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An Ensemble CNN-Based Model for Detection of Dental Caries

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Convolutional Neural Network (CNN), ResNet, DenseNet, EfficientNet, Dental Caries.

ABSTRACT

One of the most widespread oral diseases in the world is dental caries, and in order to avoid serious complications and loss of teeth, it should be detected in time and correctly. Conventional ways of diagnosis are based on visual inspection and radiographic evaluation by dental care providers and may take a long time and may be prone to inconsistency. To overcome these problems, this paper presents an ensemble Convolutional Neural Network (CNN)-based architecture that is used in the automatic detection of dental caries on the basis of dental radiographs. The offered framework combines several CNN models that together can use their complementary advantages in features extraction and classification, thus increasing detection and robustness. The model makes use of pre-trained CNN networks like ResNet, DenseNet, and EfficientNet with a transfer learning to derive deep features of dental images. These models are optimized using standard dental caries labelled datasets and predictions are clustered with ensemble methods, including weighted averaging and majority voting. Normalization, contrast enhancement, and data augmentation are image preprocessing techniques that are used to enhance generalization of models. The experimental outcomes prove that the ensemble model works better than the single CNN models in accuracy, precision, recall, and F1-score and minimizes false positives and false negatives. The suggested solution is a valid and effective dental caries detector that will identify changes in oral health and assist clinical decision-making based on the automated detection of dental caries.

INTRODUCTION

Dental caries or dental cavity is one of the most prevalent oral health issues in the whole world and occurs in any age group. They come as a result of gradual erosion of tooth enamel by bacteria activities which results into development of small holes or lesions in the teeth. The dental caries development should be detected early to avoid further worsening, discomfort, and even loss of teeth. Historically, dentists depend on visual inspection and radiographic visualization e.g. bitewing X-rays to detect cavities. These methods are however subjective and most of the time rely on the experience of the practicing practitioner and this can lead to missed lesions at an early stage or even unreliable diagnoses.

Figure 1: Sample Dental Image

Due to the rapid progress of AI, the application of DL and IP methods has become one of the potent technologies to detect dental caries automatically. Deep learning models especially Convolutional Neural Networks (CNNs) can learn complicated patterns on the dental images and detect the slight details related to cavities. Image processing methods also advance the quality of the image by increasing the contrast, decreasing noise and outlining important areas of interest within the image. Combining these technologies allows the creation of intelligent technologies that will help dentists diagnose patients correctly and in time, which will lead to improved patient outcomes and the load on health workers reduces.

Although sophisticated imaging procedures are available, dental cavity detection is a problematic issue because of fluctuations in the image quality, overlapping tooth structures, and noise and artifacts during dental radiographs. Manual diagnosis is also time consuming and also is highly subject to human error particularly in identifying caries at their initial stage, which might not be easily visible. Also, it lacks standardized diagnostic procedures, and hence, the variability in clinical judgment is observed and can influence treatment results. These have emphasized the necessity to have an automated and credible system which can identify dental cavities with high precision on a regular basis.

In addition, the current methods of automation are usually limited by lack of sufficient amounts of training data, poor generalisation between different sets of data, and the inability to efficiently capture local and global details of dental images. Most of the models only deal with either deep learning models or conventional image processing models, and never combine the power of the two methods. Thus, a hybrid structure that combines deep learning with sophisticated image processing methods is required to improve the extraction of features, the level of detection and create a powerful tool to diagnose dental cavities.

LITERATURE SURVEY

Fan et al. [7] suggested a deep learning-based model of the diagnosis of dental caries in terms of the use of OCT images. The suggested solution involves deep learning frameworks (and, specifically, Convolutional Neural Networks or CNNs) and automatically derives meaningful features of an OCT image and labels dental tissues as healthy or carious. Image preprocessing algorithms can be used to improve quality and minimize noise in an image to improve the performance of a model. This system is trained and tested on labelled OCT images, and it has good accuracy, precision, recall, and F1-score to detect dental caries. The experimental findings indicate that the deep learning-based approach is superior to the conventional diagnostic methods because it can help identify the presence of subtle changes in the structure of dental tissues. The study presented by Vijay et al. [8] suggests a hybrid learning system to detect caries in the mouth with the usage of X-rays, combining the latest deep learning algorithms with the conventional machine learning approaches. The proposed system will focus on improving the level of diagnostic accuracy and an effective automated system to detect carious lesions. The framework includes image preprocessing and feature extraction methods in order to improve the quality of dental X-ray images and record the appropriate patterns related to caries. The high-level features are obtained using a deep learning model and are subsequently fused with the traditional classifiers (K-Nearest Neighbors (KNN)). Hybrid model performance is contrasted with the stand alone KNN in order to assess the enhancement in the accuracy and robustness.

