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Canker and Cold Sore Classification Using Xception Technique

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***Abstract*— Especially common in nations of low and moderate-income, mouth disease was responsible for 177,384 fatalities worldwide in 2018. A cold sore is mild blistering of the lips or mouth area. Herpes simplex virus causes them, and they go away on their own in 7-10 days. Generally, the first three to four days of a canker sore are the most excruciating. Within 6-24 hours, the ulcer changes from a red, inflamed patch to a slight, circular depression of 3-9 mm in diameter. Canker sores cause tingling or burning before they become noticeable, but the pain subsides, and the sore heals in 10-14 days, generally without scarring. If canker and cold sores in the mouth could be automatically identified, early and cheap diagnosis of the condition could be achieved. Canker sores and cold sores are only two of the many oral disorders that can be detected and diagnosed using modern digital technologies. Diagnosing oral illnesses with deep learning is challenging. In this research, we used two classes, canker sores and cold sores, to build a novel technique. A new dataset, dubbed "Mouth Disease" (MD), has been created, and it splits diseases into two groups. An application of the Xception model is used to categorise the illness. Compared to previous approaches, the suggested Xception model showed superior performance, with an accuracy of 99.60%.**

Keywords—deep learning; CNN; Xception; medical diagnosis

I. INTRODUCTION

The mouth is an internal, oval-shaped cavity in the skull. The mouth is mainly used for eating and speech. The lips, vestibule, oral cavity, gums, teeth, hard and soft palate, tongue, and salivary glands are all mouth parts. The mouth's interior is also referred to as the oral cavity, buccal cavity, and mouth. Mouth and oral cancers, dental cavities, fluorosis, and other periodontal diseases are on the rise worldwide [1]. When we have an oral infection, the bacteria in our mouths can travel to the rest of our bodies via the bloodstream. When this occurs, a protein is made, causing the blood volume to increase. Reduced blood flow and oxygen to the heart raise the risk of a heart attack [2]. Canker sores, or oral mucosal ulcers, typically manifest on the inner cheeks, gums, and lips but can also display elsewhere on the mouth's mucous membranes. The tongue Lesions of aphthous stomatitis can show up randomly as a single symptom or in clusters, known as recurrent aphthous stomatitis (RAS) [3], [4]. You may feel a tingling, itchy, or burning sensation around your mouth when a cold sore first appears. Then, little ulcers filled with fluid develop, typically along the lower lip's border [5].

Numerous factors can lead to painful sores in the mouth, such as: biting your cheek, tongue, or lip, eating or drinking something too hot, having a tooth that is too sharp or fractured, and dentures that don't fit properly [6]. The herpes simplex virus is to blame for cold sores. They spread easily and rapidly. Tenderness, tingling, or burning may precede the appearance of a sore. Common symptoms of a cold sore include blistering and eventual crusting. Herpes can persist for a long time inside a host body. It doesn't manifest as a mouth sore unless one of several conditions is satisfied. These conditions include another disease, particularly one accompanied by a fever, hormonal changes (like menstruation); stress; and sun exposure [6].

You cannot spread canker sores to others. A crimson ring may surround a white or yellow ulcer. You might have just one or several. For whatever reason, women seem more likely to receive them than males. Unfortunately, we still don't know what triggers canker sores. Possible causes include hormonal shifts, insufficient vitamin B12 or folate in the diet, or getting sick and weakening your immune system [6]. The American Dental Hygienists' Association (ADAH) reports that by 17, 80% of American children will have had at least one cavity. About 80% of the population will suffer from periodontal disease by 2022 [7]. As many as one people in the United States experiences a dental emergency every fifteen seconds, sending them to the nearest emergency department [8]. The prevalence of dental caries among persons aged 20-64 was high (91%), with 27% having irreparably damaged teeth. The depth of a periodontal probe (PPD), the presence of blood during probing, and radiographic evidence of alveolar bone loss are all diagnostic indicators of gingivitis and chronic periodontitis [8].

