DENTISTRY IMAGE CLASSIFICATION USING MACHINE LEARNING

JUNE 1, 2023

Abstract

This review paper discusses the potential of machine learning (ML) algorithms in addressing the challenges associated with dental image analysis. Dental imaging using ML-based algorithms has emerged as a promising solution to improve the accuracy and efficiency of dental care by automating the process of disease detection, diagnosis, and treatment planning. The article highlights the existing solutions for dental image analysis using ML, including CNN, SVM, and deep learning algorithms, and explores the challenges associated with dental image analysis, such as limited availability of dental image datasets, low image quality, and lack of standardized protocols for data collection and analysis. Furthermore, the review article provides insights into the potential applications of ML-based dental image analysis in dental care, including early detection and diagnosis of dental diseases, treatment planning, and patient monitoring. The paper concludes by identifying gaps in the literature and suggesting future directions for research in this area, emphasizing the potential of ML-based dental image analysis in improving the accuracy and efficiency of dental care.

CONTENTS

1. Introduction

Dentistry image classification is a rapidly growing field that involves the use of machine learning models to accurately identify dental conditions in medical images. This technology has significant potential for enhancing the quality of dental care and improving patient outcomes. Dentists and dental technicians can use this technology to detect dental issues at an early stage, which can prevent the progression of the disease and lead to more effective treatment.

One of the main advantages of using machine learning models for dentistry image classification is that they can identify dental conditions with a high degree of accuracy. These models can be trained to identify different types of dental conditions such as cavities, gum disease, and oral cancer. Once trained, these models can quickly and accurately analyze dental images, providing dentists and dental technicians with valuable diagnostic information. Another advantage of using machine learning models for dentistry image classification is that they can improve the efficiency of dental care. These models can quickly analyze large numbers of images, allowing dentists to diagnose dental conditions more quickly and accurately. This can lead to more effective treatment plans and faster recovery times for patients.

The motivation behind dentistry image classification is to provide accurate and efficient dental diagnosis to patients. Traditional dental diagnosis can be time-consuming, and may not always be accurate. With the help of machine learning models, dentists and dental technicians can accurately and quickly identify dental conditions, allowing for more effective treatment plans and improved patient outcomes. This technology has the potential to revolutionize the field of dentistry, making dental care more accessible, efficient, and effective.

This review paper examines the current state of dentistry image classification using machine learning (ML) algorithms. We analyzed 15 papers published from 2017 to 2023, and selected the five best papers for detailed methodology discussions. Our analysis includes the types of images used, algorithms applied, and accuracy achieved in each study. Additionally, we identify the challenges associated with dentistry image classification and the potential future scope of this research area. Finally, we come to a conclusion based on the current state of the field and suggest areas for future research.

2. Problem Definition

Dental care is an essential aspect of maintaining good oral health, preventing dental diseases, and ensuring overall well-being. One of the major challenges in dental care is early detection and diagnosis of dental diseases, such as dental caries, periodontitis, and oral cancer. Traditional methods of dental examination, such as visual inspection and radiographic imaging, have several limitations in terms of accuracy, reliability, and cost-effectiveness.

To address these challenges, dental imaging using machine learning (ML) algorithms has emerged as a promising solution. ML-based dental image analysis has the potential to improve the accuracy and efficiency of dental care by automating the process of disease detection, diagnosis, and treatment planning.

However, the adoption of ML-based dental image analysis is still in its early stages, and there is a need to review the existing solutions and assess their effectiveness, limitations, and challenges. The problem statement of this review article is to provide a comprehensive overview of the current state of knowledge on dental care using dental image with ML, including the methods, techniques, and algorithms used for dental image analysis.

The review will focus on the existing solutions for dental image analysis using ML, including convolutional neural networks (CNN), support vector machines (SVM) and deep learning algorithms. The article will also explore the challenges associated with dental image analysis, including the limited availability of dental image datasets, low image quality, and the lack of standardized protocols for data collection and analysis. The review article will also provide insights into the potential applications of ML-based dental image analysis in dental care, including early detection and diagnosis of dental diseases, treatment planning, and patient monitoring. The article will conclude by identifying the gaps in the literature and suggesting future directions for research in this area.

