DEPARTMENT OF COMPUTER SCIENCE ENGINEERING,

SCHOOL OF ENGINEERING & TECHNOLOGY,

SHARDA UNIVERSITY, GREATER NOIDA

TRANSFER LEARNING TECHNIQUES IN PERFORMANCE ANALYSIS OF BRAIN TUMOR CLASSIFICATION

A project submitted

In partial fulfillment of the requirements for the degree of

Bachelor of Technology in Computer Science and Engineering

By

SHUBHAM PRIYADERSHI (2018016355)

SAUBHAGYA SHARMA (2018013604)

SHIVAM TYAGI (2018012392)

MS. KHUSHI (2018005238)

Supervised by:

Mr. Tejaswi Khanna, Asst. Professor (CSE)

May, 2022

CERTIFICATE

This is to certify that the report entitled "Transfer Learning Techniques In Performance Analysis Of Brain Tomor Classificaton " submitted by "Saubhagya Sharma (2018013604),Shivam Tyagi (2018012392),Shubham Priyadershi (2018016355),Ms Khushi (2018005238)" to Sharda University, towards the fulfillment of requirements of the degree of "Bachelor of Technology" is record of bonafide final year Project work carried out by him in the "Department of Computer Science and Engineering, School of Engineering and Technology, Sharda University".

The results/findings contained in this Project have not been submitted in part or full to any other University/Institute for award of any other Degree/Diploma.

Signature of Supervisor

Name: Mr.Tejaswi Khanna

Designation: Assoc. Prof (CSE)

Signature of Head of Department

Name: Prof. (Dr.) Nitin Rakesh

Place:

Date:

Signature of External Examiner

Date:

ACKNOWLEDGEMENT

A major project is a golden opportunity for learning and self-development. We consider our self very lucky and honored to have so many wonderful people lead us through in completion of this project.

My grateful thanks to **Mr.Tejaswi Khanna** for their guidance in our project work.

Mr.Tejaswi Khanna, who in spite of being extraordinarily busy with academics, took time out to hear, guide and keep us on the correct path. We do not know where we would have been without her help.

CSE department monitored our progress and arranged all facilities to make life easier. We choose this moment to acknowledge their contribution gratefully.

Name and signature of Students

SAUBHAGYA SHARMA (2018016355)

SHIVAM TYAGI (2018012392)

SHUBHAM PRIYADERSHI (2018016355)

MS KHUSHI (2018005238)

DECLARATION

We hereby declare that the task entitled "Transfer Learning Techniques in Performance Analysis of Brain Tumor Classification" submitted for the Final year Project is our original work. We surely have as it should be referred to and referenced the proper assets. We moreover declare that we surely have adhered to all standards of instructional honesty and integrity and characteristic now not misrepresented or fabricated or falsified any idea/data/fact/deliver in our submission. We recognize that any violation of the above may be cause for disciplinary motion thru the Institute and can also evoke penal motion from the assets which have for that reason now not been properly referred to or from whom proper permission has now not been taken while needed.

MS. KHUSHI (2018005238)

SHUBHAM PRIYADERSHI (2018016355)

SHIVAM TYAGI (2018012392)

SAUBHAGYA SHARMA (2018013604)

MOTIVATION

The motivation is to increase a software program with higher segmentation functionality to be used in clinical imaging to come across illnesses like mind tumor .Tumor and most cancers is a dangerous and death-defying ailment for human life. This look at is any other attempt to expose the significance of the photo type with inside the global of the Biocomputing field. Image type method is efficaciously enhancing the system of ailment prognosis. It is a system wherein photos are labeled into several predefined classes. Several strategies has been added for photo type like SVM, Boltzmann, random wooded area and lots of others. The motivation of this is to boom affected person protection via way of means of offering higher and extra specific information for clinical decision. This aggregate presents the higher effects and allows in prognosis of ailment extra efficaciously and in minimal time span.

ABSTRACT

The brain tumors are the extraordinarily familiar and threatening illness border to a bit age expectancy of their excessive grade hence remedy designing might be a key level to decorate the usual of life of sufferers typically various photo strategies like automatic axial tomography ct resonance imaging MRI and ultrasound photo accustomed degree the tumor in the course of a mind lung liver breast prostate and so on mainly in the course of this paintings MRI images are accustomed diagnose tumor inside the mind however the big amount of understanding generated with the aid of using MRI experiment thwarts guide type of tumor vs non-tumor in the course of a specific time but it having a few hassle i.e., accurate quantitative measurements is furnished for confined variety of images consequently trusty and automated type topic vital to forestall the loss of life price of human the automatic mind tumor type is extraordinarily hard project in large special and structural variability of near vicinity of mind tumor in the course of this paintings computerized mind tumor detection is deliberate with the aid of using victimization Convolutional neural networks CNN type the deeper layout fashion is achieved with the aid of using victimization tiny kernels.

Key words: Brain Tumor, Magnetic Resonance Imaging(MRI), Image processing,VGG16, classification, Convolutional Neural Networks, Keras.

Contents

Chapter1. INTRODUCTION

1.1 PROBLEM DEFINITION

Brain tumors are one of the very difficult diseases in bioscience. Good economic and efficiency analysis often worries a medical professional within the premature phase of neoplasm growth. Stereotactic tests based on diagnostic assay tests, that is normal gold and therefore a police meeting investigates the level of tumor in the brain [1] .Tumor detection tests are difficult for tumor patients, non-invasive thinking techniques such as resonance imaging. (MRI) is widely used in prognosis brain tumors. Therefore, improvements in the acquisition and predictability range of supported image records have become increasingly necessary. The detection of autoimmune disorders in the clinical imaging system has grown to be a growing discipline in many clinical diagnostic programs. Its software for detecting a tumor in photosynthesis is very important as it reveals facts about strange tissues this is important to emerge from treatment. Research in recent literature further confirms that spontaneous diagnostic and diagnostic identification, a supported clinical picture analysis, can be a respectable alternative because it can save medical professionals' time and further accumulate tested accuracy [2]. moreover, if computer algorithms will provide robust and multidimensional diagnostic tests for neoplasm, those system-controlled measurements can be of great help in the management of psychiatric treatment by freeing physicians.

1.2 PROJECT OVERVIEW

The tumor is nothing but extra cells growing in an uncontrolled way. Brain cells grow in such a way that sooner or later they absorb all the vitamins necessary for healthy cells and tissues, keeping them mentally inactive. Currently, doctors are finding the location and location of the tumor in the brain by searching for MR Images of the affected person's brain. This leads to misdiagnosis of the plant and is thought to be time consuming. [3] An abscess is a mass of tissue that grows out of control. We can use Deep Learning architectures CNN (Convolution Neural Network) commonly called NN (Neural Network). Transmission to find information on Brain tumor. The full functionality of the version is expected to be an image implant that is either a gift or is no longer in the image. If the tumor is a gift go back guarantee in any other way go back no[4].

1.3 HARDWARE SPECIFICATION

Processor: i5 CPU @ 2.30GHz

RAM:4 GB

System Type: 64-bit OS

1.4 SOFTWARE SPECIFICATION

Python 3 - Python is used here that's a analytical programming language like R in preference to MATLAB because of the subsequent reasons:

1. It is greater comprehensible than MATLAB

2. It records shape is advanced to MATLAB

3. Keras (with backend for TensorFlow 2.3.zero version) – Keras is a neural community API that includes TensorFlow, CNTk, Theano etc. Python programs such as Numpy, Matplotlib, Pandas accounting and ploting graph.

Tensorflow : TensorFlow is an open source planning data flow plan for all areas of operations. A number-related library is used for AI applications such as neural networks.

Keras: Keras is an open source Python library. Equipped to work on TensorFlow. It is intended to enable rapid error and error through deep neural networks.

OS: : The OS module in Python enables enabling and completing enrollment (envelope), importing, modifying and separating the current catalog, and more.

Random: Python Random module is an in-assembled module of Python which is utilized to produce irregular numbers. These are pseudo-irregular numbers implies these are not really arbitrary. This module can be utilized to perform irregular activities, for example, producing arbitrary numbers, print arbitrary an incentive for a rundown or string, and so on.

Matplotlib: Matplotlib is a Python programming language library and extension of NumPy. Provides article-based API for installing episodes in applications using the most useful GUI toolboxes such as Tkinter, wxPython, Qt, or GTK.

Pathlib: Pathlib module in Python gives different classes addressing document framework ways with semantics fitting for various working frameworks. This module goes under Python's standard utility modules. Way classes in Pathlib module are isolated into unadulterated ways and substantial ways.

