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Classification of Oral Cavity Using the Convolution Neural Network

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Abstract

The oral cavity is known as the zone between the lips and the finish of the hard sense of taste. Contains teeth, buccal mucosa and gums, lower jaw and hard sense of taste, floor of the mouth and foremost tongue of the papilla around the papilla. This work describes an automatic classification algorithm that classifies of the Cinnamon contact stomatitis and Leukoedema of the buccal mucosa.

Methods: The data set contains 20 images categorized into two types of diseases. Divide The informational index was partitioned into two preparing parts and a test part in this study.

Results: Convolution neural network (CNN) technology was used on data. Two types of jaw diseases have been taken, which are diseases that appear in the oral cavity, which are apparent and not within the tissues, and that appear in the true form to the jaw.

Conclusions: Cinnamon contact dermatitis and white edema of the buccal mucosa it can be detected with CNN with accuracy similar to that in manual diagnosis by maxillofacial specialists.

Keywords

Image Classification, Convolutional Neural Networks (CNN), Cinnamon contact stomatitis, Leukoedema of the buccal mucosa, Image Processing.

1. Introduction

The oral cavity or mouth is bounded anteriorly by the tongue, the faucial later arches only above the tonsils, with the lips laterally, with the tongue dominant and Drop back to muscle floor [1]. The tangue occupies the oral cavity surface. The oral cavity may be divided into 2 sections: the oral epithelium between the tongue and the teeth and the central oral cavity [2].

A mucous layer of stratified squamous epithelium lines that surround the interior of the mouth [3]. The oral cavity physically forms the first section of the digestive tract, which is important for nutrient intake. The oral swallowing stages include complex synchronization inside and across the different oral cavity motor systems [4].

The oral cavity contains the ears, the internal lining of the ears and buttocks (buccal mucosa), the jaws, the gums, the two-thirds front of the neck, the mouth floor behind the neck and the mouth's bony roof (hard palate). Support you breathe, speak, feed, chew, and swallow the oral cavity and oropharynx. The oral cavity structures are also susceptible to voluntary tests [5].

The oral cavity acts in regulating drug intake. The frameworks test the material during Biting and planning of an appropriate portion for reflex gulping in the oropharynx [6]. This incorporates the biting muscles to open and close the jaws, just as the muscles of the lips and cheeks to control the size of the pit and the muscles of the tongue to move and structure food particles around the mouth into the ideal bolus. [7].

Other than regulating the ingestion of pollutants, the systems In the oral hole it is answerable for the intentional guideline of the lapse of air from the lungs. This willing regulation is utilized to regulate the air average and to form the noise produced by air flow into speech and song [8]. Tumors at the mouth ground sometimes invade the sublingual area. Inflammatory pathways or metastases to stage I lymph nodes that typically involve the submandibular region. Clear extension of the oral cavity by SCC to the submandibular area is rare [9].

2. Step of Proposed System

The data set contains 20 images categorized into two types of diseases. Divide The informational index into two sections, preparing and exam part in this study. This images are classify into types of diseases.

The first step in this part is apply one filter which is mean filter, this filter will removing the noise and enhance the image. In mean filter, the size of the mask represents the smoothing degree and the loss of information. Noise that ranges randomly above and below a standard value for light may be minimized by integrating noise neighbourhood. It is given according to an algorithm.

Algorithm: Mean filter work

Input: X-ray image

Output: X-ray image without salt and pepper noise

Begin:

Step1: load n×m image from dataset

Step2: read image pixel by pixel

Step3: at this step rectangular window size is 3×3, the arithmetic mean filter will compute the average of pixels over window, this operation can be through of as convolution with uniform Rectangular mask of size 3×3.

Step4: This smooth out variations and noise is reduced.