In summary, this review article aims to provide a comprehensive and critical analysis of the existing solutions for dental care using dental image with ML. By doing so, it will contribute to the development of effective and reliable ML-based dental image analysis methods for improved dental care.

3. Related Work

Several research studies have investigated the use of machine learning (ML) algorithms for dental image analysis in recent years, with the goal of improving the accuracy and efficiency of dental care.

[1] In 2018, Lee et al. evaluated deep CNN algorithms for detecting and diagnosing dental caries on 3000 periapical radiographs, achieving diagnostic accuracies of 89.0%, 88.0%, and 82.0% for premolar, molar, and both premolar and molar models, respectively, using transfer learning with a pre-trained GoogLeNet Inception v3 CNN network for preprocessing.

[2] In 2019, Liu et al. proposed a Smart Dental Health-IoT Platform with intelligent hardware, deep learning, and mobile terminal. They collected 12,600 clinical images from 10 dental clinics and trained an automatic diagnosis model using MASK R-CNN for detecting and classifying 7 dental diseases with up to 90% accuracy, high sensitivity, and specificity.

[3] In 2020, Geetha et al. developed a dental caries diagnostic system using Laplacian filtering, adaptive threshold, morphological operations, statistical feature extraction, and back-propagation neural network on 105 intra-oral digital radiography images. Their system achieved an accuracy of 97.1%.

[4] In 2022, Andac Imak et al. proposed a novel approach for automatic diagnosis of dental caries based on periapical images. Their model used a score-based multi-input deep convolutional neural network ensemble (MI-DCNNE) with both raw and enhanced periapical images. The model achieved an accuracy score of 99.13% on a dataset of 340 images covering both caries and non-caries images.

[5] In 2023, Qayyum et al. proposed a semi-supervised learning approach for dental caries detection using a fully labeled dental radiographic dataset of 141 images. The proposed self-supervised learning strategy achieved performance improvement of approximately 6% and 3% in terms of average pixel accuracy and mean intersection over union, respectively compared to standard self-supervised learning.

[6] In 2017, Singh and Sehgal used Radon Transformation and Discrete Cosine Transformation on X-Ray images, and fused a small number of features using classifiers like Decision Tree, K Nearest Neighbour, Random Forest, Naive Bayes, Sequential Minimum Optimization, Radial Basis Function, Decision Stumps, and AdaBoost. Using 93 panoramic dental pictures, the approach produced a high accuracy and positive predictive value of 86%, with the Random Forest classifier being the most efficient.

[7] In 2019, Chen et al. proposed a quicker R-CNN and a deep neural network (DNN) for teeth identification and missing teeth prediction were trained using 1250 dental X-ray images. The trained models attained a detection precision of 0.991 when compared to annotations made by three dentists.

[8] In 2019, Navarro et el. using SVM and Decision Tree methods, created a model for recognizing and finding smooth surface carious areas in frontal tooth pictures. They employed 45 photos of smooth surface dental caries and obtained accuracy of 84% and 78%, respectively, using Decision Tree and SVM. The photos were taken with an 8-megapixel smartphone camera.

[9] In 2019, Patil et al. proposed a caries detection approach based on MPCA-based feature extraction, NN classifier, and Adaptive Dragonfly optimization algorithm. On 120 digital dental X-ray pictures with labelled anomalies provided by dental specialists, the model obtained an accuracy of 95%.

[10] In 2021, Sukegawa et al. constructed a U-Net-based CNN model for caries identification on bitewing radiographs. The model was trained on 304 radiographs and attained an accuracy of 63.29% on 50 radiograph evaluations.

[11] In 2021, Ding et al. used 570 oral pictures of patients which were enhanced to 3,990 and separated into training and test sets. For primary caries detection, the YOLOv3 algorithm achieved a mean average precision (mAP) value of 85.48% with 93.33% accuracy. This study made use of images taken with a cell phone.

[12] In 2021, Rajee et al. proposed dental image classification using the Inception ResNetV2 model with segmentation using CSDCNN, where four dental illnesses, including caries, were diagnosed with an average accuracy of 94.51% on x-ray pictures.