Shutil: The shutil in Python is a module that offers a few capacities to manage procedure on documents and their assortments. It gives the capacity to duplicate and expulsion of documents. As it were, it is like the OS Module; in any case, the OS Module has capacities managing assortments of documents.

Seaborn: Seaborn is a Python library for comprehension by viewing matplotlib. It provides an undeniable level of interaction in drawing attractive and useful measurable drawings. For a brief introduction to the ideas behind the library, you can look up the first notes or paper.

Sklearn: Sklearn is a very useful and hearty AI library in Python. It provides a cutting edge of active AI tools and measurable displays that include layout, retrieval, grouping and size reduction using a virtual interface in Python

Pandas: Pandas explain () is used to view certain basic mathematical details such as percentage, total, std etc. of a data framework or a series of numerical values. When this method is used in a series of character units, it returns the different output that is shown in the examples below. Return type: Summary of data frame statistics.

NumPy: NumPy is a Python library used for running with collections. It additionally has the cappotential to paintings withinside the area of direct polynomial calculations, 4 variables, and frames. NumPy become evolved in 2005 with the aid of using Travis Oliphant. It is an open supply enterprise and you could use it sparingly. NumPy stands for Numerical Python.

Kaggle was used to find an online database .

GitHub and Stackoverflow were used for reference in case of syntax editing errors.

Google Colaboratory (open-supply Jupyter Notebook interface with excessive GPU) - Google Colab / Colaboratory is an unencrypted Jupyter package that does not need to be set up and works perfectly in the cloud. [5] With Colab, you can really write and use code, save and analyze percentages, functional computing software, at no cost in the browser. Jupyter Notebook is an effective way to duplicate and type in your Python code to analyze facts. Instead of rewriting and rewriting the entire code, you can actually write the code types and apply them at a time.

1.4.1 Image Acquisition

Dataset:

Images are in jpg an jpeg format (s.c. Kaggle online). It contained ninety-eight healthy MRI images and one hundred and fifty-five tumor MRI images.

Chapter2. LITERATURE REVIEW

[6] Abdu Gumaei, Mohammad Mehedi Hassan The malignant increase of Cerebrum cancer can also be an important improvement based at the understanding and understanding of a physician. computerized tumor making plans may be very critical to help radiologist and doctor to diagnose brain tumors.However, the accuracy of current systems should be improved in order to achieve appropriate treatment. in the middle of this paper, we propose a striking crossover strategy with a terrific standard reading machine to create a straightforward way to organize a brain tumor. The process begins with a sharp separation in the brain images using a mixture including the extraction method, at the same time a community of covariance registers of those first rate capabilities is registered to increase them into an crucial set of things using goal factor analysis (PCA). eventually, a preferred over-mastering system (RELM) is used to distinguish a kind of mind tumor. to test and evaluate the proposed approach, the experimental gaggle become completed on a dynamic public database of mind pix. check consequences have tested that this method is notably easy as compared to the prevailing methods, and consequently the overall performance in terms of segment accuracy has advanced from 91.51% to 94.23% of randomized seize method checking out.

[7] Annisa Wulandari, Riyanto Sigit Brain tumor is one of the maximum common styles of brain tumors. there may be a way to confirm the mind tumor as carefully as you want with an MRI test. it's far problem in setting apart tumor tissue in the brain from ordinary tissue because of the same shade. The mind tumor needs to be analyzed correctly. the answer to analyzing a mind tumor to make a difference. brain tumor separation is finished to separate mind tissue tissue from other tissues which include fat, enema, everyday mind tissue and spinal fluid to overcome this weight, MRI imagery ought to be saved in the picture imaging first with slight filtration. Then the method of plant separation requires a repetitive threshold approach that calls for a totally important area. mind segregation is eliminated with the aid of giving a marker in the brain world and in areas out of doors the mind the usage of a dehydration approach after which clearing the cranium via a scalpel. during this examine, MRI pictures of the mind tumor were in

used. The effects of classification are compared with the location of the brain tumors and the location of the brain tissue. this procedure found a plant site calculation with a positive error of 10%.

[8] Mircea Gurbin The brain is one of the most complicated organs inside the body that works with billions of cells. Cerebral tumor happens while there may be an uncontrolled float of cells that shape an bizarre institution of cells around or within the mind. This institution of cells can have an effect on the ordinary functioning of the brain and may break healthy cells. mind plants are called cognitive or secondary degrees (grades 1 and a pair of) and malignant or high-grade plants (grades 3 and 4). The proposed method anticipates the difference among everyday mind and plant tumors (hypothesis or surprise). research of different varieties of brain tumors along with metastatic bronchogenic carcinoma tumors, glioblastoma and sarcoma have been carried out the usage of brain resonance imaging (MRI). The detection and dissection of MRI mind tissue is performed the use of various bendy wavelets and vector help device. correct and automated separation of MRI mind pix may be very essential in reading and interpreting remedy.

[9] Parnian Afshar, Konstantinos N. Plataniotis in line with authentic records, cancer is considered to be the second main purpose of death. most of the diverse sorts of malignant growth, the mind tumor seems to be one of the most lethal systems because of its robust nature, different traits, and occasional level of staying power. figuring out the kind of brain tumor has a profound effect on the selection of remedy and survival of the patient. Human-focused detection is regularly fallacious and questionable which ends up in a continuous flood this is important to automate the process the use of convolutional neural systems (CNNs). CNNs, or probably, omitted to take complete benefit of local relationships, which significantly impaired tumor accumulation, because the link between the tumor and the surrounding tissue can be a essential marker of the plant kind. In our latest work, we have mounted the newly upgraded CapsNets to overcome these shortcomings. CapsNets, however, is touchy to the history of the mixed image. The paper talks about this area. the primary contribution is to equip CapsNet with get right of entry to to the tumor across the tissues, with out interfering with the supposed goal. The changed

CapsNet shape, on this manner, proposes a tumor separation in the brain, which takes strong tumor limits as extra contributions inside its pipeline to growth CapsNet's core interest. The proposed technique is specially striking for its companions.

[10] T. M. Shahriar Sazzad, Misbah Ul Hoque A tumor cellular may be a kind of mobile that grows out of control of everyday forces and makes growth comparable. A mind tumor is one of the main reasons of dying every 12 months. approximately 50% of sufferers identified with a brain tumor die every 12 months from mind tumors. electronic techniques regularly diagnose mind tumors. Of all of the digital techniques, resonance imaging (MRI) is one of the maximum broadly used and popular methods for diagnosing brain tumor. throughout this studies study, a standardized technique turned into evolved in which MRI scans of gray remember have been combined to hit upon tumor within the mind. This take a look at suggested a default technique that would be advanced inside the first segment to reduce the shade version of the grey scale. Sorting feature used to dispose of unwanted sounds as high as possible to assist better differentiate. As this observe examines grayscale pics consequently; The OTSU border-based issue has been used in preference to shade separation. sooner or later, pathologists supplied information of a characteristic that used to perceive the vicinity of interest (mind tumor location). Experimental results confirmed that the proposed approach become higher perfect to provide higher consequences compared to current techniques of accuracy at the same time as keeping the desirable stage of accuracy of pathology experts.

[11] Chanlu Lin, Yi Wang, Tienfu Wang, Dong Introduces a preferred device for coherent differentiation and restoration of obsessive magnetic resonance imaging (MR), wherein low-level and occasional-decision (LSD) systems are regularly used. . traditional methods of LSD regularly produce acquired pix with distorted pathological areas, due to the shortage of a barrier among the lower and decrease extremities. To address this problem, we suggest a modified low-degree and systematic method to sparse decomposition (TLS2D), which is powerful in aside from pathological areas. also, photos located round can be received the usage of each inadequate

layout and image attention as a bendy requirement for simplicity. Experimental effects in MR mind tumor photos show that our TLS2D can offer quality overall performance in both picture detection and tumor category

[12] Sergio Pareira, Adrieno Pinto, Victor Alves among boils in the brain, gliomas are very commonplace and aggressive, main to very short expectations at their maximum degree. consequently, treatment making plans may be an important step in strengthening the quality of life of oncological patients. Magnetic resonance imaging (MRI) may additionally in addition be the maximum extensively used imaging approach to diagnose those tumors, yet the vast amount of information provided by MRI prevents hand-to-hand separation at low cost, restricting the use of correct quantitative measurements inside the hospital. in keeping with these strains, established and reliable category techniques are required; or it can be, huge and sundry neighborhood versions among mind tumors make spontaneous type a hard hassle. within the middle of this paper, we advocate an automatic separation technique supported through Convolutional Neural Networks (CNN), which scans 3x3 small kernels. the use of small pieces lets in for a miles deeper layout, while not having a positive impact against overlap, considering the small number of loads inside the system. We additionally researched the use of strength dimension as a pre-existing control degree, that is but unusual in CNN-based totally category techniques, and showed that associated statistics will increase to work differently in differentiating brain tumors in MRI snap shots. Our proposal was authorized inside the mind Segmentation assignment 2013 (BRATS 2013) internet site, and we usually received a key function for all, group, and local improvement in the cube Similarity Coefficient metric (0.88, zero.eighty three, 0.77) of the venture database. . moreover, it has received a first-of-its-kind widespread for on-line trying out. We additionally became involved in the BRATS 2015 assignment region the usage of the identical model, finding the following vicinity, with a cube Similarity Coefficient metric of 0.78, zero.65, and zero.seventy five across, center, and improvement regions, respectively.

