INCEPTION V3

Introduction

Inception V3, a cutting-edge convolutional neural network (CNN) architecture, has emerged as a powerful tool in the realm of image classification. Developed by researchers at Google, Inception V3 represents a significant advancement in deep learning, particularly in the field of computer vision (Szegedy 2015). This versatile and highly efficient model has been widely employed in various applications, including the analysis of medical images for tasks such as identifying and classifying brain tumors. The utilization of Inception V3 in the context of brain tumor image classification underscores its capacity to handle complex visual data and extract meaningful features. With its intricate design incorporating parallel convolutional layers and inception modules, the model excels in capturing both local and global patterns within images, making it particularly well-suited for tasks demanding nuanced understanding, such as identifying abnormalities in medical scans.

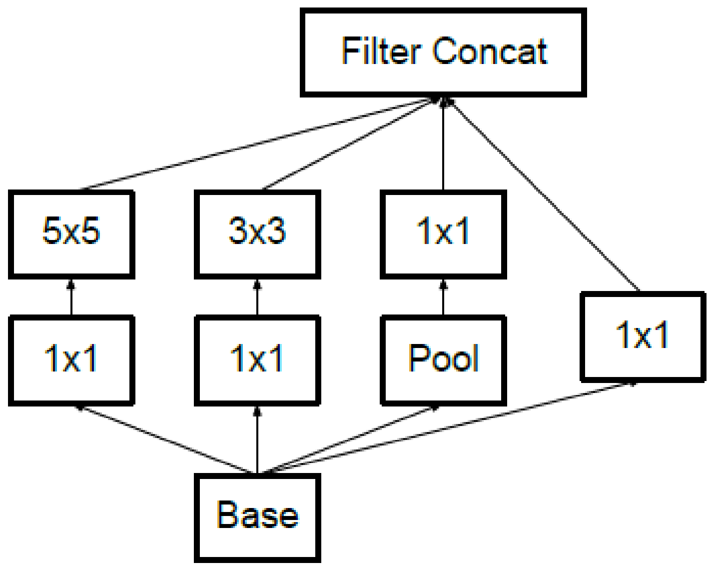
This report delves into the application of Inception V3 for image classification, specifically focusing on its role in the analysis of brain tumor images. By harnessing the capabilities of this advanced neural network architecture, we aim to explore its efficacy, performance, and potential contributions to the crucial field of medical image analysis. The significance of employing state-of-the-art deep learning models like Inception V3 becomes evident as we strive to enhance diagnostic accuracy, automate processes, and ultimately improve patient outcomes in the domain of healthcare.

Architecture

In 2015, the inception of the Inception V3 model marked a milestone with 42 layers and a superior error rate compared to its predecessors. Noteworthy optimizations contribute to its excellence:

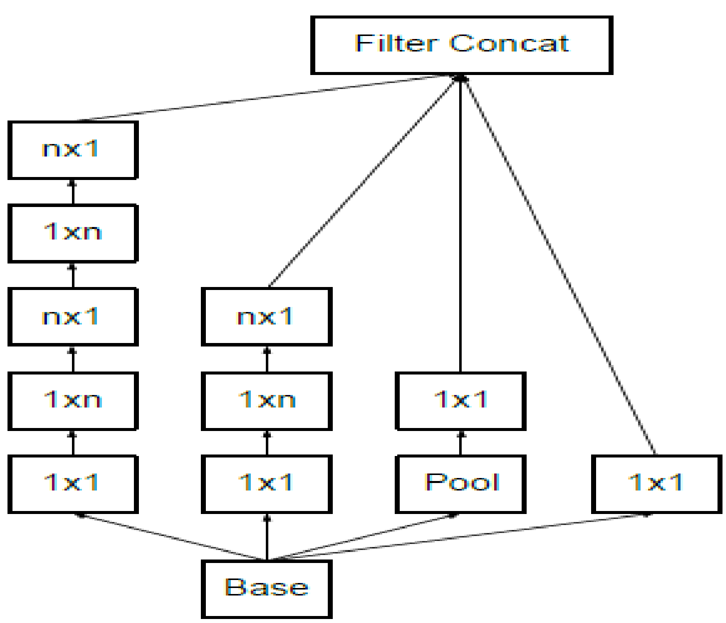
1. Factorization into Smaller Convolutions

   Inception V3 innovatively employs factorization into smaller convolutions, utilizing compact filters like 1x1 and 3x3 convolutions. This approach optimizes computational efficiency and enhances the model's capacity to capture intricate features, elevating its performance in image classification.



