Dental Caries Detection Through Resnet 50 Using Adam Optimizer

RITESH MOURYA[1], GANESH PATIL[2]

[1, 2] *PG Student, Department of IT, Thakur College of Science and Commerce, Thakur Village, Kandivali (East), Mumbai, Maharashtra, India*

Abstract— Almost everybody at some point of their life faces the issue of oral cavity. This study aims to identify dental caries in humans, brought on by plaque buildup on the teeth. A thin, sticky coating called dental plaque forms all around the teeth. The primary source of this dental plaque is excessive or frequent consumption of foods high in starch, such as burgers and pizza, also foods high in sugar, such as sweets and chocolates. Cavity forms on teeth when sugar and starch-containing food and beverages are consumed in excess without being thoroughly rinsed from the mouth afterward. Humans should recognize dental caries as soon as they appear on their teeth to prevent them from spreading. Therefore, to identify this caries, we require an algorithm that is quick and adequate to inform us of the state of the teeth/tooth. Residual Neural Network (Resnet50), commonly known as ANN, is the neural network type we use in this research report. Image processing and recognition science have made great strides in recent years. Deep and complex neural networks are developing. It has been that a Neural Network can become more reliable for tasks involving images by adding additional layers to it. However, it might also make them less accurate. We have used the residual neural network in this situation.

Indexed Terms—ANN, Deep Learning, Dental caries detection, Oral cavity, Residual Neural Network, Resnet50.

I. INTRODUCTION

Between the ages of 20 and 64, about 92% of individuals develop dental caries in their permanent teeth. Adults from wealthier and better-educated homes have experienced more degradation. Around 26% of adults between the ages of 20 and 64 have untreated decay. 3.28 decaying or missing permanent teeth and 13.65 missing permanent surfaces are average among adults aged 20 to 64. Both males and females are reported to have caries in their teeth, with males having an estimated 90.57% of them while females have an estimated 92.66% [1]. This happens because of poor dental hygiene or infrequent tooth care, which can also result in several dental problems. Tooth extraction may be necessary if dental caries is severe enough to cause inflammation, infection, and pain in the teeth. The goal of this study is to use a technique or algorithm known as ANN (Artificial Neural Network), often referred to as Residual Neural Network, to detect dental caries in humans. Patients can easily prevent dental caries at a personal level by taking good care of their teeth thanks to the detection of dental caries, also known as tooth decay, which occurs in the hard tissue of teeth owing to the action of microorganisms. This detection of tooth decay will take place at an early stage, or essentially from the moment it begins. If caries were not discovered at the early stages, they could develop into more complicated problems and necessitate more expensive treatments. Therefore, it is essential to identify this caries accurately and at an early stage. The science of image processing and recognition has made great strides in recent years. Deep and complicated deep neural networks are developing. It has been demonstrated that a Neural Network can become more reliable for tasks involving images by adding additional layers to it. However, it may potentially reduce their accuracy. Residual Networks can be used in this situation. Deep learning experts frequently add a lot of layers to extract crucial details from difficult images. Therefore, the initial layers may detect edges, while the latter layers may detect recognized forms, such as automobile tires. However, if we increase the network's layer count beyond 30, its performance degrades, and its accuracy drops. This runs counter to the notion that a neural network will become better as more layers are added. This is not the result of over fitting because, in that instance, dropout and procedures might be used to completely resolve the problem. It mostly exists because of the well-known vanishing gradient problem [2].

II. LITERATURE REVIEW

In the research namely “Dental Caries early detection using Convolutional Neural Network for Tele dentistry” by Devesh Saini, Richa Jain, Anita Thakur states that Dental plaque is a precursor of several oral illnesses like carries, gingivitis, and periodontitis. Hence the detection of this disease is important for maintaining the oral health of the human being. Self-detection and taking steps for diagnosis is our priority. So, this paper aims for early and simple detection of the tooth with caries and non-caries. Applying different CNN model to classify these diseases have provided us with considerable good results. Results show that the inception-V3 outperformed our dataset with 99.89% accuracy and a loss of 0.01% when compared to the other models like VggNet16, VggNet19. This classification work with CNN helpful in the e-health domain and IoT concept to handle remotely patients [3]. In 2017, Angelino et al. LED imaging system by interlinking NIR source as well as an intraoral camera to evaluate the low sensitivity regions of the teeth. There is a non-ionizing and safe approach in the range of NIR while detecting the translucency of the teeth. Further, to obtain caries in the ten consenting human subjects, the image of the teeth was provided by NIR and this NIR was responsible for providing the supplementary evaluations. Further, the de- mineralized areas were revealed along with the deep and superficial cracks utilizing the camera-wand system. This method had high clinical utility, simple to use, was user- friendly, and it was low in cost, while compared to radiographs [4]. In 2007, Keem and Elbaum formulated a new technique with the desire of processing the Digital Imaging Fiber-Optic Trans-illumination Images and recording the changes in the image (DIFOTI) that were obtained at distinct times. The three major contributions of this research were (a) segmentation of the teeth based on wavelet modulus maxima. (b) Estimation of the location of caries tooth and its orientation by utilizing first and second moments of DIFOTO Gray level. (c) Quantitative monitoring by multi-resolution wavelet magnitude representation [5]. In 2018, Rad et al. formulated a novel segmentation method based on Level Set (LS). The proposed model detected the tooth caries in two phases: generation of the morphological information of the dental image by utilizing the generated IC and by using the motion filtering and the back-propagation neural network, the segmentation of the intelligent level set was made. The outcomes of the segmentation procedure were found to be much more accurate compared to the outcomes of the other caries detection method. Further, the feature map and the integral projection technique were employed to isolate the caries tooth from the other good tooth. The feature map was better in obtaining the caries area from the other area [6].

III. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) area unit procedure models supported biological neural networks that area unit won't approximate functions that area unit typically unknown. Neural networks area unit galvanized, especially, by the behavior of neurons and the electrical signals they transmit between input (such as from the eyes or nerve endings within the hand), processing, and output from the brain (such as reacting to lightweight, touch, or heat). The linguistic communication of neurons remains being studied. Most artificial neural networks jibe them a lot of advanced biological counterparts solely in look however area units are very effective at their supposed tasks (e.g., classification or segmentation) [7]. A residual neural network (Resnet50) is a man-made neural network (ANN). it's an Associate in Nursing open-gated variant of the route web. Skip connections or shortcuts area units won’t miss some layers. Typical Resnet50 models are area units enforced with double or triple-layer skips that contain non-linearities and batch social control in between. Models with many parallel skip area units are mentioned as "Dense Nets" [8]. Within the context of residual neural networks, a non-residual network is also delineated as an evident network. Primarily, skipping effectively simplifies the network, mistreatment fewer layers within the initial coaching stages. These speed learning by reducing the impact of vanishing gradients as their area unit fewer layers to propagate through. The network then restores the skipped layers bit by bit because it learns the featured house. Towards the tip of coaching, once all layer's area unit is enlarged, it stays nearer to the manifold and so learns quicker [9].

A neural network while not residual elements explore a lot of the featured house. This makes it prone to perturbations that cause it to depart the manifold and necessitates further coaching information to recover. Deeper neural network area units are tougher to coach. we tend to expressly explicate the layers as learning residual functions about the layer inputs rather than learning unreferenced functions [10]. This comprehensive empirical proof showing that these residual network area units are easier to optimize and may gain accuracy from significantly enhanced depth. Residual neural networks ordinarily referred to as Resnet50, or area units are the kind of neural network that applies identity mapping. What this implies is that the input to some layer is passed directly or as a road to another layer. Skip affiliation is essentially identity mapping wherever the input from the previous layer is supplementary to the output of the opposite layer.

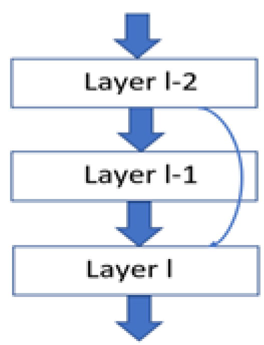

Fig. 1. Skip Connections

The Benefits of Resnet50 Networks with many layers possibly thousands can be trained quickly and with a low training error rate. By applying identity mapping, Resnet50s assist in solving the vanishing gradient problem. In summary, it can be concluded that the skip connections added to the Resnet50 architecture greatly improved the performance of the multi-layer neural network. Resnet50s are essentially distinct networks with minor changes. The design follows the same functional steps as CNN or other architectures however, an extra step is included to address several problems, such as the vanishing gradient problem.

IV. METHODOLOGY

In this research, we collected data from the internet for the condition of dental caries. The distribution of training images and validation images was 80% and 20%, resulting in 400 pictures for training and 400 images for validation. The resolution of the tooth image input is modified to 180x180 pixels for the ANN, which has three layers. Relu activation is used in the activation procedure at each layer where it serves as the default activation function. The relu function uses arithmetic computation. For optimization, we used the SoftMax function related to the cross-entropy function. For optimization, we used Adam optimization. The Adam optimizer combines concepts from many previous optimizers Adam uses a previous gradient average that decays exponentially, just like the momentum optimizer.

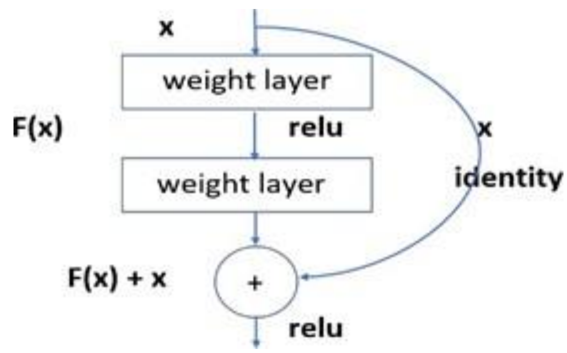

Fig. 2 Residual learning: a building block.

Here we are defining a transfer learning model which takes the input from this Resnet50, and the output is the prediction and the final layer. Now we can keep the layer of the transfer learning model trainable. Then after that, we are going to test the testing dataset. In the end, we have used the confusion matrix.