Chapter 3. SYSTEM DESIGN AND ANALYSIS

3.1 Requirement Identification

PROPOSED WORKFLOW

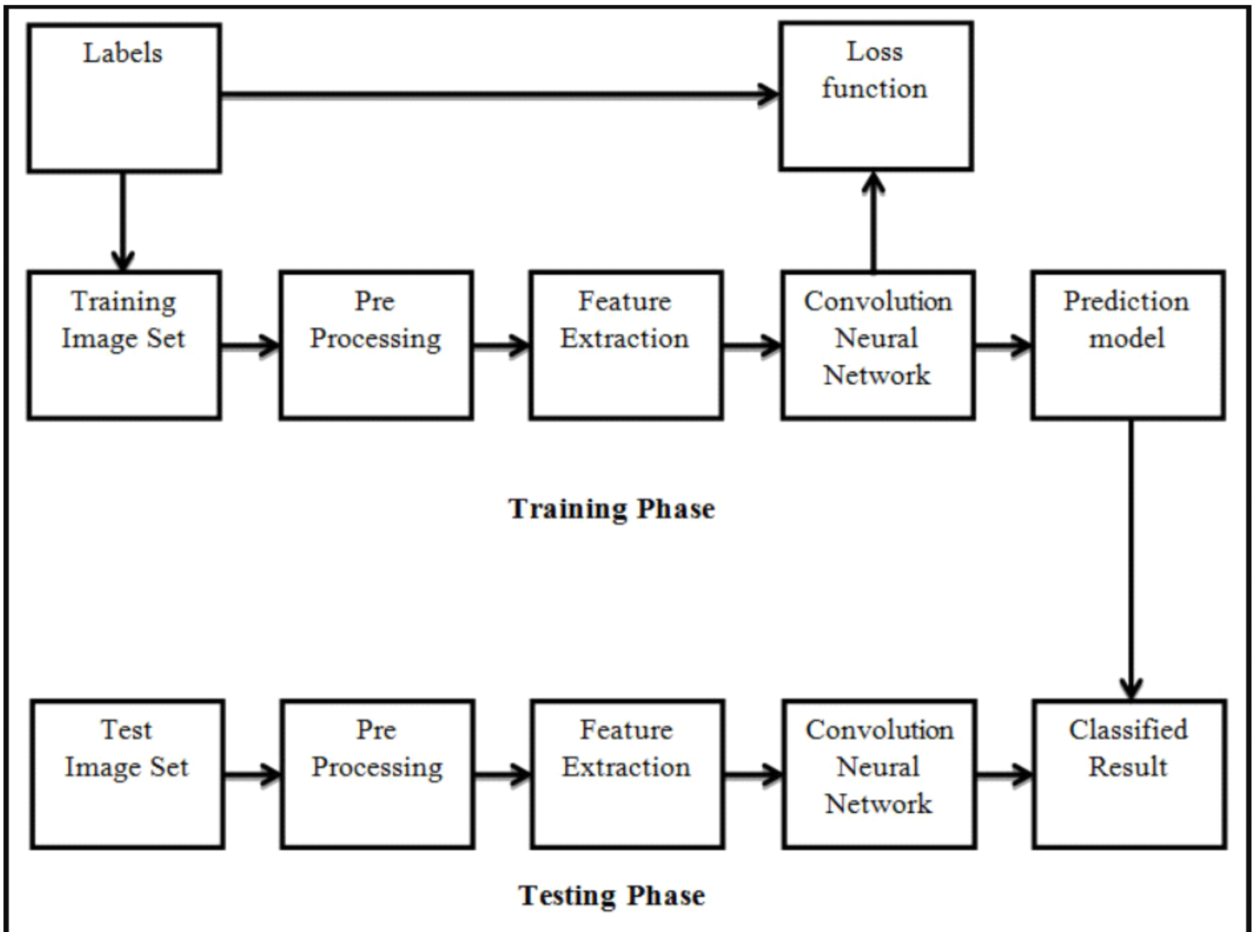

Figure 1: Block diagram of proposed brain tumor classification using CNN

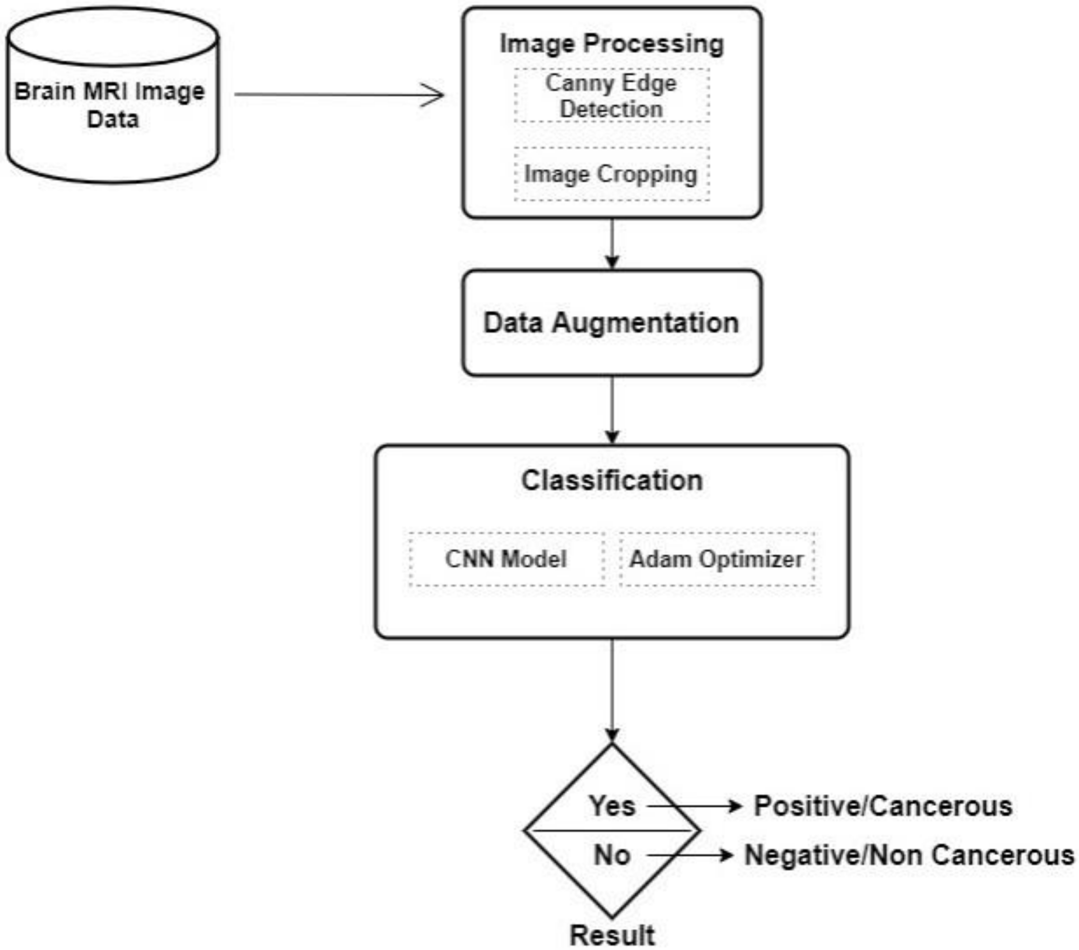

Figure2: Block Diagram for All Trasfer Learning Models

a. At a basic level, there is a PC primarily based entirely on procedures for obtaining tumor block and to differentiate the type of tumor using the Artificial Neural Network Algorithm for MRI images of different patients.

b. The 2nd level entails the use of various photograph processing strategies which include histogram measurement, function and exclusion factor are used to detect tumor in the brain within MRI images in cancer-prone patients.

c. These diagrams are presented as a single way to detect a tumor in the brain automatically to increase and decrease the prognosis time.