The use of deep learning with Convolutional Neural Networks (CNN) for medical image analysis has been

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successfully implemented in healthcare to detect breast cancer, skin cancer, and diabetic retinopathy. Apical radiographs reveal bone loss around the gums, lesions at the tip of the teeth, and caries. The advent of CNN has allowed dentists to detect them with high to acceptable accuracies. Medical professionals can benefit from machine learning techniques for the early detection and diagnosis of mouth illnesses. Data from this study, such as micrographs of plaque, x-rays, and fluorescence images, can only be used for clinical purposes. Liu et al. [9] constructed a MASK using their collected data. The R-CNN technique can aid in diagnosing a wide range of oral health issues, including cavities, plaque, osteoporosis, and periodontal disease. Li et al. labelled each tooth type—incisors, canines, premolars, and molars—using deep learning.

Interest in applying deep learning to various information processing tasks, such as computer vision, text analytics, and object recognition, has recently increased. Most efforts to enhance object detection up until recently have centred on convolutional Neural Network models. CNN's have found widespread use in areas like image recognition and speech synthesis in recent years. To improve data collection and classification accuracy, CNNs are increasingly used in favor of conventional approaches. Many deep neural networks are inappropriate for mobile-based facial picture categorization applications because their evaluation during the assessment step is both time-consuming and costly.

Previous research has neglected to address the issue of canker and cold sores occurring together. Many problems hampered the work that had been done before using these methodologies. Canker and cold sores weren't included in the available datasets, although there were many others for the mouth and oral cancer. This study intends to rectify inconsistencies in the existing literature by adding canker sores and cold sores to existing dataset of the mouth and teeth that only contain caries, amalgam filling failure, molar decay grades, and mouth cancer.

The current study offered a Classified Canker and Cold Sores using Xception Method, which can identify the data set that the researchers have put together. Transfer learning models, such as Xception, were utilized to develop the model.

- To classifies Canker sore and cold sore are two classes by a Classified Canker and Cold Sores using Xception Method.
- To develop a Mouth Diseases (MD) dataset consisted of canker sore and cold sore classes.
- To improve the accuracy of the existing models.

II. LITERATURE REVIEW

To identify or diagnose oral health issues, image processing, and computer vision problems must be solved. Many research projects have examined the feasibility of using AI-based image processing, particularly DL-based image processing, to detect and analyze different types of oral illnesses. Dental caries, fluorosis, periodontitis, a cracked tooth, dental calculus, plaque, and tooth loss are only a few of the said conditions that have previously garnered the attention of scientists.

Dental periapical radiographs can diagnose oral disorders such as caries, ABR, and IRR, and a faster variant of the recurrent neural network (R-CNN) has been presented [10]. Automatic periodontitis staging utilizing a deep-learning hybrid technique was demonstrated using dental panoramic radiographs. The radiographic bone level (or CEJ level) was identified as a single structure for the entire hand using deep learning to analyze panoramic x-ray images. A novel hybrid framework could automatically identify and categorize periodontal bone loss in each tooth. In this scenario, we use a deep-learning hybrid architecture for detection and traditional CAD processing for classification [11].

Vellappally et al. [12] predicted a 99.23% accuracy rate for detecting chemicals and nutrients (salt, sugar, fat) using deep learning neural network techniques on a validated food quality dataset. Dental caries and nondental caries were identified using a GoogLeNet Inceptionv3 model pre-trained by Jae-Hong Lee et al. [13]. They used maxillary premolar 778 pictures, maxillary molar 769 images, mandibular premolar 722 images, and mandibular molar 731 images as periapical radiography data sets. The proposed model achieved a 91% success rate.