2. Spatial Factorization into Asymmetric Convolutions

   A significant improvement involves spatial factorization through asymmetric convolutions. By decomposing standard square filters into varied widths and heights, Inception V3 independently captures features along horizontal and vertical



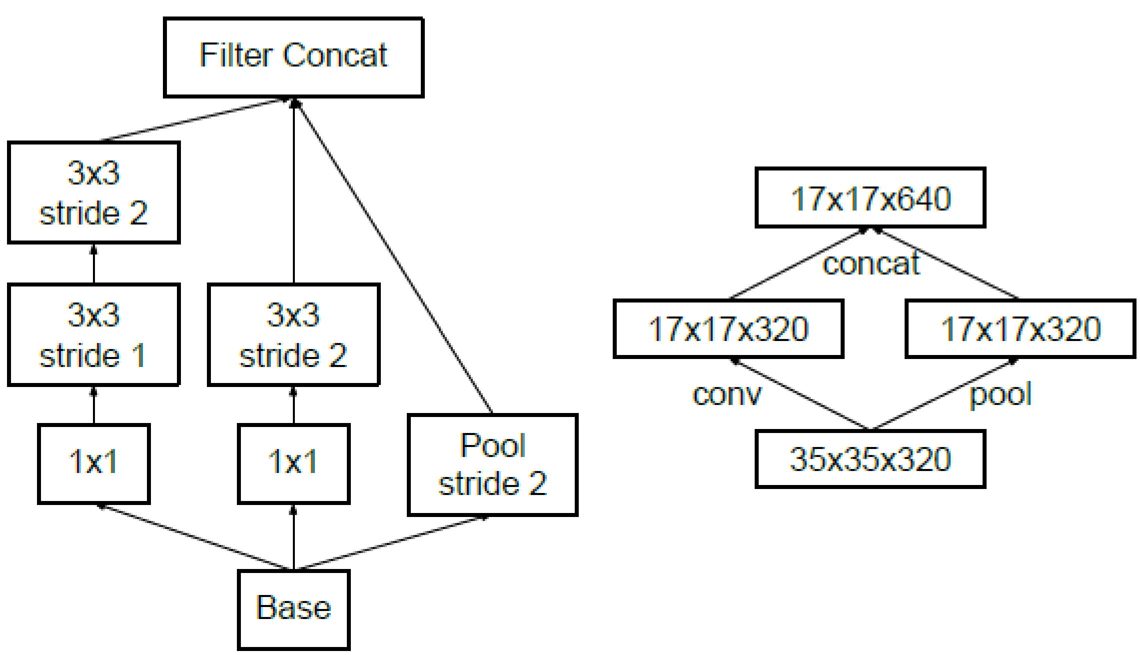
axes. This enhances spatial understanding, enabling precise discernment of complex patterns.