Image Preprocessing: As input for this device is MRI, scanned photograph & comprise noise. So, our main goal is to do away with noise in enter photograph. As defined into device go with the drift we're the usage of excessive by skip clear out for noise elimination and preprocessing.

Image Augmentation: Deep Neural Networks need huge measure of preparing information to accomplish great execution. To construct a strong picture classifier utilizing next to no preparation information, picture increase is generally expected to help the exhibition of deep networks. Picture expansion falsely makes preparing pictures through various approaches to handling or mix of different handling, like irregular revolution, moves, shear and flips, and so on.

Feature Extraction: Function Extraction is used for location detection of the pictures. It is manner of amassing better stage statistics of photograph which includes shape, texture, color, and contrast.

Tumor Identification: In this section, we are having dataset formerly gathered thoughts MRIs from which we are extracting features. expertise base is created for comparison.

3.2 WORKING OF CNN MODEL

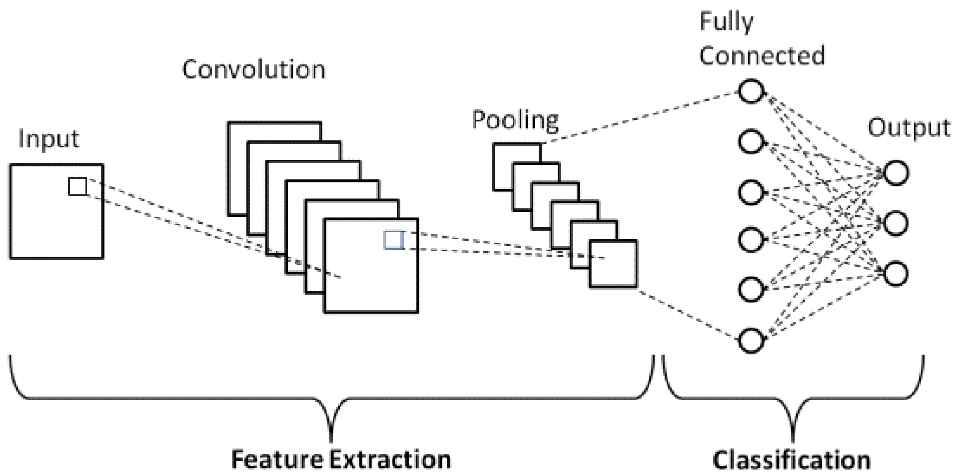

Figure 3: Basic CNN Architecture

Layer of CNN model:

1.Convolution 2D

2.MAX Poolig2D

3.Dropout

4.Flatten

5.Dense

6.Activation

A. **Convolution 2D:** In the Convolution 2D extract the featured from enter image. It given the output in matrix form.

B. **MAX Pooling2D**: In MAX Pooling 2D it captures very large details on a modified performance map.

C. **Cessation**: Cessation is randomly determined by neurons that are skipped during training.

D. **Flatten**: Complete the feed output into a fully integrated layer. Provides statistics in the listing form.

E. **Density**: A Linear function where each installation is attached to each exit in a weighted manner. It is compatible with an indirect activation feature.

TRANSFER LEARNING

Transfer learning is a system studying process in which we reuse a formerly skilled model as the start line for a new paintings model.

to position it honestly — a one-on-one version is also intended for a 2d activity, that is related as performance that permits for faster progress whilst modeling a 2d job.

By using applying transfer mastering to a brand new job, one can get a good deal higher overall performance than training with simplest a small quantity of records.

Transfer learning is not unusual that it isn't always unusual to teach picture model or sports associated from starting.

Instead, researchers and statistics scientists pick initially a pre-educated model that already is aware of how to classify objects and examine common features such as edges, shapes in pics.

VGG16, ResNet, and Inception are not unusual examples of fashions primarily based on switch mastering.

STRATEGIES OF TRANSFER LEARNING:

1. INDUCTIVE: In this situation, the supply and targeted domains are the same, however the supply and target operations are special. Algorithms try to use supply domain bias to help improve centered performance. relying on whether the supply domain incorporates categorised records or now not, this can also be divided into classes, together with learning approximately a couple of obligations and learning to educate your self, respectively.

2. UNSUPERVISED: This placing is similar to the tutorial transfer itself, with a focus on unattended sports on a goal area. source and target domains are the same, however features are exclusive. In this situation, the label statistics is not to be had for any domain.

3. TRANSDUCTIVE: In this situation, there are similarities among supply and goal features, however the corresponding domains are extraordinary. in this setting, the supply domain has a whole lot of classified information, even as the target area does not. this may additionally be taken care of into categories beneath, relating to settings in which characteristic fields are one of a kind or peripheral possibilities.

PRE TRAINED MODEL

The pre-trained model has recently been updated to the database and contains loads and trends that address the highlight of any database to which it is configured. Highlights learned are usually adapted to a variety of information. For example, a model based on a large database of bird pictures will contain prominent readings such as edges or flat lines that you can familiarize with your database. ResNet and Inception have been the key to major advances in image processing recently, with amazing performance at relatively low computer costs. Origin ResNet joins Start Engineering, and the remaining organizations.

WHY ARE WE USING PRE TRAINED MODEL?

- The problem with not using one is that you - depending on what you have - will spend a lot of time training your model from the beginning. You will need to do a lot of math and testing to build the right CNN architecture.
- You may not have a data set large enough for your model to integrate well enough and you may not have calculator resources for that.
- Keep in mind that ImageNet has 1000 classrooms so pre-trained models are trained to work in many different fields.
- The hard work of developing boundaries has already been done for you, now all you have to do is properly adjust the model by playing with hyperparameters so thus, the previously trained model is a life saver.

INCEPTION RESNET V2

Inception ResNet-v2 is a Convolutional brain network developed with more than 1,000,000 images from ImageNet data set. The organization has 164 deep sections and can split pictures in 1000 objects, like console, mouse, pencil, and many more creatures. Later, the organization learned the richness of the visual effects. The organization has a 299-by-299 image capture size, and the result is a sequence of class opportunities tested.

It is figured out in light of a mix of the Inception structure and the Residual association. In the Inception-Resnet block, different estimated Convolutional channels are joined with remaining associations. The use of lingering associations not just evades the corruption issue brought about by profound constructions yet in addition diminishes the preparation time.

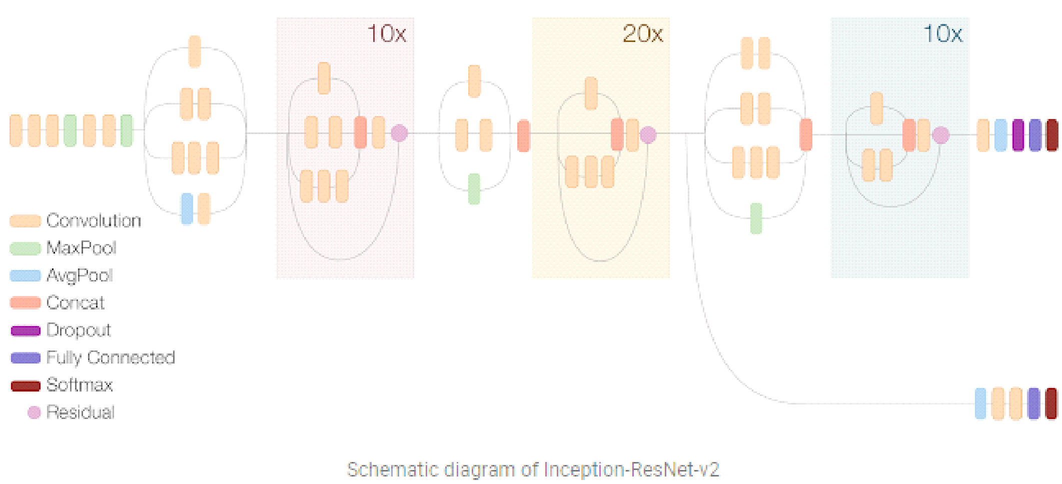

Figure 4: Inception ResnetV2

WORKING OF VGG 16

Transfer Learning Information on is an information sharing methodology that decreases the size of the schooling information, the time and the computational charges while building profound acquiring information on models. Move learning information permits to switch the acquiring information on of a pre-taught variant to a pristine adaptation. Move learning information on has been used in various applications, which incorporates growth characterization, programming program disease expectation, leisure activity prevalence and opinion classification.[18] Here, general execution in the following CNN rendition is as contrasted and famous switch acquiring information on strategy VGG16.