The gingival probe depth was automatically predicted utilizing training data with ground truth measurements [14] using computer vision algorithms and an off-the-shelf camera. This method was carried out to save time. Although this work predicted gingival inflammation depths with a certain degree of accuracy, Rana et al. [15] pointed out that it ignored essential parameters such as inflammation and bleeding indices, hypervascularization, and papillary margin quality.

Although the Mask-RCNN model was initially developed for the detection, localization, and instance segmentation of natural images, Johnson [14] showed that it is also capable of segmenting nuclei in a wide variety of microscopy images. With a few tweaks to Mask-RCNN, they could provide usable results. Similar to the work suggested here, we employ Mask-RCNN on a tough dataset consisting of photos of cold and canker sores that exhibit a wide range of clinical presentation and severity. In [16], the authors presented a deep learning approach for detecting various teeth diseases using the DetectNet neural network. These included radicular cysts, nasopalatine duct cysts, dentigerous cysts, odontogenic keratocysts, ameloblastomas, glandular odontogenic cysts, myxomas, myxofibromas, adenomatoid odontogenic tumours. The suggested model achieved 91% accuracy while being trained on a dataset the authors constructed. Based on self-generated dental X-ray images, a Faster R-CNN technique was proposed to recognize teeth, such as upper right, upper left, lower left, and lower right, with an accuracy of 91% [17]. A deep convolutional neural network (CNN) technique was suggested [18] using the Keras framework in Python to recognise premolars and molars (caries, restorative crowns) from the periapical radiography data set.

- Existing Technologies

Do et al. [19] recently presented a similar study for melanoma detection and segmentation, which is not in the oral health sector but is nonetheless interesting. They are primarily concerned with making mobile image analysis for identifying malignant melanoma (MM) more widely available. Melanoma (MM) is a malignant neoplasm of the epidermal pigment cells. The use of smartphone visible light photos for automatic melanoma identification was novel to their work. They say most prior efforts centered on dermoscopic pictures acquired in sterile clinical settings using expensive machinery. Within the scope of our planned work, this strategy is analogous. Using a UNet-based convolutional neural network, Fabijanska [20] suggests performing cell segmentation. The web is educated to recognize differences in pixel values at cell boundaries. Next, the network-generated edge probability map is binarized and skeletonized to produce edges no wider than a single pixel. The author used her method on a dataset of 30 corneal endothelium pictures showing varying-sized cells and found that it had an AUROC of 0.92. In the end, the DICE averaged out to 0.86.

Thomas [21] utilized the grey-level co-occurrence matrix and the grey-level run-length; Krishnan [22] operated higher order spectra, a local binary pattern, and the laws of texture energy; and many other early publications concentrated on texture-based characteristics. More recent papers [23], [23], [24], [25], [26], [27], [15], [28], [29] have made use of deep learning, which is a method for learning complex patterns that makes use of artificial neural networks that have many layers of neurons and relies on enormous datasets and rapid processing power. These articles [23], [23], [24], [25], [26], [27], [15], [28], [29] made use of a specific type of neural network called a deep convolutional neural network (CNN), the topologies of which expressly assumed that the inputs were photographs. CNN has experienced a meteoric increase in popularity within the computer vision field ever since AlexNet [30] took first place in the ImageNet [31] image categorization competition in 2012. The most important findings from the related research are presented in Table I.

TABLE I. RELATED WORK SUMMARY

Author	Title	Year	Description
Krishnan [32]	Automated oral cancer identification using mhistopathological images: a hybrid feature extraction paradig	2012	Histopathological images. Texture-based features with a fuzzy classifier used for 3-class image classification. 158 images from 42 individuals
Aubreville [32]	Automatic classification of cancerous tissue in images of the oral cavity using DL	2017	Confocal laser endomicroscopy provides in vivo cell structure images. 7894 images from 12 individuals.
Anantharaman [32]	Oro vision: Deep learning for classifying orofacial diseases	2017	Standard white light images of oral cavity structures. CNN is used for binary image classification.
Gupta [32]	Tissue Level-Based DL Framework for Early Detection of Dysplasia in Oral Squamous Epithelium	2019	Histopathological images. CNN is used for 4-class image classification. 2688 images from 52 individuals.

