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A Novel Variant of Deep Convolutional Neural Network for Classification of Ovarian Tumors Using CT Images

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Abstract:	Deep Learning models have shown tremendously impressive performance on image classification tasks. Several Convolutional Neural Network architectures have evolved over the years, the very first one starting with AlexNet winning the challenge in 2012. In the medical imaging domain, progress has been made in obtaining high-quality data for analysis and using state-of-the- art artificial intelligence algorithms for solving complex problems and providing answers to key questions using data. One such problem that is of crucial importance and interest to medical researchers is to classify tumors into two categories benign and malignant. In research work focuses on proposing a novel variation of CNN architecture and a comparison of the performances of state-of-the-art ILSVRC winning architectures for the task of classifying ovarian tumors as benign or malignant by training and evaluating them on a dataset of ovarian CT scan images with the help of cloud services such as Google Cloud Platform. The work uses Vertex AI to build and run the model on and Google Cloud Storage to store the dataset along with the model and its results. The proposed novel variation of CNN architecture has attained an accuracy of 97.53%.

Highlights

1. Though Computerized Tomography can contain minute and subtle details of ovarian tissue which would be predominantly used to provide discrimination in classification as benign or malignant, yet there are substantially limited studies.

2. This research work mainly focused on comparing the various variants of CNN architecture for the task of classification of tumors into benign and malignant using CT scan dataset.

3. To take care of the limitations of the existing work, the current research work is designed to include Computerized Tomography (CT) scanned ovarian images to detect and classify tumours as benign or malignant using newly state-of-the-art deep learning model and to compare the results with the classification carried out by expert radiologists.

A Novel Variant of Deep Convolutional Neural Network for Classification of Ovarian Tumors Using CT Images

Abstract. Deep Learning models have shown tremendously impressive performance on image classification tasks. Several Convolutional Neural Network architectures have evolved over the years, the very first one starting with AlexNet winning the challenge in 2012. In the medical imaging domain, progress has been made in obtaining high-quality data for analysis and using state-of-the-art artificial intelligence algorithms for solving complex problems and providing answers to key questions using data. One such problem that is of crucial importance and interest to medical researchers is to classify tumors into two categories benign and malignant. In research work focuses on proposing a novel variation of CNN architecture and a comparison of the performances of state-of-the-art ILSVRC winning architectures for the task of classifying ovarian tumors as benign or malignant by training and evaluating them on a dataset of ovarian CT scan images with the help of cloud services such as Google Cloud Platform. The work uses Vertex AI to build and run the model on and Google Cloud Storage to store the dataset along with the model and its results. The proposed novel variation of CNN architecture has attained an accuracy of 97.53%.

Keywords: Deep Neural Networks, Big Data, Computational Intelligent Framework, Cloud Computing.

1 Introduction

1.1 Convolutional Neural Networks for Image Classification

The convolutional operation with padding, followed by layers of pooling and activation functions form the basis of convolutional neural networks. Various combinations of these operations and layers have resulted in novel architectures, each more powerful than the previous one as demonstrated in ILSVRC over the course of 10 years starting in 2012. The winner of the 2012 challenge was a classical convolutional neural network and ever since then, newer improvements have been made each year in the subsequent winning architectures, which reflects in the classification and object detection performances of these algorithms at a large scale. Starting with AlexNet as the winner of the 2012 challenge, ZFNet in 2013, second-VGG-16 in 2014, followed by the first GoogLeNet in 2014 has proved to be breakthroughs each year in terms of their classification performance. 2015 onwards an error rate of less than 4% was achieved by the newly proposed algorithms, precisely, an error rate of 3.57% with the advent of the ResNet in 2015 and a rate of 3.30% for second-ResNeXt in 2016. The CUImage in the 2016 challenge, followed by the latest architecture, SENet in 2017 and PNASNet- 5 in 2018 demonstrated even lower error rates. Thus, over the years CNNs have proved to be the most powerful models for extracting lower and higher-level features based on the architectures and remain as the top preference for any image classification task today.