The article Fitria et al. [9] showed the creation of a dental caries detection intraoral clinical image dataset, which is tailored to deep learning. The dataset is built based on high-resolution intraoral images gathered in the clinical setting, which will guarantee inter-patient population diversity, as well as differences in lighting and caries severity levels. The process of dataset development involves the acquisition of the image, expert annotation of the data, data cleaning and the preprocessing to achieve accuracy and consistency. To achieve a valid ground truth, dental professionals label the images manually and determine the carious and non-carious locations to use in training and evaluation. Other measures like normalization of images, image augmentation and image quality evaluation are undertaken to improve the utility of datasets. Dhake et al. [10] introduced a general survey of the field of dental disease detection in terms of the quality of deep learning algorithms when applied to different radiographic imaging modalities. The survey considers a broad variety of deep learning models, such as Convolutional Neural Networks (CNNs), transfer learning-based models, such as ResNet, VGG, DenseNet, and the latest architectures, including U-Net and attention-based networks, which proved to be effective in the detection of caries and other oral diseases.

Pravinbalaji et al. [11] suggested a sophisticated deep learning framework to detect and classify comprehensive caries in the dental area through a multi-modal based on the YOLOv8 and cascading learning models. The suggested system to use is based on the use of various imaging modalities such as intraoral pictures and dental X-rays that offer more comprehensive and dependable evaluation of caries. The model uses YOLOv8 to detect object locations in real-time and identify possible carious sites in dental images, and then a cascaded deep learning system to identify the detected carious sites in various steps of caries. Pre processing of images like normalization, contrast enhancement and augmentation are used to enhance the robustness of the model. Multi-modal integration of the features of various imaging sources increases the potential of the model to detect both the surface-level and structural abnormality. The authors

Preethika et al. [12] came up with a deep learning-based system that would recognize dental caries on mobile intraoral images that had gone through the pre-processing stage with the intention of offering a convenient and accurate diagnostic tool. The advanced image preprocessing techniques that the proposed approach uses include normalization, contrast, noise, and region-of-interest extraction to enhance the image quality and emphasize the important dental structures. The methodology to achieve this is a deep learning model, including a Convolutional Neural Network (CNN) based on transfer learning which is used to automatically extract discriminative features and classify an image as a carious or not.

The researchers suggested a framework to identify dental caries on pre-processed mobile intraoral images based on the DL, which is expected to offer an easy-to-use and accurate diagnosis tool (Saini et al. [13]). The suggested method will encompass the high-end image processing features, such as normalization, contrast-enhancement, noise-reduction, and the extraction of regions-of-interest, to enhance the quality of images and outline the dental structures of interest. A CNN with transfer learning is used as a deep learning model that automatically uses discriminative features and classifies images as carious or non-carious. The findings suggest that combining the use of preprocessing and deep learning can dramatically improve the accuracy of detection, even in the problematic imaging environments. Ying et al. [14] suggested a deep-learning-based solution to the problem of caries segmentation of dental X-ray images, which allows the automatic and accurate localization of abnormal areas. The suggested architecture is based on a deep neural network, e.g. a U-Net design or an encoder-decoder system, used to segment pixels with caries on them. This model is trained with annotated dental X-ray images with carious areas marked by dental professionals. Noise reduction, contrast enhancement and normalization are employed as preprocessing methods to enhance image quality and segmentation performance. The network is trained locally and globally to effectively mark carious regions even in the problematic ones where the structures intersect.

ENSEMBLE CONVOLUTIONAL NEURAL NETWORK (CNN)

Dental caries is one of the most common oral diseases in the world, as it can occur in people of all age groups, causing them pain, infection and even loss of teeth in the event of a late diagnosis. Proper and prompt diagnosis is the key to successful treatment and prevention of the deterioration of the disease. Historically, the methods of dental caries detection have been based on the visual examination and radiographic assessment, including the bitewing X-rays, carried out by the dental practitioners. Nevertheless, these are mostly subjective, time-consuming and rely on the expertise of the clinician making them prone to inconsistent diagnosis particularly at the early stages of caries where the visual signs are delicate.

As a result of the development of the artificial intelligence, Convolutional Neural Networks (CNNs) have become an impressive device used in automated image analysis in dental practice. CNNs are capable of learning complicated characteristics of dental images and detecting patterns related to carious lesions with high precision. Nevertheless, individual CNNs can be limited to the ability to describe various features because of differences in image quality, lighting, and anatomy of different patients. These difficulties may result in decreased generalization and inconsistency of the performance when used in actual clinical information.