3. Utility of Auxiliary Classifiers

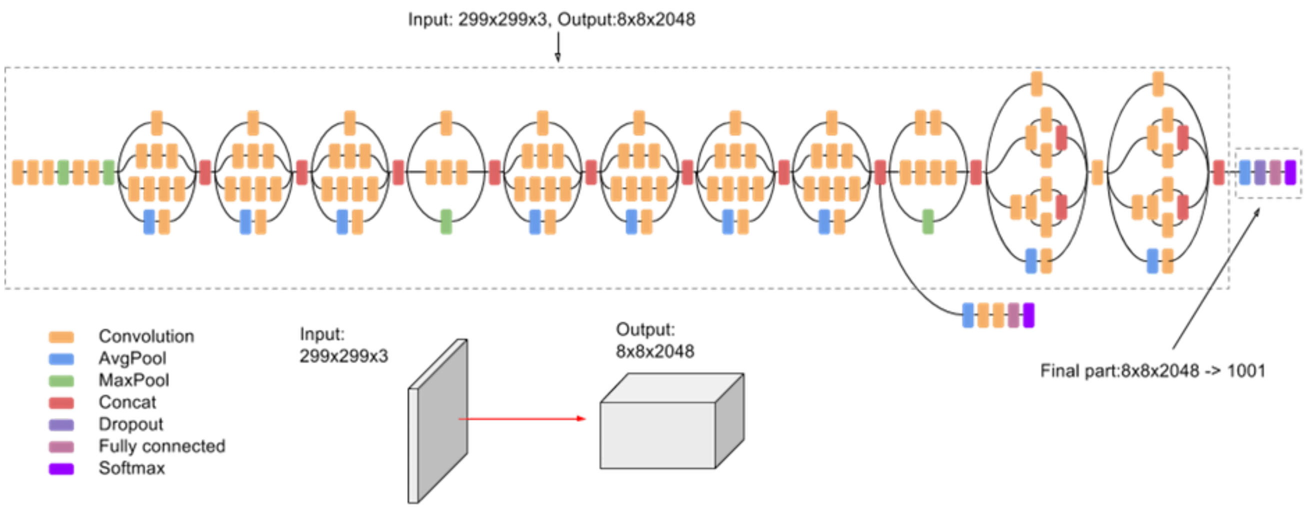
Inception V3 incorporates auxiliary classifiers at intermediate layers during training. These additional classifiers serve a dual purpose by providing supplementary signals for the model's training and addressing challenges related to vanishing gradients. This optimization enhances the learning process, leading to improved convergence during training and enhanced generalization.

4. Efficient Grid Size Reduction

The model implements an efficient strategy for grid size reduction, particularly in stages focused on dimensionality reduction. Rather than relying solely on pooling operations, Inception V3 combines techniques such as strided convolutions and factorized pooling. This balanced approach ensures a reduction in spatial dimensions while preserving essential information, contributing to the model's efficiency and accuracy in various applications.



In total, the inception V3 model is made up of 42 layers which is a bit higher than the previous inception V1 and V2 models. But the efficiency of this model is really impressive. The final Inception V3 Model looks like this :



Optimizer

The current model showcases three flavors of optimizers: SGD, momentum, and RMSProp.

Stochastic gradient descent (SGD) is the simplest update: the weights are nudged in the negative gradient direction. Despite its simplicity, good results can still be obtained on some models. The updates dynamics can be written as:

$$w_{k+1} = w_k - \alpha \nabla f(w_k)$$

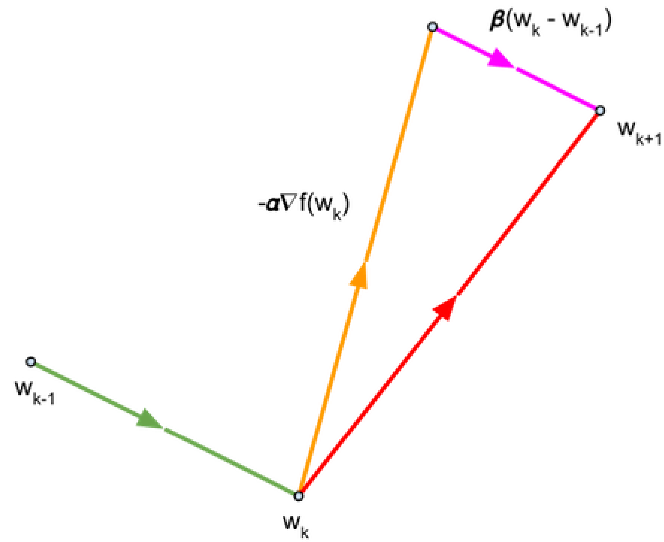
Momentum is a popular optimizer that frequently leads to faster convergence than SGD. This optimizer updates weights much like SGD but also adds a component in the direction of the previous update. The following equations describe the updates performed by the momentum optimizer:

which can be written as:

$$z_{k+1} = \beta z_k + \nabla f(w_k)$$

$$w_{k+} \qquad \qquad - w_{k-1})$$

$$w_{k+1} = w_k - \alpha z_{k+1}$$



The last term is the component in the direction of the previous update.