In recent times, technology has crossed the barriers of hardware limitation to a large extent. Implementing tasks that require high-end machines with expensive hardware configurations can easily be accomplished due to the Cloud computing technology. Leading tech giants such as Google, Microsoft, Amazon etc. are active in this domain to provide users with resources that can be rescaled on demand. These cloud services allow us to perform high computational tasks that are challenging on a local system, in a simple and cost-effective manner by offering resources like Virtual Machines, storage buckets, GPUs, TPUs etc., and charge a fee proportional to their usage. In our proposed work, we have used Google Cloud Platform along with Google Storage Buckets to create a VM and build models using TensorFlow on it, to analyze CT scanned ovarian images to identify benign and malignant tumors.)

In this paper, we have implemented the state-of-the-art ILSVRC winning architectures for our classification task and proposed a novel variation of an architecture customized for getting high classification performance for our CT-Scan dataset.

1.2 Benign and Malignant Tumor Classification using CT Scan Images

In the medical imaging domain, Computed Tomography Scan (CT Scan) has proved to be one of the most efficient and accurate techniques for obtaining detailed images of internal body organs. The radiology technologists are the associated personnel who perform these CT scans of patients. CT scan data collected for various patients spread across hospitals is used for our research purpose. In addition, the reconstructed images in the 3 different planes, viz. the axial, sagittal, and coronal planes provided by the volume acquisition CT has helped generate a variety of data with different variations for training our image classification models. These are images of tumors in patients collected from various hospitals for the 3 different views, which are either benign or malignant. Classification of tumors into two categories – benign and malignant is of utmost research interest and importance in the medical domain. The solid mass of tissue called the tumors that form may be cancerous or non-cancerous depending on their nature – benign or malignant. While benign tumors are mostly non-cancerous in nature and rarely life-threatening, owing to their nature of being localized and not affecting nearby tissues, malignant tumors, on the other hand, can spread to other parts of the body and prove to be cancerous. These malignant tumors prove to be life-threatening if not treated effectively at the right time. Hence, it is crucial in the medical field to identify and classify the tumors into two categories - benign and malignant for necessary actions to be taken to treat patients with these conditions.

In this paper, we have proposed a novel variation of the ResNet CNN architecture and provided a comparison of its performance with state-of-the-art ILSVRC winner architectures (from 2014 onwards) for the task of classifying tumors into benign and malignant using CT scan image dataset. The organization of the paper is as follows: Section 2 provides a literature survey of the relevant work performed in this area, Section 3 provides the research gap, motivation behind this research work and highlights its novelty, Section 4 describes the methodology of classification and implementation of the CNN architectures in details, along with the dataset details and proposed novel architecture. Section 5 demonstrates the classification performance of the CNN architectures on the CT Scan dataset and provides a comparison of the same. along with a brief discussion of these results, followed by a conclusion in Section 6.

2 Related Work

Jorge et al. [1] compared different CNNs and transfer learning techniques for classification of breast tumor using ultrasound images. In [2], Rahimeh et al. also provided a CNN based classification approach for benign and malignant tumors. P Dhivya et al. in [3] presented a novel ensemble approach for classification of tumors using pre-trained CNNs on the breast histopathology images dataset. In [4], Yunendah et al. have implemented the classification on the skin cancer dataset. Hong et al. in [5] have proposed a multi-model weighted fusion framework (WFF) for similar classification on spinal tumors using MRI images and age information. J Seetha et al. in [6] have proposed an approach for brain tumor classification using CNNs. In [7], Elaheh used a single layer CNN for classifying histopathology images of breast as benign or malignant. In [8], Feiqian et al. provided a technique for automated detection and classification of breast nodules using scanned images generated from Automated Breast Ultrasound (ABUS) machine. In [9], Ramya et al. have proposed a novel MIDNet18 algorithm which achieves higher accuracy than the AlexNet algorithm on test images for brain tumor classification. In [10], M.S. Fuad et al. have provided a comparison of two CNN model architectures AlexNet and GoogLeNet for brain tumor classification. In [11], Taki et al. used pre-trained VGG19, ResNet50 and EfficientNetB0 for classification of benign and malignant forms of skin cancer using dermoscopic images. In [12], Qiyuan et al. have developed a deep transfer learning technique to classify breast lesion into benign and malignant types using 4D information in DCE MRI images. Sumaiya et al. in [13] have achieved an accuracy of 99.86% for automatic breast cancer detection using CNN on histopathological images dataset. Hongbin et al. in [14][15][16] have used transfer learning along with deep CNNs to classify parotid tumors in CT images into benign and malignant and achieved an accuracy of 97.78%. Dipanjan et al. in [17][18][19] have proposed a new non-sequential deep hybrid model ensemble for classification of malignant tumors. In [20], Taher et al. used transfer learning for detection of benign and malignant tumors in skin. Maleika et al. in [21][22][23] used deep learning to classify 4 types of breast abnormalities using deep CNNs. Chunxiao et al. in [24][25] proposed a multi-task CNN model for distinguishing breast lesions. In [26], He Ma et al. proposed a novel CNN architecture - Fus2Net for classification of breast tumor as benign and malignant using ultrasound images. In [27], Javad et al. applied CNNs across cancer types and provided comparisons which reveal shared special behaviors. Hassan in [28] used different CNN techniques to classify brain MRI scan images and achieved an accuracy of more than 95% with some of the architectures. Sushama et al. in [29][30][31][32] have implemented the AlexNet CNN for lung cancer detection using the CT scan dataset.