V. RESULTS

In this research, the dataset has 400 images taken from a dental clinic of which 200 images were photos containing caries and 200 photos with non-caries. We took 200 images for the training model and 200 images for the testing. These images are classified into two classes namely caries and normal. All these images were trained and tested using the residual neural network with the Adam optimizer method, an optimizer having a default learning rate of 0.001, and implement categorical cross-entropy. It is an algorithm for optimization techniques for gradient descent. Adam optimizers generally produce a better result when working with a large problem involving a lot of data and parameters. It requires less memory and is efficient. Intuitively, it is a combination of the 'gradient descent with momentum algorithm and the 'RMSP algorithm. We did 10 epochs(iterations), and we can compare loss and accuracy performance in Fig. 1.

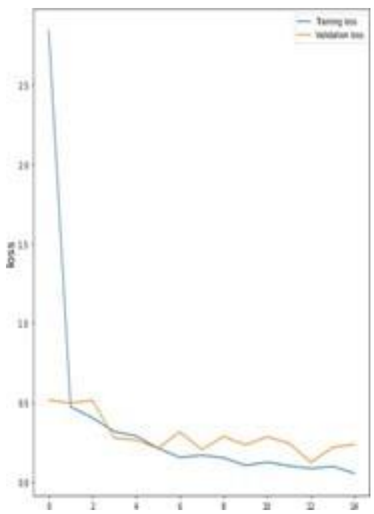

Fig.3 Loss

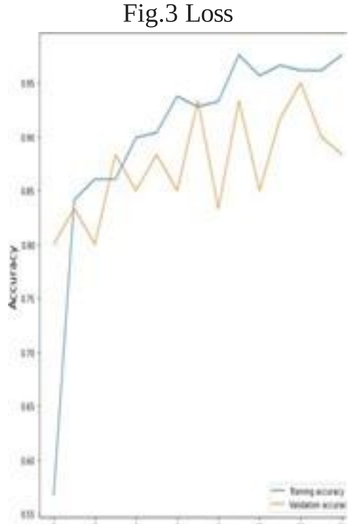

Fig. 4 Accuracy

Fig.3 and Fig.4 Shows the loss and accuracy during the training process, we can see the loss gets minimal and zero after certain epochs and gets 97.60% accuracy during the training process of the images. For the testing process the graph is classified into two categories such as actual and predicted, we can see the performance in Fig. 5. Below,

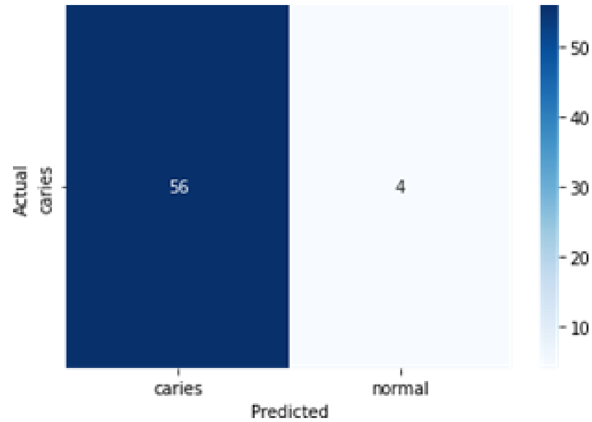

Fig. 5. Predicted

Fig. 5. Shows the performance of the resnet50 on the dental caries images. We got the test accuracy: of 93.33%.

TABLE I. RESULTS DEPICTING ACCURACY GAINED BY ResNet50

Epochs	Accuracy	Validation Accuracy
Epoch 1/10	2.8370	0.5673
Epoch 2/10	0.4751	0.8413
Epoch 3/10	0.4057	0.8606
Epoch 4/10	0.3190	0.8606
Epoch 5/10	0.2917	0.8990
Epoch 6/10	0.2142	0.9038
Epoch 7/10	0.1567	0.9375
Epoch 8/10	0.1698	0.9279
Epoch 9/10	0.1545	0.9327
Epoch 10/10	0.1065	0.9760
Epoch 11/10	0.1258	0.9567
Epoch 12/10	0.1040	0.9663
Epoch 13/10	0.0864	0.9615
Epoch 14/10	0.0998	0.9615
Epoch 15/10	0.0572	0.9760

CONCLUSION

In this research, we saw several oral diseases, including caries, gingivitis, and periodontitis are preceded by dental plaque. Therefore, it's crucial to find this disease early to preserve people's dental health. Self-detection and establishing a diagnosis are our first goal. The purpose of this paper is to identify caries in teeth quickly and easily. For the dataset purpose, we used colored images of the tooth. The length of the images was 404x350. Applying the resnet50 model or residual neural network algorithm we can see we get an accuracy of 93.30% with a learning rate of 0.001% using Adam optimizer which was considered pretty good in comparison to the VggNet16, VggNet19 but when compared to the models like CNN and R-CNN, ResNet50 failed to surpass them with the help of Adam optimizer.

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