For the momentum,
we use the value of 0.9.
RMSprop is a popular optimizer first proposed by Geoff Hinton in one of his lectures. The following equations describe how the optimizer works:

$$g_{k+1}^{-2} = \alpha g_k^{-2} + (1-\alpha) g_k^2$$

$$w_{k+1} = \beta w_k + \frac{\eta}{\sqrt{g_{k+1^{+\epsilon}}^{-2}}} \nabla f(w_k)$$

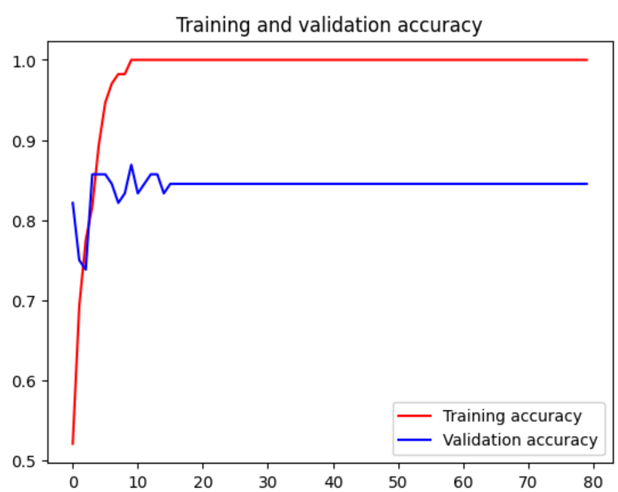
For Inception v3, tests show RMSProp giving the best results in terms of maximum accuracy and time to attain it, with momentum a close second. Thus RMSprop is set as the default optimizer. The parameters used are: decay
 = 0.9, momentum
 = 0.9, and = 1.0.

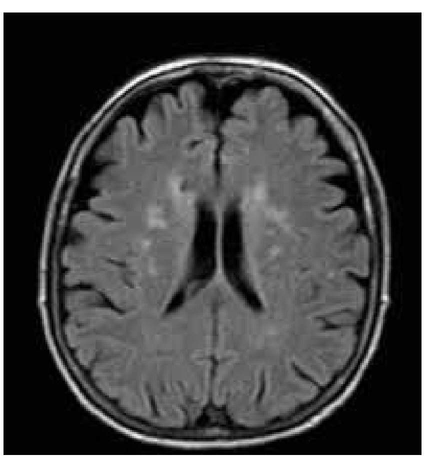
DataSet : [Kaggle_Dataset_BrainTumor]

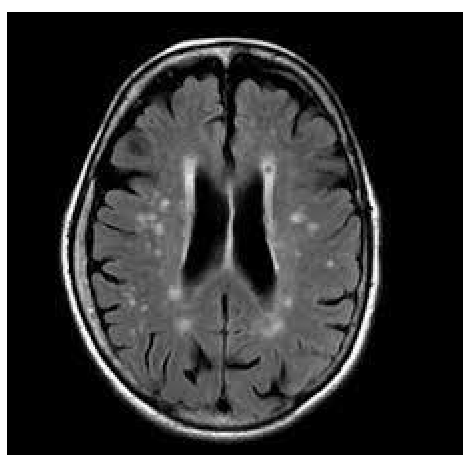
Output :

Total Files : 253 .jpg = 245 Images
.png = 2 Images
.jpeg = 6 Images

Epochs Fed : 200 -400
Img Size : 75*75
Accuracy : 60% (Min) and 84% (Max)







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