3 Motivation

The research work in this domain so far have used some selected CNN techniques or variations for classification of tumors. A comprehensive comparison of state-of-the-art techniques has not been performed on the CT scan dataset of tumors for classification into benign and malignant. Also, a novel variation of the ResNet architecture customized to the CT scan dataset, to be used for transfer learning or fine-tuned later has not been performed. Hence our research aims to bridge this gap by providing a comparison of performances of the ILSVRC winning models after 2014 and introducing a novel variation for achieving a good performance on this dataset.

The proposed novel architecture in this study – ResNet60 is a custom architecture with the ability to classify tumors into benign and malignant with a validation accuracy of 97.5%. In addition, the comparison of classification performances for the state-of-the-art CNN architectures on this dataset shows that the proposed novel architecture is best suited for the classification task on the CT Scan dataset. The motivation behind this work is to provide this custom architecture which can be further used for the classification using Transfer Learning and can also be fine- tuned to train on newly collected CT Scan data to accurately classify localized images of tumors in the CT Scan image data into the two categories – benign and malignant and thereby helping the medical practitioners and researches to effectively distinguish between these two types of tumors from images and prescribe necessary next steps for treatment.

4 Methodology and Implementation

To implement our work, we have used the Google Cloud AI Platform or Vertex AI in order to train and use the neural network. A project is created in the GCP where several pre-defined neural networks are available which can be used directly or you can build your own model. Buckets are created in Google Storage Buckets to store the images which would act as a data source for our model. The pre-processed dataset is stored in the bucket created. An instance of a Virtual Machine is created to support these tasks. VMs of multiple types of configurations are available to choose from ranging from one CPU, 3.75 GB RAM to as high as 96 CPUs, 680 GB RAM. Not only CPUs but GPUs and TPUs can also be used as per the user's requirements. A maximum of 8 NVIDIA GPUs, 80GB VRAM each can be deployed to run parallelly. Different types of data disks can also be selected such as SSD, HDD and Standard Persistent Disks or can connect to a Cloud Storage Bucket.

The Jupyter notebook instance is used to write the script to train and test the model. All the required packages would already be installed and readily available. The input data is selected as the bucket created where the dataset is stored. Importing the data from the local machines or external storage service is also possible. TensorFlow is used in our implementation to build the model. The model is then evaluated using the performance metrics and parameters are tweaked accordingly until we obtain a satisfactory result. The model is exported back to the Cloud Storage Bucket. Please note that all the services used here follow the pay-per-use model and thus would be charging only for the resources selected, according to their utilization. The price increases with an increase in the performance and capabilities of the resources. Fig 1. depicts the process of the implementation of a model on Google Cloud Platform.