Figure 5:VGG16 Architecture

VGG16 is a Convolutional neural organization. Layer 1 convolution has a fixed image length of 224 x 224 RGB. The image is provided with a variety of dynamic layers, in which the channels are used with a small 3 × 3 responsive head (which is the minimum length of adherence to left / right, top / bottom, focus). In the settings, it uses a 1 × 1 conversion channel, and can be seen as a direct change of input channels. The conversion step is accompanied by something like a single pixel, as well as a local reduction of convolution. Layer input option for protected area after conversion, for example 1 pixel of 3 × 3convolution layers. Spatial integration is done using 5 major integration layers, which recognize a few layers of convolution (currently not all of the conv. Layers are detected by large integration). Maxpooling is done with a 2 × 2 pixel window, in step 2.

The Three Fully Connected (FC) layers have a wide range of dynamic multi-layered views in the unusual and main builds with 4096 channels each, the third makes the ILSVRC 1000 channels and contains 1000 channels each. class. The final layer is a soft-max layer. Fully compatible layer configurations are the same for all networks. [19]

All hidden layers are sorted by default (ReLU). It is also stated that there are now no longer one (but one) network that includes LRN, as simplification now is not adversely affect normal operation of the database, and contributes in continuous storage usage & calculation measure. [20]

MOBILENET V2

MobileNetV2 is a characterization model created by Google. It gives continuous characterization capacities under registering imperatives in gadgets like cell phones. This execution use move gaining from ImageNet to your dataset. Here, we will stroll through how you can prepare MobileNetV2 to perceive picture grouping information for your custom use case.

To apply move figuring out how to MobileNetV2, we make the accompanying strides:

• Download information utilizing Roboflow and convert it into a Tensorflow Image Folder Format

• Load the pre-trained model and stack the characterization layers on top

• Train and Evaluate the model

• Calibrate the model to increment precision after union

• Run a derivation on a Sample Image

Innovations With MobileNetV2

MobileNet V2 is CNN brain network engineering technology which is good on mobile phone. This is based on a modified lingering structure here the remaining associations depend on a modified persistence structure between the bottleneck hierarchies. In between the layer of roadway development surface uses light depth convolution to channel the highlights into a non-linearity source. Overall, the MobileNetV2 design includes a basic fully convolutional layer with 32 channels and 19 remaining bottlenecks.

The MobileNet V2 engineering uses a reversed remaining design where the info and result of the leftover squares are meager bottleneck layers. It likewise utilizes lightweight convolutions to channel highlights in the development layer. At last, it eliminates non-linearities in the tight layers. The overall architecture looks something like this:

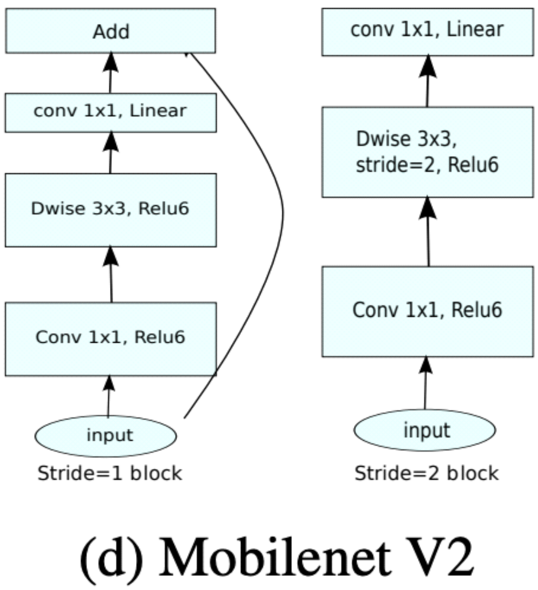

Figure 6: MobilNetV2 Architecture

As a result, MobileNetV2 outperforms MobileNetV1 with higher accuracies and lower latencies:

3.4 PROPOSED PSEUDOCODE

1. First we have imported all the library files and connected with our google drive.

2. We created separate functions for plot_categories, plot_metrics and plot_cm.

3. Then we performed the Data Augmentation part.

4. Then we used class weights to give all the classes equal importance on gradient updates.

5. Then we used our simple CNN Model and ran it to some epochs to get validation_results and validation_predictions.

6. Then we used Inception ResnetV2 Model and ran it to some epochs to get validation_results and validation_predictions.

7.Then we used simple VGG16 Model and ran it to some epochs to get validation_results and validation_predictions.

8.Then we used simple MobileNetV2 and ran it to some epochs to get validation_results and validation_predictions.

9.After evaluating the data from all the models above we created a table specifying all the metrics and concluding which model performed well for the particular data set(number of epochs ran are same for all model).

IMPLEMENTATION

Image Augmentation : Deep Neural Networks need huge measure of preparing information to accomplish great execution. To construct a strong picture classifier utilizing next to no preparation information, picture increase is generally expected to help the exhibition of deep networks. Picture expansion falsely makes preparing pictures through various approaches to handling or mix of different handling, like irregular revolution, moves, shear and flips, and so on.

Image Data Generator: An augmented picture generator can be handily made involving Image Data Generator API in Keras. Image Data Generator produces groups of picture information with ongoing information increase. The most fundamental codes to make and arrange Image Data Generator and train profound brain network with increased pictures are as per the following.

```
train_datagen = ImageDataGenerator(rescale=1./255,
                                   rotation_range=10,
                                   width_shift_range=0.05,
                                   height_shift_range=0.05,
                                   zoom_range=0.05,
                                   horizontal_flip=True,
                                   vertical_flip=True,
                                   brightness_range = [0.5, 1.4],
                                   validation_split=0.2)
```

Figure 7: Image Data Generator

Confusion matrix :A confusion matrix is an approach to surveying the exhibition of an arrangement model. It is a correlation between the main truth (genuine qualities) and the anticipated qualities given by the model for the objective variable.

A confusion matrix is helpful in the directed learning class of AI utilizing a named informational collection. As displayed underneath, it is addressed by a table. This is an example disarray network for a parallel classifier (for example 0-Negative or 1-Positive).

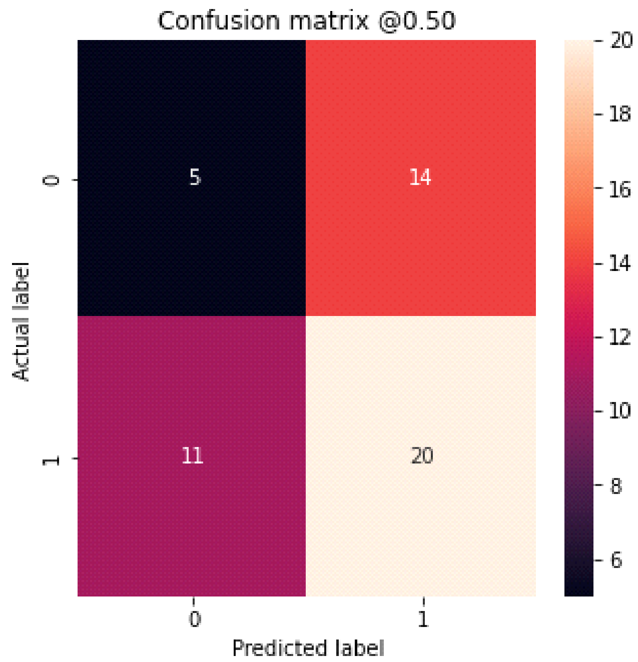

Figure 8: Confusion matrix

The confusion matrix is addressed by a positive and a negative class. The positive class addresses the not-ordinary class or conduct, so it is generally less addressed than the other class. The negative class, then again, addresses ordinariness or an ordinary way of behaving.

Here are the four quadrants in a confusion matrix:

Genuine Positive (TP) is the result when the model accurately forecasts a positive phase.

Genuine Negative (TN) is the result when the model accurately forecasts a negative phase.

Misleading Positive (FP) is the result when the model mistakenly forecasts a positive phase.

Misleading Negative (FN) is the result when the model incorrectly forecasts a negative phase.