Step5: the result will be remove salt and pepper noise from X-ray image

End

3. Convolution neural network work

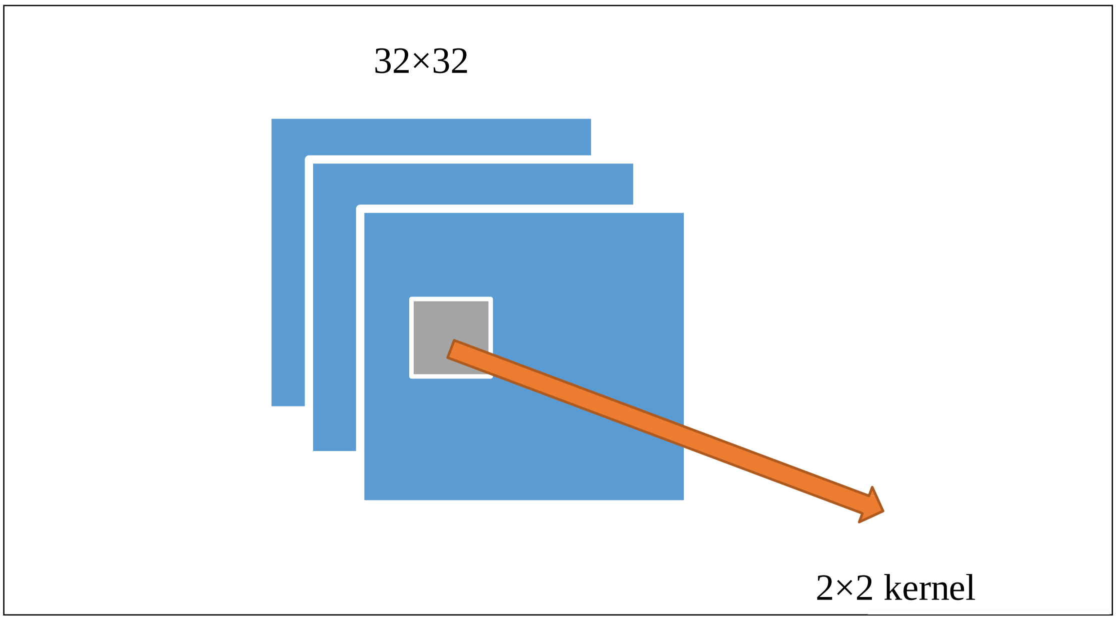
At this part the images are entered directly into the convolution neural network (CNN) algorithm and this thing helped to get good results but if the image isn't good change may lose the algorithm detection and learning. Dividing the pictures on diseases and each disease contained the pictures of it and the pictures were saved each disease individually and in total and each group has a difference in the number of pictures why provided equal number of pictures for totals [10].

Convolutional NNs (CNNs) are multi-layered NNs that are specialized in detecting visual features Straightforwardly from picture pixels and are all around perceived for distortion quality. The layers are [11]:

- **Convolution Layer:**

A convolutionary layer is parameterized by map digit, map dimension, and kernel scale. Each layer is equally large with M maps (32, 32, Figure (3.8) show shape of picture. Each guide in layer L_n is associated with all guides in layer $_{n+1}$. Neurons in a particular guide share their loads however have distinctive information fields,

Figure (1): Input layer 3 maps with 1024 neurons in each map



- **Padding Layer**

Using usually tiny kernels, this can only sacrifice a few pixels with each particular convolution, but it can add up when more consecutive deep convolutional layers are adhering. One simple approach to this issue is to attach additional filler pixels along The constraints of our information document, in this way expanding the powerful size of the picture. Figure (2) an example show how padding layer work.