[13] In 2021, Majanga et al. created a caries detection system by combining blob detection, a sequential model in Keras, and a convexity threshold value of 0.9. The method used 120 dental radiographs (augmented to yield 11,114 pictures) and achieved a 97% accuracy. Other detection methods were surpassed by the suggested technique, resulting in efficient and dependable dental care.

[14] In 2022, Thanh et al. developed a mobile-phone-based diagnostic tool for smooth surface caries detection using deep learning algorithms. The study used a training dataset of 1902 iPhone 7 photos of smooth surface teeth from 695 people. Four deep learning models were tested, with YOLOv3 and Faster R-CNN showing the highest sensitivity of 87.4% and 71.4%, respectively, for cavitated caries, and above 71% specificity for VNC.

[15] In 2022, Estai et al. used a CNN-based DL system for caries detection on 2468 bitewing radiographs. Their system achieved recall, precision, specificity, accuracy, and F1 scores of 0.89, 0.86, 0.86, 0.87, and 0.87, respectively, indicating promising results for detecting proximal surface caries on bitewings.

4. Methodology

Here, we will briefly discuss the methodologies of the five best papers selected for our review.

In [1], A unique score-based multi-input CNN ensemble (MI-DCNNE), which is used in this study's methodology, is used to identify dental caries. Pre-processing, Deep Convolutional Neural Network, and score-based fusion are the three stages that make up the system. Filters are used to clean up the panoramic raw images during the pre-processing stage, and a multi-input convolutional neural network model is created based on a previously trained deep model. The constructed multi-input CNN model is fused utilizing the score-based fusion procedure in the final stage. In order to modify the AlexNet architecture for the purpose of detecting dental caries, the suggested system uses a transfer learning methodology. In the process of score-based fusion, the output matrices of various CNN architectures are combined. A new score in MXN size is then generated using a particular equation, and class labels are established based on the maximum value of each line.

In [2], the methodology used in this study involves the semi-automatic labeling method to establish a training sample set to improve efficiency in detecting dental diseases. The dental images were initially labeled by a detector for seven types of dental diseases, followed by confirmation of images with labeling or classification errors through manual screening by dental disease experts. The training samples set was calibrated by 20 dental disease experts. The designed MASK R-CNN method was chosen for accurate detection and segmentation of the dental target. The MASK R-CNN network adds a branch predicting the segmentation mask in each interested area based on Faster R-CNN. The ResNet-50-C4 backbone is adopted for the lower convolution network used for feature extraction, and TensorFlow and Mask R-CNN open source are used in the training model. Categories NUM CLASSES, image size IMAGE MIN DIM, and the size of the anchor RPN ANCHOR SCALES are set based on the training sample library, and the method of limiting training time is adopted to avoid overfitting.

In [3], the suggested methodology for detecting dental caries entails analyzing a dataset of 105 dental X-ray pictures taken from SJM Dental College in India utilizing an intraoral Gender X-ray machine with RVG sensor. A clinician reviewed the images for caries, and caries was found by interpreting the radiodensity of the images. Following that, the images were scaled, enhanced with a Laplacian filter, then segmented with adaptive threshold and morphological processing. Sixteen statistical features were retrieved from the segmented image, and classification was performed using a feedforward backpropagation neural network (FFBPNN) with one hidden layer and sixteen input nodes and 10-fold cross-validation. The output layer had two nodes for distinguishing between caries and normal pictures, and the system's diagnostic performance was assessed using WEKA. As an activation function, the sigmoid function was utilized, and the classification performance of the system was evaluated by adjusting the number of nodes in the hidden layer, learning rate, and number of iterations.

In [4], the goal was to create a deep convolutional neural network system for automated detection of dental caries using periapical radiography pictures. 3000 periapical radiography pictures of maxillary and mandibular premolars and molars were included in the collection. Preprocessing and picture augmentation were carried out, and transfer learning was carried out using a pre-trained GoogLeNet Inception v3 CNN network. The training and validation datasets were utilized to estimate and generate ideal deep CNN algorithm weight factors, and statistical analysis was performed to evaluate the test dataset's diagnostic accuracy, sensitivity, specificity, PPV, NPV, ROC curve, and AUC. P values of 0.05 were deemed statistically significant.