III. MEYHODOLOGY

A. Materials and Methods

Such self-learning algorithms are essential to the field of artificial intelligence. Such algorithms are adaptable and evolving as more information is gathered about the project. Technology to address these issues is constantly growing. These mental representations are necessary for self-learning programs to operate. Artificial neural networks (ANNs) have their nodes (neurons) connected in layers, just as real neural networks. This neural network serves as a data repository, an algorithmic processor (with positive or negative weighting), and a sensory output mechanism. ANNs' multi-tiered structure and sensitivity to minor patterns show great promise. These networks can engage in "deep learning".

B. Dataset

A dataset of sufficient quality is necessary to operate deep learning models effectively. A new dataset was created using pictures of mouth disorders (MD) found on the internet (dental sites, etc.). Cases of canker and cold sores were included in the MD dataset (see Figure 1). This dataset has two groups, and each group represents a unique collection of concerns relating to individuals' dental health. As seen in Table II that follows, we have solicited the assistance of dentists to guarantee that each of our presentations will only include images depicting the condition covered in that particular talk.

(a) (b)

Fig. 1. Canker and Cold Sores classes of Mouth Disease (MD) dataset.

TABLE II. SUMMARY OF ORIGINAL IMAGES OD (MD) DATASET

Class Labels	Samples
Canker Sores	78
Cold Sores	79
Total Samples	**157**

C. Images Resizing

The MD dataset was expanded to a new, larger size of 224 × 224 with the help of some scripts written in Python. In return for a considerable decrease in the model's usefulness, the time spent processing data will be significantly reduced.

D. Data Augmentation

The picture data generator function in the Keras library in Python allowed us to avoid over-fitting and increase the diversity of the training set. To reduce the computer's processing load, we could make all the pixel values in the same ballpark. Therefore, the parameter value (1./255) determined that the range of allowable pixel weights is 0-1 inclusive. Photographs were rotated by 25∘ using the rotation transformation. The images were transformed using a width shift range transformation technique with a width shift parameter of 0.1. This resulted in a random shift to the right or left of the image. We could make vertical modifications to the training images by setting the height shift range parameter to 0.1. A ”shear transformation” was used to get this result; this involved keeping one axis of the image fixed while stretching the other by a shear angle of 0.2. Using the zoom range feature, we arbitrarily changed the degree to which the photographs were magnified. A value greater than 1.0 indicates that the images were zoomed in, while a value less than 1.0 indicates that the images were zoomed out. The picture needed to be flipped horizontally; thus, the flip command was used. To achieve our goals, we employed a brightness transformation with a range of 0.5-1.0 (where 0.0 denotes no brightness and 1.0 indicates maximum brightness). So, we employed the same fill mode as the original with a 0.05-point channel shift to get the most faithful replication possible. As part of the channel shift transformation procedure, the channel values are shifted by a random number within the allowable range. Table III shows the results.

TABLE III. USED DATA AUGMENTATION TECHNIQUES

Transformations	Setting
Scale transformation	ranged from 0 to 1
Rotation transformation	25°
Zoom transformation	0.2
Horizontal flip	True
Shear transformation	20°

E. Training, Validation, and Testing

The MD dataset was split into training, validation, and test sets. While the training dataset was used to teach the model, the validation and test datasets were used to measure its accuracy and decide whether it was effective. In light of this, we divided our data set into 60% for training, 20% for validation, and 20% for testing. According to the information presented in Table IV, a total of 1638 photographs were utilized throughout the various stages of the construction and evaluation of the MD dataset. In the current study, the researchers trained their model on 60% of all pictures categorized as either a canker sore or a cold sore. Using the MD dataset, the remaining 40% of the new photographs were randomly selected to participate in either a validation or testing phase. The proposed Classified Canker and Cold Sores using Xception Method successfully predicted the labels for each image in a dataset of periodontal images. The dataset was comprised of images.

