-recommended approach and expert predictions in terms of accuracy.

Table 3. *Comparison of Proposed Models' Accuracy with Other Approach Found in Literature.*

Sr. No.	Author Name	Method Used	Diseases Name	Accuracy
1	Tuan et. al. [7]	Fuzzy Based	Cracked, Hidden, Cavities, Missing, Periodontitis	91.30%
2	Prajapati et. al. [8]	CNN (Architecture: VGG-16)	Dental caries, Periapical infection and Periodontitis	88.46%
3	Fakhriyet. al. [19]	Random Forest	Normal, Abscessed, and Impacted tooth	71.46%
4	Proposed Method	CNN-Fuzzy	Abscess, Fracture, Impacted, Irreversible Pulpitis and Reversible Pulpitis	92.80%

The CNN-Fuzzy system's diagnosis is consistent with dentists' predictions. We conclude that the proposed approach is functioning in a similar manner to the general intelligence of the dentists as it has been thoroughly verified and the diagnosis given by the system is consistent with those provided by dentists. This increases trust in the system's ability to assist dentists in diagnosing dental diseases by minimizing false diagnoses. This approach provides dentists with a "second view" kind of service and might be able to minimize the current false diagnosis problem in dental practices.

Our proposed approach has a few limitations. First of all, because our CNN model was trained exclusively on periapical x-ray images, it cannot diagnose on other dental x-ray images. The second



limitation is that our model's diagnosis options are restricted to pulpitis disorders that are both reversible and irreversible, abscesses, fractures, and impacted teeth. Thirdly, we had only taken into account a small number of symptoms, which had an impact on our approach's ability to accurately diagnose the patient. In the future, these limitations will be overcome by training models using databases of additional disorders in addition to those mentioned above and various dental x-ray forms, such as bitewing, panoramic, occlusal and CBCT images. Additionally, we can incorporate more sensor-based patient symptoms to further improve diagnostic accuracy. The tremendous potential of these CNN-Fuzzy approaches may prove to be very promising in developing symptom and radiograph-based computer-aided clinical decision-making systems for other dental diseases from all types of dental radiographs.

Figure 6. *Surface view of all CNN-Fuzzy model rules for dental disease diagnosis.*

Conclusions

To aid dentists in clinical decision-making, a CNN-Fuzzy-based approach was developed. An expert can use this method as a "second view" to assist in the diagnosis of abscess, fracture, impacted, reversible and irreversible pulpitis. Dentists frequently struggle to diagnose diseases due to the ambiguity and impreciseness of the sign-symptom values, as well as the extremely small value differences of pixels in the Gray-scale in the disease region of radiographs, making dental disease classification difficult and leading to misdiagnosis. The CNN-Fuzzy approach's accuracy is 92.8%, which is 6.4% higher than an expert prediction, proving its ability for computer-aided clinical decision-making systems of dental diseases and also increasing confidence in the dentist's decision-making, leading to more efficient disease diagnosis.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable.

HUMAN AND ANIMAL RIGHTS

No animals/humans were used for studies that are the basis of this research.

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

Not applicable.

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CONFLICT OF INTEREST

The authors declare no conflicts of interest, financial or otherwise.

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