Metrics:

Loss: Loss is the Penality for bad forecast. That is, misfortune is a number showing how awful the model's expectation was on a solitary model. The mean error across samples for each update (batch) or the average of all updates for the samples is called loss.

Epoch: Epoch is a term used in AI and indicates the number of phases of all AI computational data ready to be completed. Data sets are usually grouped into clusters (especially when information is vast). Some people use the word cycle freely and refer to putting one episode in a model as an emphasis.

In the case of a batch size is a complete data set, the number of years is the number of cycles. For practical reasons, this is usually not the case. Many models are made in more than one year. The total connection where the data set size d, period number is e, cycle number is I, and group size is b * will be d * e = I * b.

Accuracy: The accuracy metric is usually calculated as a ratio of right forecasting to total no of items tested.

Precision: Precision is used to calculate total number of positive layout of the positive phase that are correctly from total no of forecasted layout.

Recall: It is the % of positive patterns that are accurately classified and calculated as recall.

AUC: It is an analysis of ROC curve which calculates the classifier capabilities to discriminate in different classes.AUC measures how good a model is able to differentiate from positive & negative classes. When the AUC is more, the better the model is.

<u>CNN Model:</u> In this code snippet we have created our CNN model.

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(filters = 64 , kernel_size = (3,3), activation="relu", input_shape=(224,224,3)),
    tf.keras.layers.MaxPooling2D(pool_size = (3,3)),
    tf.keras.layers.Conv2D(filters = 32 , kernel_size = (3,3), activation="relu"),
    tf.keras.layers.MaxPooling2D(pool_size = (3,3)),
    tf.keras.layers.Conv2D(filters = 32 , kernel_size = (3,3), activation="relu"),
    tf.keras.layers.MaxPooling2D(pool_size = (3,3)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(units = 512 , activation="relu"),
    tf.keras.layers.Dropout(rate = 0.5),
    tf.keras.layers.Dense(units = 1 , activation="sigmoid")
 ])
```

```
model.compile(optimizer = tf.optimizers.Adam(learning_rate = 0.0008),
              loss = "binary_crossentropy",
              metrics=metrics)
```

Figure 9: CNN Code snippet

InceptionResnetV2

```
base_model = tf.keras.applications.InceptionResNetV2(input_shape=(224,224,3),
                                                    include_top=False,
                                                    weights='imagenet')


base_model.trainable = False

model = tf.keras.Sequential([
                              base_model,
                              tf.keras.layers.Flatten(),
                              tf.keras.layers.Dense(128, activation = 'relu'),
                              tf.keras.layers.Dropout(rate = 0.2),
                              tf.keras.layers.Dense(1, activation='sigmoid')
                            ])

model.compile(optimizer = tf.optimizers.Adam(learning_rate = 0.0001),
              loss = "binary_crossentropy",
              metrics=metrics)
```

Figure 10: Inception ResnetV2 Code snippet

VGG 16

```
base_model = tf.keras.applications.VGG16(input_shape=(224,224,3),
                                         include_top=False,
                                         weights='imagenet')

base_model.trainable = False

model = tf.keras.Sequential([
                          base_model,
                          tf.keras.layers.GlobalMaxPooling2D(),
                          tf.keras.layers.Dense(4096, activation = 'relu'),
                          tf.keras.layers.Dropout(rate=0.5),
                          tf.keras.layers.Dense(1, activation='sigmoid')
                        ])

model.compile(optimizer = tf.optimizers.Adam(learning_rate = 0.0001),
              loss = "binary_crossentropy",
              metrics=metrics)
```

Figure 11:VGG16 Code snippet

MobileNetV2

```
base_model = tf.keras.applications.MobileNetV2(input_shape=(224,224,3),
                                               include_top=False,
                                               weights='imagenet')

base_model.trainable = False

model = tf.keras.Sequential([
                              base_model,
                              tf.keras.layers.GlobalAveragePooling2D(),
                              tf.keras.layers.Dense(1024, activation = 'relu'),
                              tf.keras.layers.Dropout(rate = 0.2),
                              tf.keras.layers.Dense(1, activation='sigmoid')
                            ])

model.compile(optimizer = tf.optimizers.Adam(learning_rate = 0.00008),
              loss = "binary_crossentropy",
              metrics=metrics)
```

Figure 12:MobilenetV2 Code snippet

RESULTS

1. Simple CNN Model-

a. Confusion matrix

```
Non-tumor detected (True Negatives):  5
Non-tumor incorrectly detected (False Positives):  14
Tumor missed (False Negatives):  11
Tumor detected (True Positives):  20
Total case:  31
```

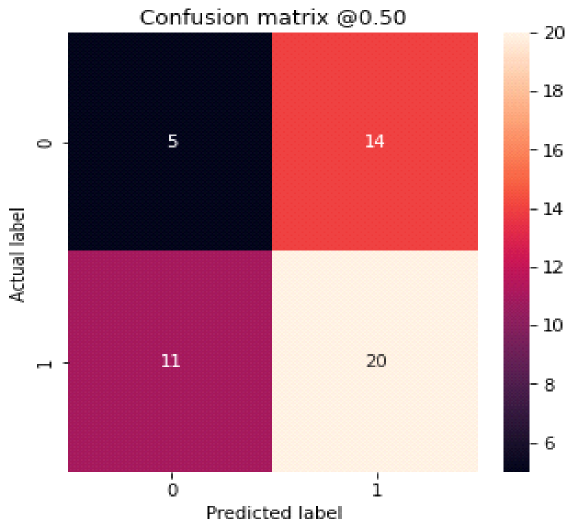

Figure 13 : for 40 epochs