TABLE IV. SPLIT (MD) DATASET AFTER DATA AUGMENTATION

Split	Classes	Label Samples	Total Samples
Training	Canker Sores	480	1020
	Cold Sores	540	
Validation	Canker Sores	160	309
	Cold Sores	149	
Testing	Canker Sores	160	309
	Cold Sores	149	
Total			**1638**

F. The Proposed Methodology: Xception Base Model

To connect the depth-separable convolution process with the conventional convolution used in convolutional neural networks, scientists have developed inception modules (a depthwise convolution followed by a pointwise convolution). By analogy, an Inception module with a fixed maximum height can be thought of as a depthwise separable convolution. Based on these results, we present a unique design for a deep convolutional neural network in which depthwise separable convolutions are used in place of the Inception modules. We show that Xception [33], our design, outperforms Inception V3 on a larger, more comprehensive image classification dataset consisting of 350 million images and 17,000 classes. On the ImageNet dataset, however, Xception [33] performs somewhat better than Inception V3 (for which Inception V3 was built). Since the amount of parameters in the Xception architecture is the same as that of the Inception V3 architecture, the performance improvements are attributable to the Xception design’s more efficient use of model parameters rather than its larger capacity. The bare bones of the Xception architecture are shown in Figure fig:Incep-Arch.

G. Evaluation Measures

- Classification Accuracy:

The accuracy of a classification system can be evaluated by determining what percentage of its predictions were correct and what percentage were incorrect.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{1}$$

- Precision:

When analyzing the effectiveness of a model, classification accuracy may not always be the most appropriate metric to employ. For instance, this is one of the scenarios where there is a considerable gap in socioeconomic status. It's a safe bet to assume that each sample is of the highest possible quality. If the model isn't picking up any new information, it would be irrational to infer that all components belong to the best class. Therefore, when we talk about accuracy, we refer to the fluctuation in findings you receive while measuring the same object several times with the same tools. The term "precision" refers to one of these statistics and can be defined as follows:

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

- Recall:

Another critical parameter is called recall, and it refers to the percentage of input samples that are of a type that the model can accurately predict. The formula for the recall is as follows:

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

- F1 Score:

The f1 score is a statistic utilized to contrast recall and precision.

$$\text{F1Score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

- ROC Curve:

Classifier effectiveness in cutoff value can be visualized using a receiver operating characteristic (ROC) curve. The widely-applied ROC curve can be used to determine the best possible model threshold. At several limits, the TPR appears to be vying with the FPR.

IV. Results and Discussion

We used high-powered Graphical Processing Units (GPUs) under an unconfigured Google Colab Pro account for training and testing. We used transfer deep learning models for this task. All experiments with the proposed Classified Canker and Cold Sores using Xception Method used the Adam optimizer with a learning rate of 0.0001, and the model was trained with Sparse Categorical Cross entropy loss functions. The training iterations for this model were 10, with an initial batch size of 8, and the best val_loss models were retained throughout the process. Among the Xception model recommendations were the following settings: 8 batches, 10 epochs, early pausing, and model saving depending on val_loss.

- We used the Mouth Disease (MD) dataset to evaluate the Xception base model's accuracy.

A. The Performance Analysis of the Proposed Model: Xception Base Model

To accomplish complex tasks, the Xception neural network design employs depth-separable convolutions. Scientists at Google developed it. The Inception module is used in convolutional neural networks. Google describes it as a "middle ground" between the traditional convolution and the depth-wise separable convolution method (a depth-wise convolution followed by a pointwise convolution). An infinitely tall Inception module is comparable to a depth-wise separable convolution, as this interpretation shows. The critical difference is the usage of depthwise separable convolutions in place of Inception modules. They suggest a novel Inception-like architecture for deep convolutional neural networks using this realization.