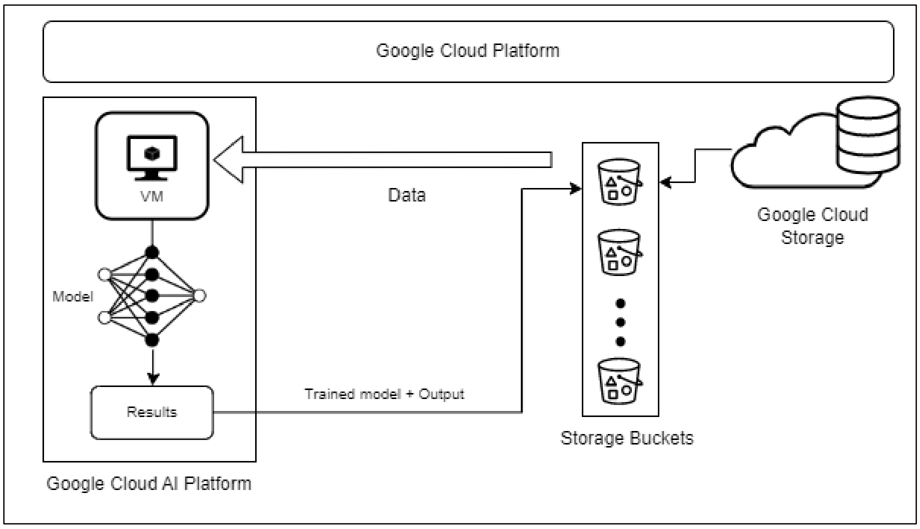


Fig. 1. Generic cloud implementation of an ML model

4.1 Dataset

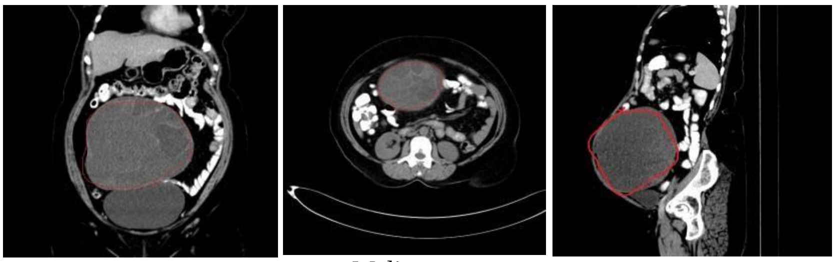
The dataset comprises a set of 5725 annotated ovarian CT scan images of tumors belonging to the benign and malignant classes for 53 different patients from SDM College of Medical Sciences and Hospital located in Dharwad, Karnataka, India. The dataset contains the reconstructed images in 3 different planes, viz. the axial, sagittal, and coronal planes. The tumors have been localized and annotated by marking nearly circular shaped polygonal structures around them. Table 1 shows the distribution of benign and malignant images for the train and test datasets.

Table 1. Dataset Distribution

Train		**Test**	
Benign	**Malignant**	**Benign**	**Malignant**
3009	1155	1128	433

Fig. 2 provides some sample images of benign and malignant tumors along with annotations.

Benign:



Malignant:

Fig. 2. Sample annotated CT Scan images of benign and malignant tumors

4.2 Data Preprocessing and Dataset Preparation for Training and Evaluation

The dataset suffers from class imbalance problem, where the number of benign samples is relatively higher than malignant samples. The annotated images were cropped based on the annotation boundary around the tumors for the classification models to effectively extract and learn features of the localized tumor and focus only on this region of interest for training and validation purposes. Fig. 3 provides an example of the cropping operation performed on these annotated images for benign and malignant tumors.

Benign: Malignant:
Original Image Cropped Image Original Image Cropped Image

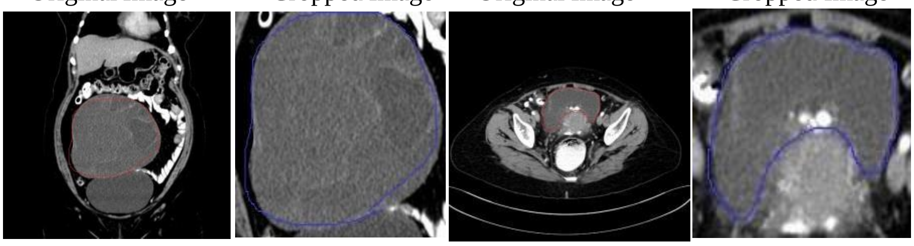


Fig. 3. Benign and malignant tumor CT scan images and their cropped counterparts

4.3 Proposed and Implemented Architectures

We have implemented the below state-of-the-art CNN architectures for classification of tumors into the two classes benign and malignant using the CT Scan dataset:

1. GoogLeNet (Inception-v1)
2. Inception-v4
3. VGG16
4. VGG19
5. ResNet50
6. ResNet60 (proposed novel architecture)
7. EfficientNetB0
8. DenseNet121

Out of the above architectures, the ResNet60 is the novel architecture proposed by us, which showed highest accuracy on both the training and validation datasets. The results of the proposed novel ResNet60 have been compared with the rest of the architectures as mentioned above for the same number of training epochs (200) and on the same dataset.