Ensemble CNN methods have been proposed to address these drawbacks, in which several CNN models are jointly trained to enhance detection capability. Ensemble learning uses the merits of the various models, including ResNet, DenseNet, and EfficientNet, to learn complementary features and increase the classification accuracy. Ensemble CNN models reduce errors, improve robustness and offer more reliable results by combining predictions of several networks via strategies such as averaging or voting. Such a strategy may serve as an effective way to use automated dental caries detection to assist clinical decision-making and promote intelligent dental care systems.

Step-by-Step Process of Algorithm

The input layer is the start point, where the dental images of either the X-ray or intraoral images are fed to the system. The images can be of different sizes, quality and lighting effects. The images are resized to a constant size that can fit into deep learning models so that they have uniformity. It is the point of the system where raw dental data are injected to undergo further processing. Then, the preprocessing layer that boosts the quality of the input images to improve the quality of the model follows. Normalization, contrast enhancement and noise removal are some of the techniques used in this stage. Such operations are useful in bringing out significant dental structures, including enamel and possible carious structures, and even suppressing the undesired artifacts. This is an important step since deep learning models are dependent on high-quality data as input data to learn the features.

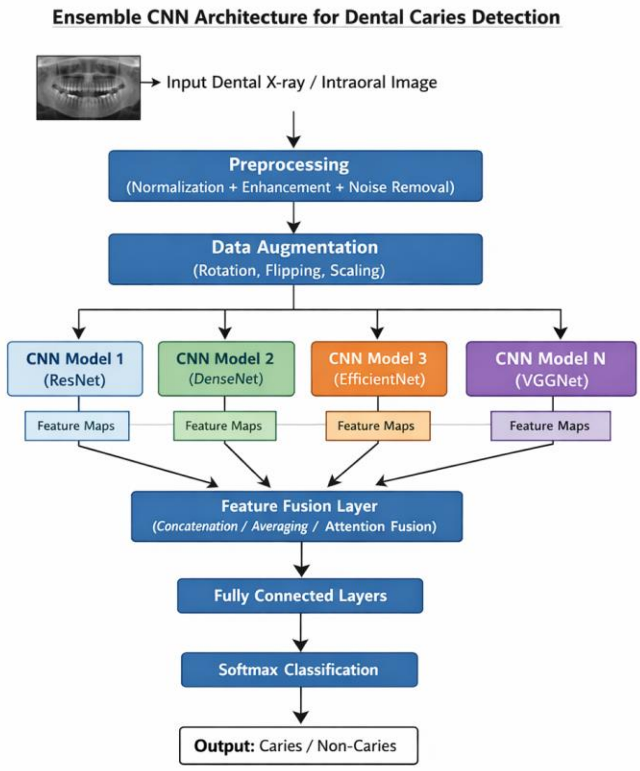

Figure 2: Architecture Diagram for Ensemble CNN

After preprocessing, the data is fed through the data augmentation layer whereby the dataset is synthetically enlarged by manipulations, like rotation, flipping, scaling and translation. This assists the model in generalizing more since it is exposed to different orientations and conditions of dental images. It further minimizes overfitting and enhances robustness when dealing with small data. This augmented data is introduced into various parallel networks in the feature extraction layer that comprises of various CNNs including ResNet, DenseNet, EfficientNet and VGGNet. The inputs are processed with each CNN and give us unique feature maps of such patterns as edges, textures, and regions of cavity. As the models are of different architecture, they reflect complementary features, which will lead to a higher representation of dental caries.

The outputs of the network of all CNN models are subsequently added together in the feature fusion layer after feature extraction. This layer combines the feature maps with the methods of concatenation, averaging, or attention-based fusion. This is aimed at developing an integrated feature representation that has the merits of each of the respective models. This integration enhances the caries detection capability of the system to a large extent, particularly in fine and sophisticated patterns. These combined features are then forwarded to a fully connected layer which is a high level reasoning unit. This layer converts a combination of features to a form understandable by classification based on learning complex relationships between extracted features and classes of output. It serves more or less as a decision making point prior to ultimate prediction.

DATASET DESCRIPTION

The Dental Cavity Detection Dataset is a very large set of dental images to be used in the process of automated cavity detection by using deep learning methods. It normally comprises many labeled images of two classes of cavity (caries) and non-cavity (healthy teeth) to provide a balanced representation of a successful model training. As an experiment, the data is usually split into training and testing, with the training set being approximately 80% of all images and the testing set being 20%. As an example, when working with a set of approximately 3,000 images approximately 2,400 are used to train the model and 600 images are used to test the model. Images are scanned as dental X-rays or intraoral cameras and annotated by specialists where it is necessary to guarantee the accuracy. The dataset is varied in terms of lighting, angle, cavity severity and thus suitable in building strong and scalable dental caries detection algorithms.