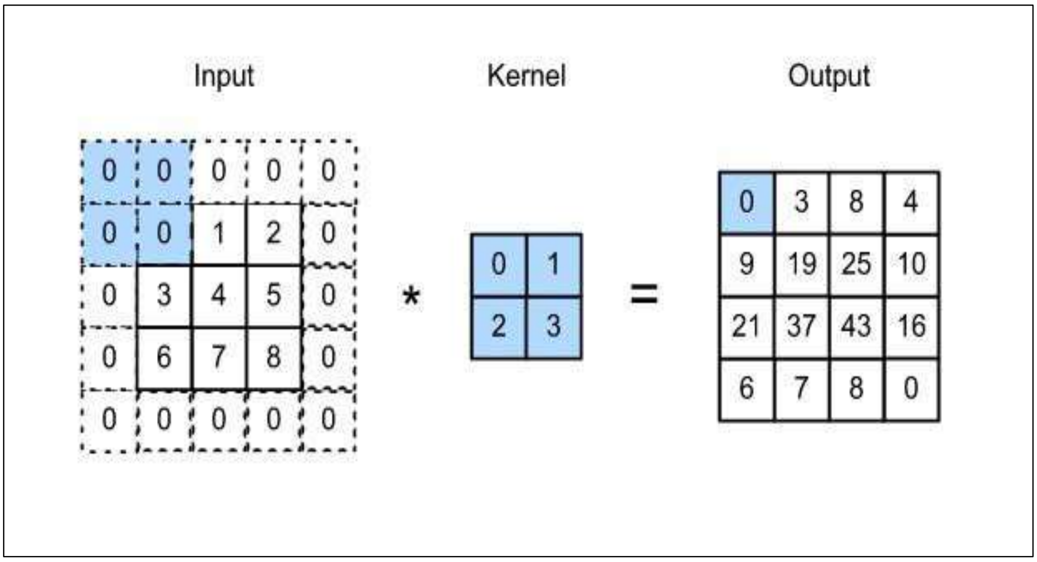


Figure (2): Two-dimensional cross-connection with cushioning. The concealed segments are the information and bit cluster components utilized by the primary yield component.

- **Stride**

Allude to the quantity of lines and segments crossed as the step per slide. Utilized advances for stature and width, up until now. In some cases, this might need to utilize a bigger step. Figure (3.11) Show a double-dimensional cross-correlation process with a vertical and horizontal phase. It tends to be seen that when taking out the second thing from the principal section, the twist window slides down three lines.

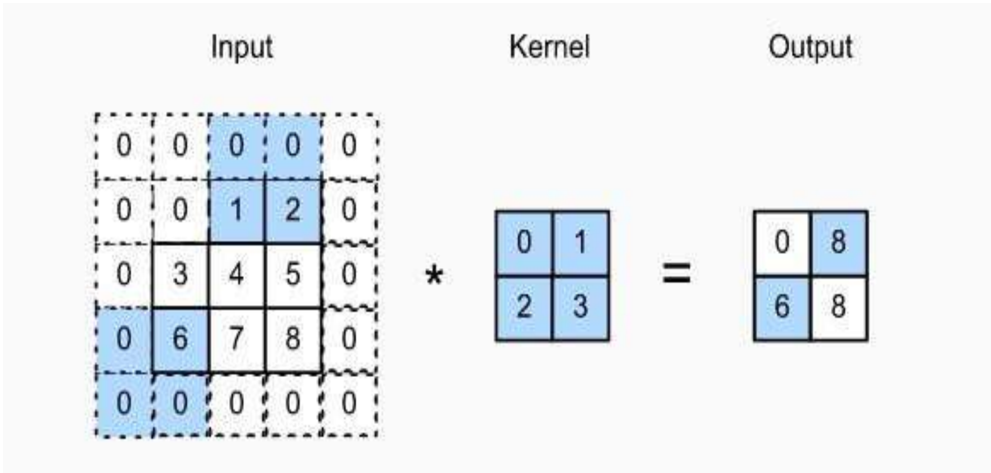


Figure (3): Cross-relationship with steps of 3 and 2 for stature and width separately.

- **Pooling**

When detecting lower-level elements, such as edges that always want To be to some degree fixed for interpretation representations. For illustration, on the off chance that the picture X has a sharp outline among highly contrasting and moves the whole picture by one pixel to one side, i.e., Z[i, j] = X[i, j+1], at that point the yield for the new picture Z can greatly differ. The edge will shift by one pixel, and all the activations with it. In fact, events almost ever happen at exactly the same place.

- **Training a Network**

Preparing a system is a procedure of looking for pieces in convolution layers and loads in completely linked layers that reduce discrepancies between performance foretelling on a training dataset and assigned ground truth labels. Backpropagation algorithm is the technique used to train neural networks, in which misfortune capacity and slope decrease calculation assume significant jobs. A model yield under various pieces and loads is controlled by a misfortune work by forward engendering on a preparation dataset, and learnable boundaries, to be specific bits and loads, are adjusted by the misfortune esteem using, among others, an advancement calculation named backpropagation and slope plummet.

4. EXPERIMENTAL RESULT

The proposed framework is constructed utilizing the Python programming language as a windows application. As indicated by the accompanying prerequisites, equipment particulars: The framework will take a shot at any gadget with at least 1 GB of memory, 2.1 GHz processor. Ten pictures were taken to distinguish it and learn to equip the model for the default system. With this, a data of 20 pictures was obtained as shown in the figure (4). A Mean filter was used on this data as shown in Figure (5). The photos were taken for learning and the model was prepared for examination by the system. And extension in 4 pictures two pictures for each disease.