```
Non-tumor detected (True Negatives):  16
Non-tumor incorrectly detected (False Positives):  3
Tumor missed (False Negatives):  7
Tumor detected (True Positives):  24
Total case:  31
```

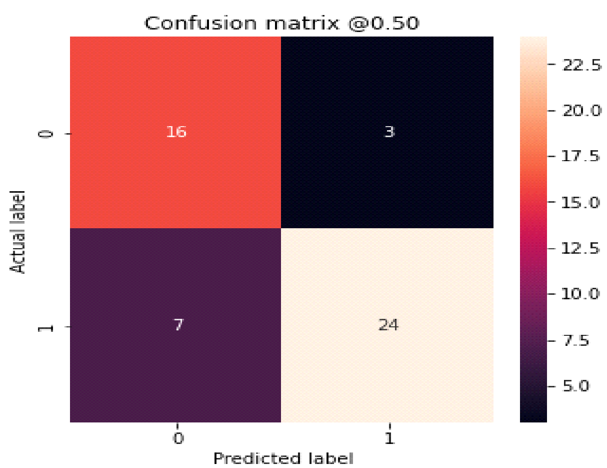

Figure 14 : for 100 epochs

b. Graph:

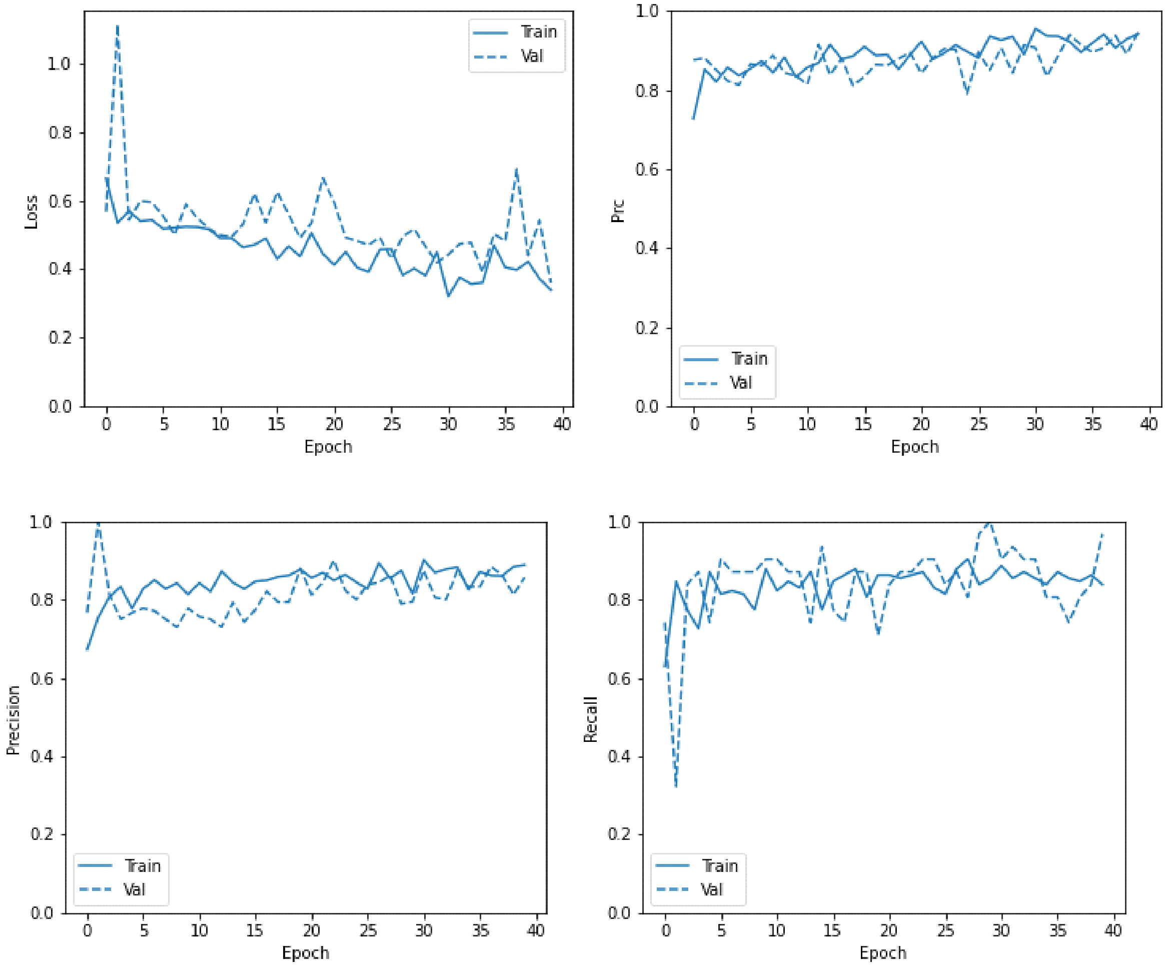

Figure 15 : for 40 epochs

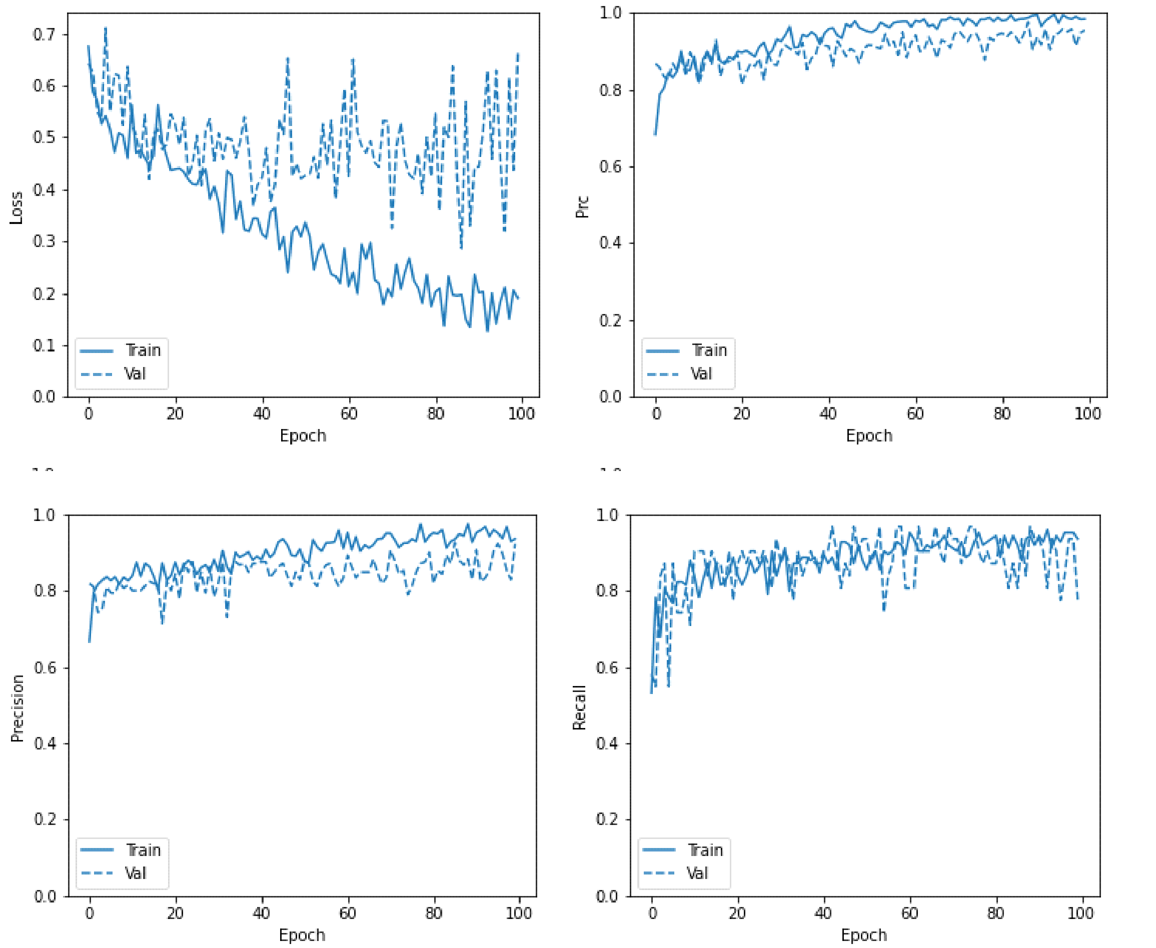

Figure 16: for 100 epochs

INCEPTION RESNETV2

a. Confusion matrix

```
Non-tumor detected (True Negatives):  16
Non-tumor incorrectly detected (False Positives):  3
Tumor missed (False Negatives):  3
Tumor detected (True Positives):  28
Total case:  31
```

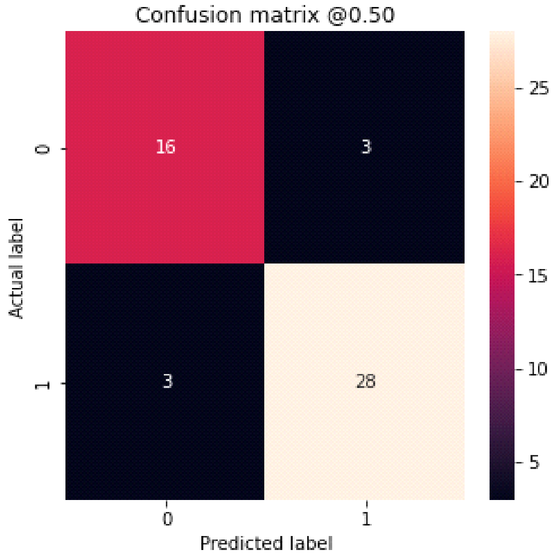

Figure 17: for 40 epochs