In [5], the authors describe their methodology for data preprocessing, data statistics, and problem formulation in order to detect dental caries using deep learning models. They implemented a carefully designed data annotation method that involved training a team of annotators by a dental expert, annotating dental images according to expert guidelines, and validating and rectifying annotations by experts. They used the widely used tool "Labelme" for annotating dental radiographs. The final dataset contained a total of 229 dental radiographs, of which 141 were annotated and 88 were unlabeled. They formulated caries detection as a segmentation problem and used self-supervised learning to address the challenge of data annotation in medical settings. They trained the teacher model MT using the labelled dataset DL in a supervised learning fashion, and then used the unlabeled dataset DU to train the student model MS using self-training. They used binary cross entropy loss to minimize and enhance the performance of student model MS in segmenting caries regions in unlabeled dental radiographic images.

.

Comparison

Paper Number	Year	Pre-processing	Deep Learning Model	Fusion Method	Data Annotation
[1]	2018	Filters to clean up panoramic raw images	Multi-input CNN model based on transfer learning	Score-based fusion	Not discussed
[2]	2019	Semi-automatic labeling method	Mask R-CNN network with ResNet-50-C4 backbone	Not discussed	Images labeled by detector, errors confirmed by dental experts, training set calibrated by 20 dental experts.
[3]	2020	Scaling, enhancement with Laplacian filter, segmentation with adaptive threshold and morphological processing	Feedforward backpropagation neural network with one hidden layer and 16 input nodes, sigmoid activation function	Not discussed	Clinician reviewed caries images, extracted 16 features, and performed classification using FFBPNN with 10-fold cross-validation.
[4]	2022	Deep convolutional neural network system for automated detection of dental caries using periapical radiography pictures	Preprocessing and picture augmentation	Pre-trained GoogLeNet Inception v3 CNN network	Not discussed
[5]	2023	Segmentation problem formulation, Self-supervised learning, Binary cross-entropy loss	Teacher model: trained on labeled data. Student model: trained on labeled + unlabeled data using self-training	Not discussed	Expert-guided data annotation with trained annotators and expert validation.

5. Conclusion

In conclusion, the application of machine learning (ML) algorithms in image categorization in dentistry has shown considerable promise in enhancing the accuracy and efficiency of dental care. The studies reviewed have shown that ML-based dental image analysis may automate disease identification, diagnosis, and treatment planning, delivering significant diagnostic information to dentists and dental professionals.

However, significant problems remain, including the restricted availability of dental image databases, poor picture quality, and a lack of standardized processes for data collection and processing. Future research in this field should prioritize hardware design and image acquisition device efficiency, as well as the development of algorithms with improved efficiency and recognition rates, reduced false alarm rates, and lower false alarm rates.

Furthermore, the research that have been examined have indicated prospective applications of ML-based dental image analysis, such as early identification and diagnosis of dental disorders, treatment planning, and patient monitoring. These applications have the potential to increase the efficiency and effectiveness of dental care, resulting in faster recovery times and better patient outcomes.

Overall, using ML-based dental image analysis to improve dental care is a viable option, and future research in this area has the potential to make substantial contributions to the field.

6. Future Scope of the Project

The review paper on Dentistry image Classification using ML has a vast scope for future research and development. Firstly, the hardware design can be improved to enhance the quality of the dental image data collected. This can include using better lenses to avoid image blurring and ghosting during data acquisition, and expanding the lens angle to ensure complete coverage of larger teeth.

Secondly, the image capturing device can be improved to increase data collection efficiency. This can be accomplished by speeding up image acquisition, automating image processing activities, and eliminating human error in data collecting.

Thirdly, there is a need to improve the efficiency and accuracy of the algorithms used for data analysis. This can be done by exploring new deep learning models, including convolutional neural networks, support vector machines, and deep learning algorithms. Moreover, incorporating transfer learning techniques can significantly improve the accuracy of the classification models by leveraging pre-trained models to speed up the training process.