Proposed ResNet60 Architecture

The architecture takes images of size 224x224x3 as input and performs zero padding, followed by a convolutional 2D layer with 64 filters each of size 7x7 and strides (2,2). This is the first convolutional layer (Conv1) following by a batch normalization layer and a ReLU activation layer. After this, a max pooling 2D layer is applied with pool size (3,3) and strides of (2,2). After this, there are convolutional and identity blocks in the following arrangement:

Stage 1: It comprises a convolutional block followed by 2 identity blocks. For each of these blocks, the convolutional layers have 64, 64 and 256 filters respectively

Stage 2: It comprises a convolutional block followed by 3 identity blocks. For each of these blocks, the convolutional layers have 128, 128 and 512 filters respectively

Stage 3: It comprises a convolutional block followed by 5 identity blocks. For each of these blocks, the convolutional layers have 256, 256 and 1024 filters respectively

Stage 4: It comprises a convolutional block followed by 2 identity blocks. For each of these blocks, the convolutional layers have 512, 512 and 2048 filters respectively

Stage 5: It comprises a convolutional block followed by 2 identity blocks. For each of these blocks, the convolutional layers have 512, 512 and 2048 filters respectively

Stage 6: It comprises a convolutional block followed by 2 identity blocks. For each of these blocks, the convolutional layers have 1024, 1024 and 4096 filters respectively

Then there is an average pooling 2D layer of pool size (2,2) and padding as "same".

Convolutional Block:

The arrangement of layers for each convolution block is as shown below:

- Convolutional 2D Layer with specified number of filters of size (1,1) each, strides specified as (2,2) and padding as "valid"
- Batch Normalization Layer
- ReLU Activation Layer

- Convolutional 2D Layer with specified number of filters of specified size as (3,3), strides as (1,1) and padding as "same"
- Batch Normalization Layer
- ReLU Activation Layer

- Convolutional 2D Layer with specified number of filters of size (1,1) each, strides as (1,1) and padding as "valid"
- Batch Normalization Layer

- Convolutional 2D Layer with specified number of filters of size (1,1) each, strides specified as (2,2) and padding as "valid"
- Batch Normalization Layer

- ReLU Activation Layer

Identity Block:

The arrangement of layers for each Identity block is as shown below:

- Convolutional 2D Layer with specified number of filters of size (1,1) each, strides specified as (1,1) and padding as "valid"
- Batch Normalization Layer
- ReLU Activation Layer

- Convolutional 2D Layer with specified number of filters of specified size (3,3) each, strides specified as (1,1) and padding as "same"
- Batch Normalization Layer
- ReLU Activation Layer

- Convolutional 2D Layer with specified number of filters of size (1,1) each, strides specified as (1,1) and padding as "valid"
- Batch Normalization Layer

- ReLU Activation Layer

The structure of each convolutional and identity block and architecture diagram for the proposed ResNet60 architecture have been shown in Figs. 4, 5 and 6.