PERFORMANCE METRICS

The programming environment and specialized libraries in image processing and model development are among the software requirements of dental cavity detection based on deep learning. The system is generally coded in Python and facilitated by NumPy and Pandas to process data, OpenCV and PIL to handle image preprocessing, and Matplotlib and Seaborn to visualize the data. To develop deep learning models, methods like Frameworks like TensorFlow, Keras and PyTorch are utilized to build and train CNN or ensemble models. Such development tools as Jupyter Notebook or Google Colab can be used to flexibly experiment, and a database such as MySQL or MongoDB can be used to store image data and results. All these software tools make it possible to efficiently preprocess, train, evaluate, and deploy dental caries detection systems. The hardware specifications will be based on the complexity of the deep learning models and the dataset size. To implement a simple system, one will need a computer with an Intel i5/i7 processor, 8-16 GB RAM, and SSD storage. Nevertheless, a system with a GPU (in particular, NVIDIA CUDA-enabled GPUs) can be used to perform the training much faster and process large amounts of data as it is capable of computing the deep learning operations significantly faster. Scalable computing resources, high-performance storage, and the ability to process data in parallel can be offered with the help of the cloud platforms such as Google Cloud, AWS, or Microsoft Azure in large-scale or real-time applications. More expensive systems of 32 GB RAM and multi-core processor support better performance and less training time. The performance metrics in the classification are applied to assess the effectiveness of the proposed model to identify dental cavities. Important measures are accuracy, which is a measure of overall correctness and precision, which is a measure of how many cases that are predicted as cavity are actually correct, and recall (sensitivity), which is a measure of how many cases which are actually cavity are actually recognized by the model. F1-score is a balanced measure of precision and recall which is particularly significant in case of medical datasets. Besides, specificity quantifies the proper identification of non-cavity cases, checks the model to be able to distinguish between classes. These measurements will guarantee that the entire evaluation of the model is conducted to show its dependability and efficacy in detecting dental caries.

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}}$$

$$\mathrm{Pre} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$\mathrm{Sn} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\mathrm{Sp} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$$

$$F1S = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

RESULTS AND DISCUSSIONS

Table 1 shows the quantitative performance analysis of three models, CNN, ResNet101, and the proposed approach, on dental cavity detection on using conventional classification metrics. Base CNN model has moderate performance with the accuracy of 88.45, precision of 89.43, and sensitivity of 90.67 (Sn) which implies it can identify cavities but with certain limitations of dealing with complex patterns and false alarms. The deeper architecture ResNet101 achieves higher results of 93.45% accuracy, 94.12% precision, and 93.89% sensitivity, and thus, a higher feature extraction ability and improved classification. It is also more specific (92.67) and F1-score (91.67) which means that it is more balanced in performance than the basic CNN model. Conversely, the proposed method is much better in all the metrics with an accuracy of 98.67%, precision of 97.91, sensitivity of 98.67, specificity of 98.67, and F1-score of 98.67. These findings show that the model is capable of identifying cavity and non-cavity cases with low errors. The sensitivity level is high such that nearly all cavity cases are properly recognized whereas the specificity is high and enforces recognition of healthy teeth. Also, the F1-score is high, which is a well-balanced model with the low false positives and false negatives. All in all, the suggested solution is stronger, more reliable and effective in the detection of dental caries than traditional and deep learning frameworks.

Table 1: Quantitative performance of Algorithms

Parameters	CNN	ResNet101	Proposed Approach
ACC	88.45	93.45	98.67
Pre	89.43	94.12	97.91
Sn	90.67	93.89	98.67
Sp	88.89	92.67	98.45
F1S	87.23	91.67	98.67

CONCLUSION

This paper introduces an Ensemble CNN-based model to detect dental caries automatically. The proposed method with several CNN architectures is very effective at extracting various and complementary features of dental images resulting in better detection accuracy and robustness. The combination of preprocessing and data augmentation also promotes the quality of the input data and model generalization so that it can safely operate under different imaging conditions. The results of the experiments prove that the ensemble model performs much better than single CNN models in terms of accuracy, precision, recall, and F1-score, as well as it minimizes the number of false positives and negatives. Subtle carious lesions and more complicated patterns in dental images can be more effectively discovered by the model through feature fusion and ensemble strategies. In general, the suggested system is an extremely efficient, precise, and scalable system of dental caries detection, which can aid in clinical decision-making and lead to the further development of AI-based dental care systems.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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