Lastly, to train the ML models, a larger dataset of dental disease photos is necessary. This can be accomplished by gathering additional dental imaging data from many sources, such as dental clinics, hospitals, and research institutes, such as X-rays, CT scans, and intraoral images. Furthermore, the dataset must be standardized to ensure consistency in data quality, annotation, and analysis among models.

Overall, the future scope of the review paper on Dentistry image Classification using ML includes improving hardware design, enhancing the image acquisition device, improving the algorithms used for data analysis, and collecting a larger dataset of dental disease images. The advancements in these areas can significantly improve the accuracy and efficiency of dental disease diagnosis and treatment planning, and ultimately improve the quality of patient care.

7. References

[1] Lee, J. H., Kim, D. H., Jeong, S. N., & Choi, S. H. (2018). Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm. Journal of dentistry, 77, 106-111.

[2] Liu, L., Xu, J., Huan, Y., Zou, Z., Yeh, S. C., & Zheng, L. R. (2019). A smart dental health-IoT platform based on intelligent hardware, deep learning, and mobile terminal. IEEE journal of biomedical and health informatics, *24*(3), 898-906.

[3] Geetha, V., Aprameya, K. S., & Hinduja, D. M. (2020). Dental caries diagnosis in digital radiographs using back-propagation neural network. Health information science and systems, 8, 1-14.

[4] Imak, A., Celebi, A., Siddique, K., Turkoglu, M., Sengur, A., & Salam, I. (2022). Dental caries detection using score-based multi-input deep convolutional neural network. IEEE Access, 10, 18320-18329.

[5] Qayyum, A., Tahir, A., Butt, M. A., Luke, A., Abbas, H. T., Qadir, J., ... & Abbasi, Q. H. (2023). Dental caries detection using a semi-supervised learning approach. Scientific Reports, 13(1), 749.

[6] Singh, P., & Sehgal, P. (2017, July). Automated caries detection based on Radon transformation and DCT. In 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE.

[7] Chen, H., Zhang, K., Lyu, P., Li, H., Zhang, L., Wu, J., & Lee, C. H. (2019). A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. *Scientific reports*, *9*(1), 1-11.

[8] Navarro, P. K., Cadongonan, J. K., Reyes, M. E., & Goma, J. D. (2019, June). Detecting smooth surface dental caries in frontal teeth using image processing. In *Proceedings of the 2019 3rd High Performance Computing and Cluster Technologies Conference* (pp. 167-171).

[9] Patil, S., Kulkarni, V., & Bhise, A. (2019). Algorithmic analysis for dental caries detection using an adaptive neural network architecture. Heliyon, 5(5), e01579.

[10] Sukegawa, S., Yoshii, K., Hara, T., Yamashita, K., Nakano, K., Yamamoto, N., ... & Furuki, Y. (2020). Deep neural networks for dental implant system classification. Biomolecules, 10(7), 984.

[11] Ding, B., Zhang, Z., Liang, Y., Wang, W., Hao, S., Meng, Z., ... & Lv, Y. (2021). Detection of dental caries in oral photographs taken by mobile phones based on the YOLOv3 algorithm. Annals of Translational Medicine, 9(21).

[12] Rajee, M. V., & Mythili, C. (2021). Dental image segmentation and classification using inception Resnetv2. IETE Journal of Research, 1-17.

[13] Majanga, V., & Viriri, S. (2021). Automatic blob detection for dental caries. Applied Sciences, 11(19), 9232.

[14] Thanh, M. T. G., Van Toan, N., Ngoc, V. T. N., Tra, N. T., Giap, C. N., & Nguyen, D. M. (2022). Deep learning application in dental caries detection using intraoral photos taken by smartphones. Applied Sciences, 12(11), 5504.Vasdev, D., Gupta, V., Shubham, S., Chaudhary, A., Jain, N., Salimi, M., & Ahmadian, A. (2022). Periapical dental X-ray image classification using deep neural networks. Annals of Operations Research.

[15] Estai, M., Tennant, M., Gebauer, D., Brostek, A., Vignarajan, J., Mehdizadeh, M., & Saha, S. (2022). Evaluation of a deep learning system for automatic detection of proximal surface dental caries on bitewing radiographs. *Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology*, *134*(2), 262-270.