Figure (4): The oral cavity lesion (the Cinnamon contact stomatitis and Leukoedema of the buccal mucosa).

Figure (5): Show the results of applying mean filter

The final CNN developed in this study generated classification of oral cavity. Accuracy and loss were calculated as shown in Fig. (6) and Fig. (7) respectively, depending on the number of algorithmic learning attempts (epovh) and the verification rate (learning). The learning algorithm works in epovh = 100, verification = 0.0000001 as show in the table. The accuracy was measured on 20% of the images. The learning rate was very good in excellence and privacy.

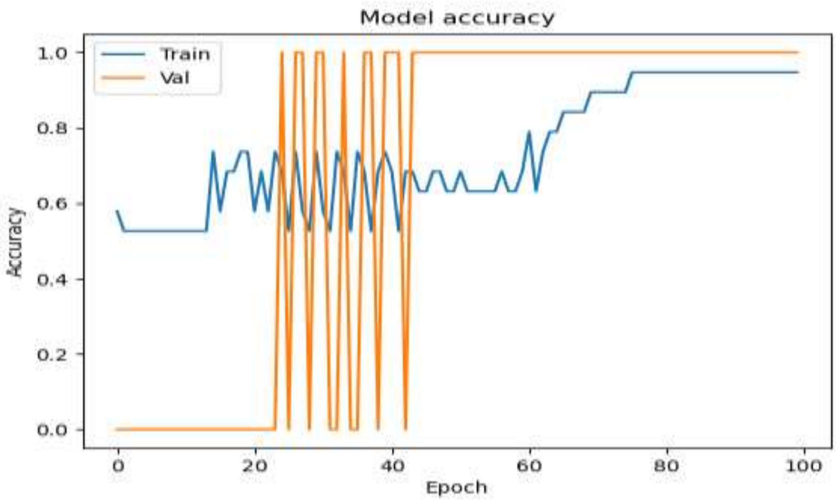


Figure (6): illustrate accuracy model (0.0000001- 100)

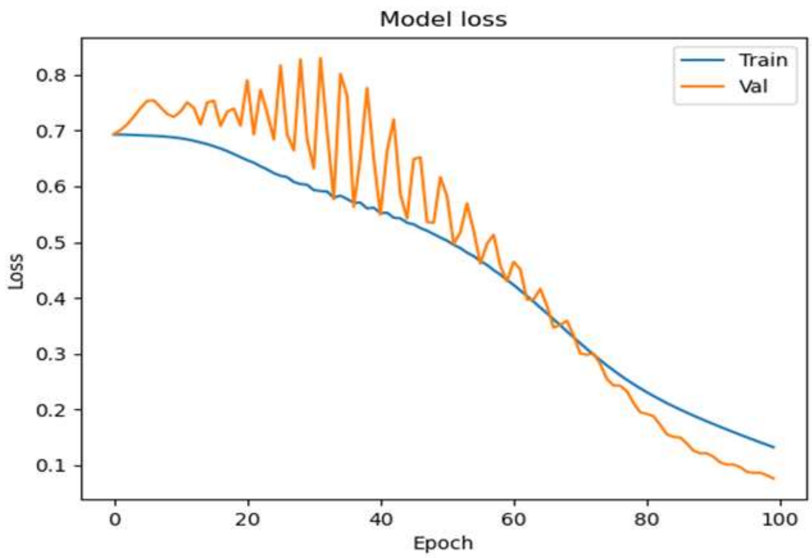


Figure (7):

illustrate loss model (0.0000001- 100)

Table (1): illustrate case of processing images (0.0000001- 100)

Loss	0.0774
Accuracy	0.9474
Val-loss	0.0370
Val-accuracy	1.0000

5. Conclusions

The accuracy of the produced CNN was close to that of diagnostic oral and maxillofacial experts oral cavity. CNN can assist screening for the Cinnamon contact stomatitis and Leukoedema of the buccal Mucosa in a much shorter period and contribute to popular the oral and maxillofacial surgeons' workload. Further investigation to further validate and improve CNN should be carried out so that it can be widely used for such screening and diagnostic applications.

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