- Depth-wise Separable Convolution

Compared to traditional convolutions, depth-separable variants are expected to significantly reduce processing time.

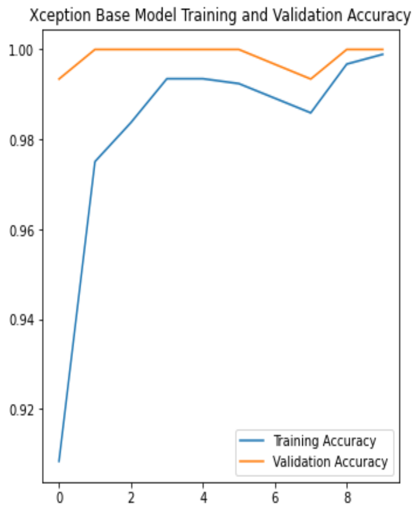
- Pointwise Convolution

Using a kernel of size 1×1×N across the K× K ×C volume, pointwise convolution functions identically to conventional convolution. As before, this enables the generation of a volume with dimensions K × K ×N.

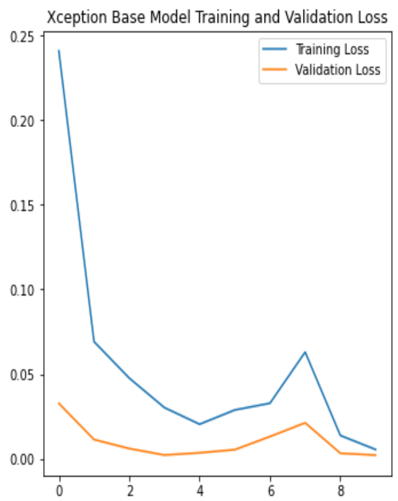
Xception's model flips the sequence around. Two types of convolution are used: pointwise and depthwise. We see the Xception model's architecture laid out. This diagram shows that there are three fundamental elements to the Xception architecture. The initial flow that information travels through is called "entry". The data then passes through the middle flow eight times before being sent out the exit.

B. The Performance of Xception Base Model

The Xception base model's performance on the MD dataset was analyzed. By the end of the last epoch, the model's validation accuracy had risen from 99.34% at the end of the first epoch to 100%. Figure 2 displays the training accuracy's progression from 90.84% following the first epoch to 99.89% following the last epoch. Figure 2 shows how Xception's validation loss dropped dramatically from 3.27% initially to just 0.22%. Just like the initial loss, the training loss was 24.08% after the first period and dropped to 0.55% by the completion of training.



(a)



(b)

Fig. 2. The Xception Base Model: (a) Accuracy (b) Loss Graph

Table V below analyses how well the Xception base model performed when presented with a test set that had no prior exposure. When the test set was applied to all classes, the model achieved an accuracy of 99.60% on average;

however, Xception achieved 100% precision, recall, and F1-score on the canker and cold sore classes, respectively.

TABLE V. PRECISION, RECALL, F1 SCORE, AND ACCURACY OF THE XCEPTION BASE MODEL

Performance Measures	Precision	Recall	F1 Score	Accuracy
Canker Sores	99.90%	100%	100%	99.60%
Cold Sores	100%	100%	99.50%	100%
Average Accuracy				**99.60%**

A confusion matrix allowed us to assess several models' classification accuracy visually. Rows that are not on the diagonal of the confusion matrix represent predictions that did not come true. In the associated Xception base model for each class, increased classification accuracy was represented by darker colors, while lighter colors showed the presence of misclassified samples. To evaluate Xception's overall performance, we will use the confusion matrix from the test set (shown in Figure 3). Data from the confusion matrix shows that the Xception baseline model made reliable predictions for all classes of images. According to the confusion matrix, all data were correctly identified when using the factory settings for the Xception model, and 0.40% were misclassified. The confusion matrix for the Xception base model showed that it did a great job differentiating between canker sore and cold sore samples.