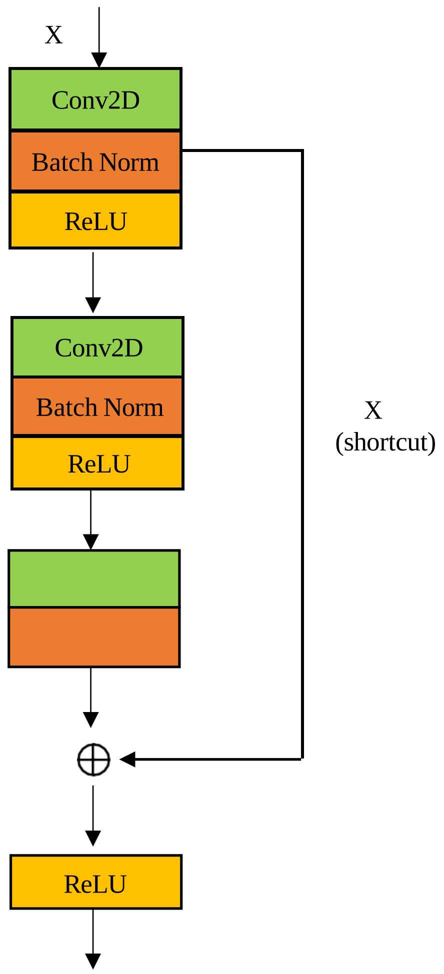


Fig. 4. Inception Block

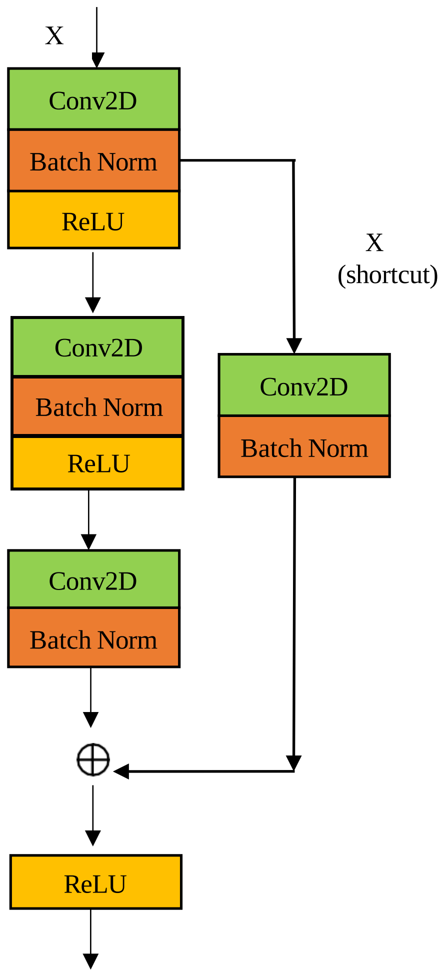


Fig. 5. Convolution Block

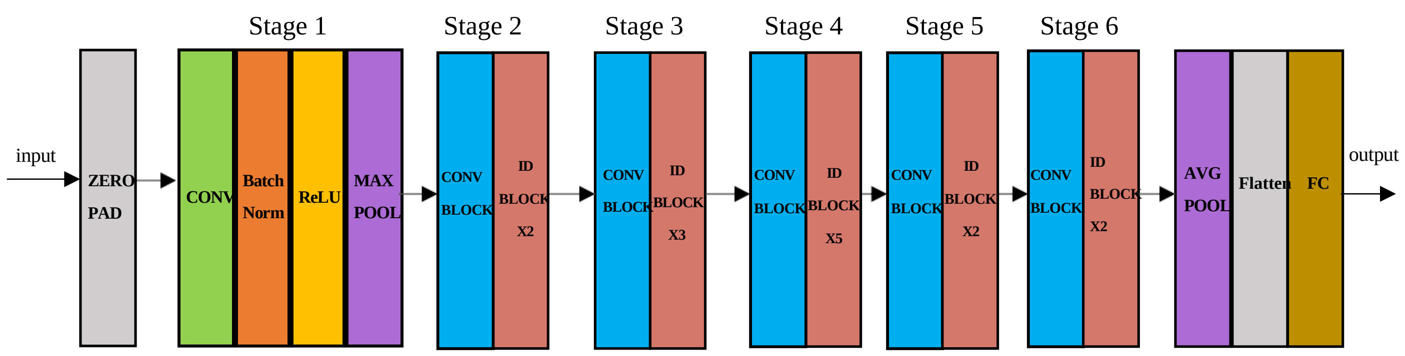


Fig. 6. Proposed Novel Resnet60 Model Architecture

5 Results and Discussion

The above-mentioned architectures were trained and validated on the dataset distribution as shown in Table 1 using the following hyperparameter settings of the models:

Input Size: 224x224x3, Optimizer: Adam, Number of epochs for training: 200
Steps per epoch: 10, Validation steps: 5, Loss: Sparse Categorical Cross Entropy (for Inception modules) and Binary Cross Entropy (for other modules)

Table 2. Comparison of Model Performances on the CT Scan dataset for train and validation