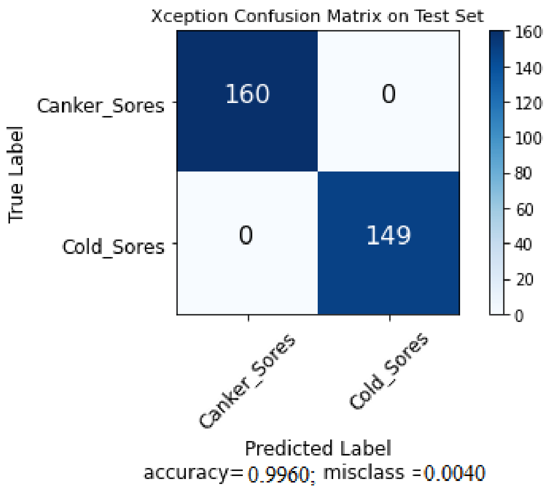


Fig. 3. Xception Base Model Confusion Matrix on Test Set.

C. *Comparison with State-of-the-Art Studies*

The Xception methodology did not apply to the study of literature. It means that a comparison of the studies cannot be performed. The state-of-the-art methods for identifying oral health problems are compared to our model. Table VI shows that the suggested strategy outperformed other recent studies regarding accuracy.

TABLE VI. CLASSIFICATION ACCURACY OF PROPOSED MODEL ON TEST SET

Model Name	Accuracy
Xception Base Model	99.60%

White spot lesions, fluorotic lesions, and other (carious, hypomineralized) lesions were correctly diagnosed using a dataset created by Askar et al. [32] using a CNN-based SqueezeNet model; however, the proposed model performed better. With the CNN-based model, Ekert et al. [34] achieved 96% accuracy on a dataset consisting of panoramic radiographs. Depending on their structure and function, it classifies the teeth into various subgroups, such as incisors, canines, premolars, and molars. Abdalla-Aslan et al. [35] used the Cubic SVM model, which resulted in an accuracy of 93.6%, to classify dental restorations in the panoramic radiography dataset. The model shown in [36] can classify maxillary sinus areas on panoramic radiographs into three distinct categories—healthy, inflammatory, and cystic—with an accuracy of 91%. The proposed model had a 99.60% success rate, surpassing all previous techniques by a wide margin. Table VII demonstrates that the suggested model's accuracy is far higher than that of the state-of-the-art models.

TABLE VII. COMPARISON WITH STATE-OF-THE-ART STUDIES

Ref. Year	Method	Disease	Dataset	Accuracy
[32] 2021	Squeeze-Net	White spot, Fluorotic, Other lesions	Self-created	87%
[34] 2019	CNN	Incisors, Canines, Premolars, Molars	Periapical radiographs	96%
[35] 2020	Cubic SVM	Amalgam filling, Composite filling, Dental implant, Root canal, Crown, Core	Periapical radiographs	93.6%
[36] 2021	Detect-Net	Healthy, Inflammatory, Cysts	Panoramic radiographs	91%
Proposed Method		**Canker Sores and Cold Sores**	**Mouth disease (MD)**	**99.60%**

V. CONCLUSION AND FUTURE WORK

We determined that deep learning models were proficient at recognizing cankers and cold sores. However, some models demonstrated only moderate stability, given the sparse training and testing datasets. We did this by creating our dataset on mouth diseases (MD), including common conditions such as canker sores and cold sores. A unique Classified Canker and Cold Sores using Xception Method has been created to divide the populations into those two categories, as was previously indicated. The suggested Classified Canker and Cold Sores using Xception Method was built on top of transfer learning frameworks like Xception. Various data augmentation strategies have been implemented to improve the precision of the presented method further. The proposed model achieved 99.60% in terms of accuracy, which is a significant improvement over the base method. More disorders and a more effective, generalizable dataset should be included in subsequent research.

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