Model	Variant	Train Accuracy	Train Loss	Test Accuracy	Test Loss
Inception	GoogleNet (Inception v1)	92.88%	0.213	93.1%	0.2783
	Inception v4	94.12%	0.1132	82%	44.5312
VGG	VGG16	73%	2.2215	72.9%	2.3980
	VGG19	76.88%	0.3267	75.1%	0.5987
ResNet	ResNet50	94.25%	0.1987	90%	0.5278
	Resnet60 (Novel)	**96%**	**0.1845**	**97.53%**	**0.1354**
EfficientNet	EfficientNetB0	72.56%	0.5498	74.9%	0.5970
DenseNet	Densenet121	72%	2.1367	91.78%	0.4578

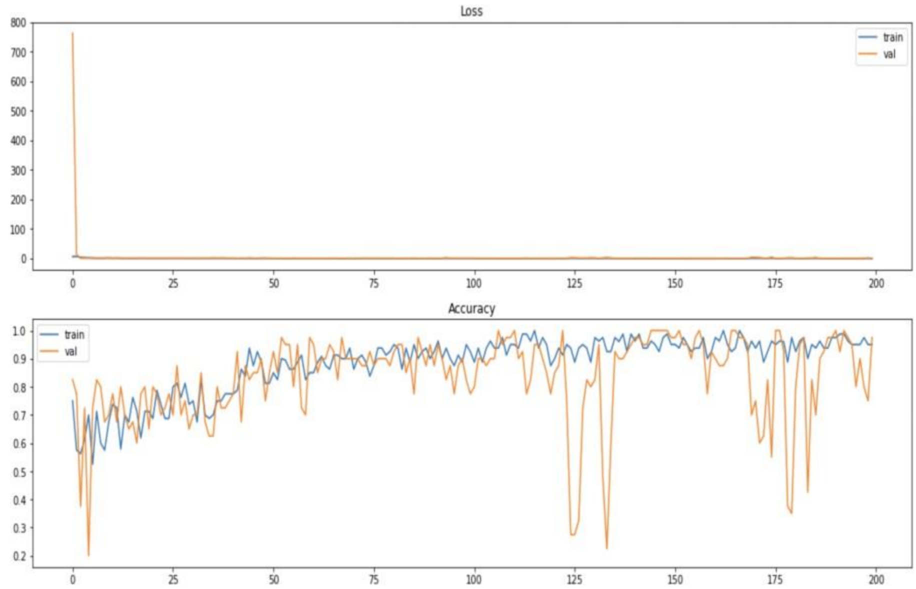


Fig. 7. Graph for variation of train and validation loss and accuracy across epochs for proposed ResNet60 novel architecture

The training and test results (loss and accuracy) after 200 epochs of training for different architectures have been summarized in Table 2. It can be observed that the proposed ResNet60 architecture shows the highest accuracy for both the train and test datasets after the same number of epochs of training. On performing cross validation of samples for train and testing, it is observed that ResNet60 consistently shows higher performance than the other architectures. Hence, our proposed novel ResNet60 architecture is the best fit for classification of tumors into the categories benign and malignant for our CT scan dataset.

Fig. 7 shows the variation of train and validation loss and accuracy across the epochs for our proposed ResNet60 architecture. It is observed that initially the validation loss is very high and gradually as epochs progress, the train and validation loss tend to converge and oscillate around a constant value very close to 0. The train and validation accuracy initially oscillates between 60% and 70% with a slight upward trend and from 50 epochs onwards increases gradually and starts oscillating between 80% and 90% and finally settles to a value of 95% for training accuracy and 97.5% for validation accuracy. The results show that the proposed ResNet60 exhibits a steady learning and does not suffer from the bias or variance problems since it is able to fit very well on the training dataset and is also able to generalize well on the test dataset.

6 Conclusion and Scope of Future Work

In this paper, our aim is to compare the various variants of CNN architecture for the task of classification of tumors into benign and malignant using CT scan dataset. Most of these architectures are the ILSVRC winners. We have also proposed a novel ResNet60 architecture which gives the highest accuracy of 96% on the training dataset and 97.53% on the test dataset. Hence it is the best fit for the benign and malignant tumor classification for the CT Scan dataset. Due to class imbalance in the dataset and these architectures requiring a considerable amount of data for training, following are the possible next steps of continuing this research work:

- Obtain performance of the proposed novel ResNet60 model on newly collected test data by generating inferences using transfer learning
- Fine tune and train the proposed ResNet60 model on newly collected data for higher accuracy
- Implement and observe the results for the new state-of-the-art architectures on the CT Scan dataset

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