```
Non-tumor detected (True Negatives):  18
Non-tumor incorrectly detected (False Positives):  1
Tumor missed (False Negatives):  5
Tumor detected (True Positives):  26
Total case:  31
```

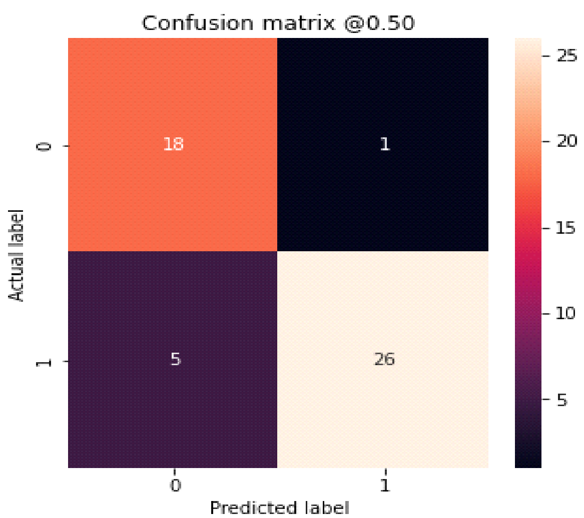

Figure 18: for 100 epochs

b. Graph

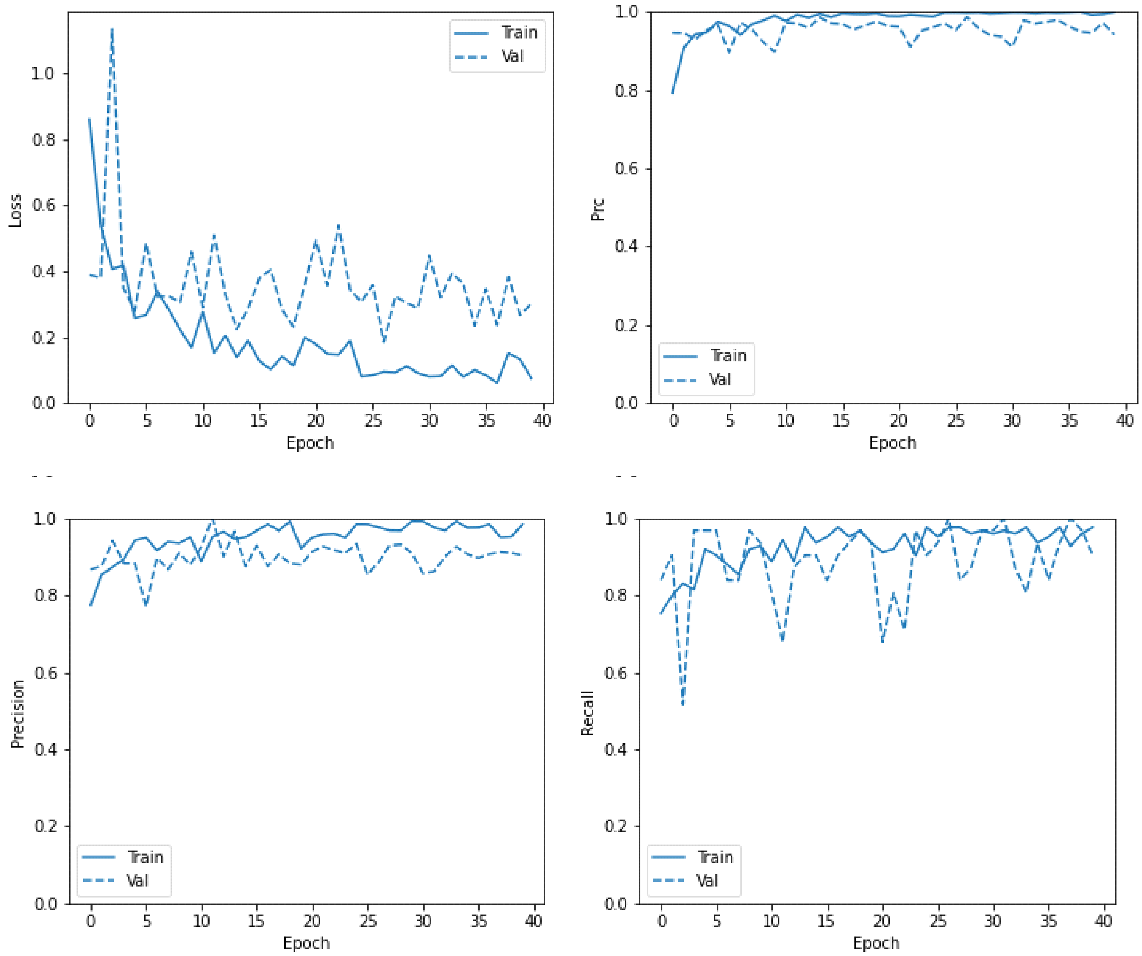

Figure 19 : for 40 epochs

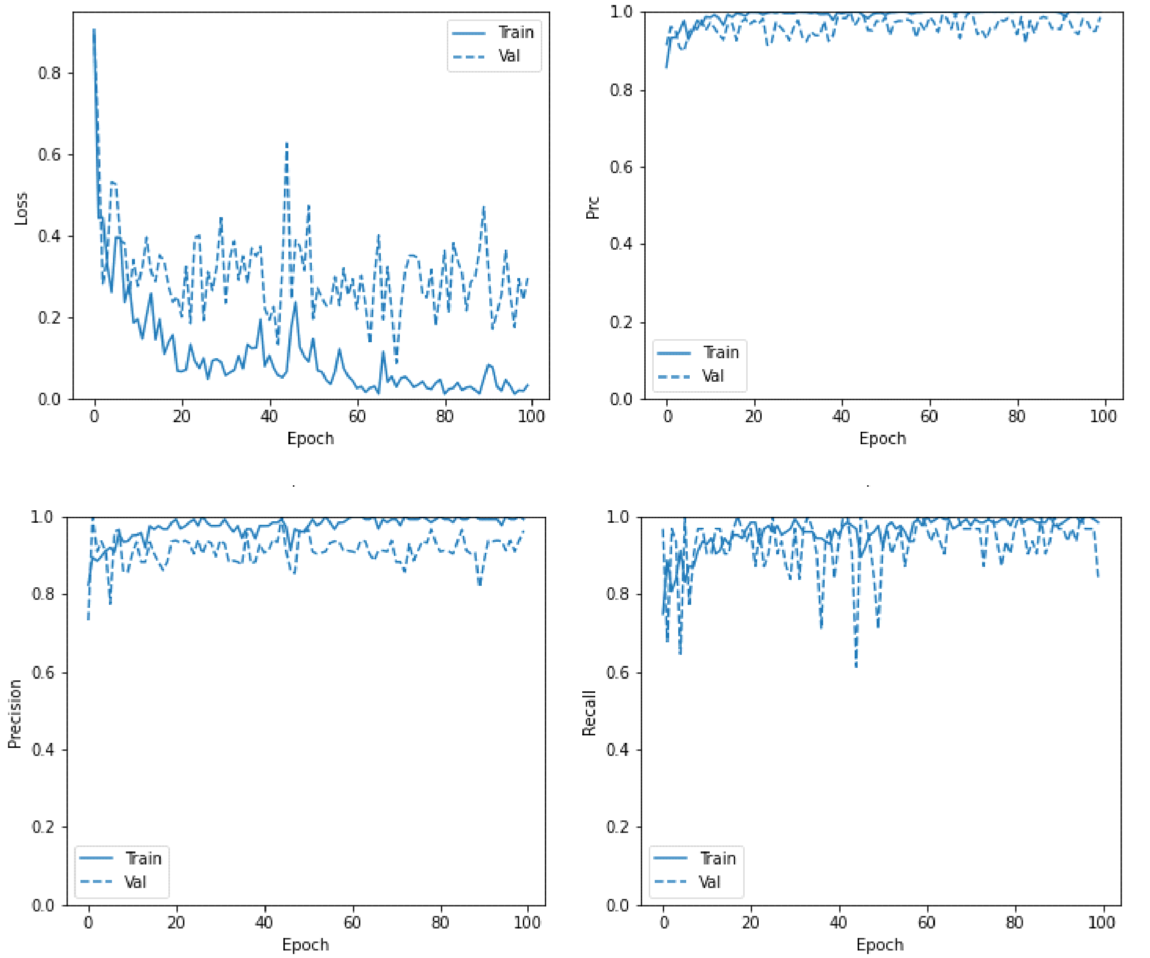

Figure 20: for 100 epochs

VGG 16

a. Confusion matrix

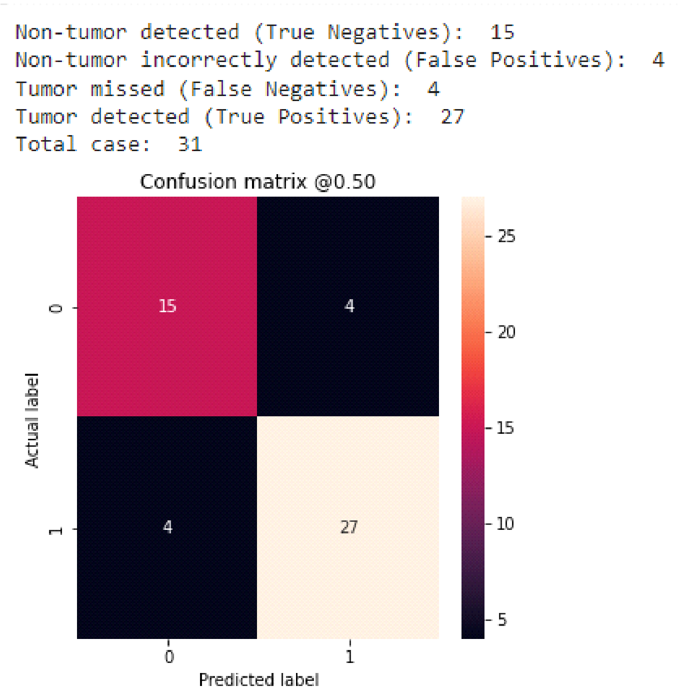

Figure 21: for 40 epochs

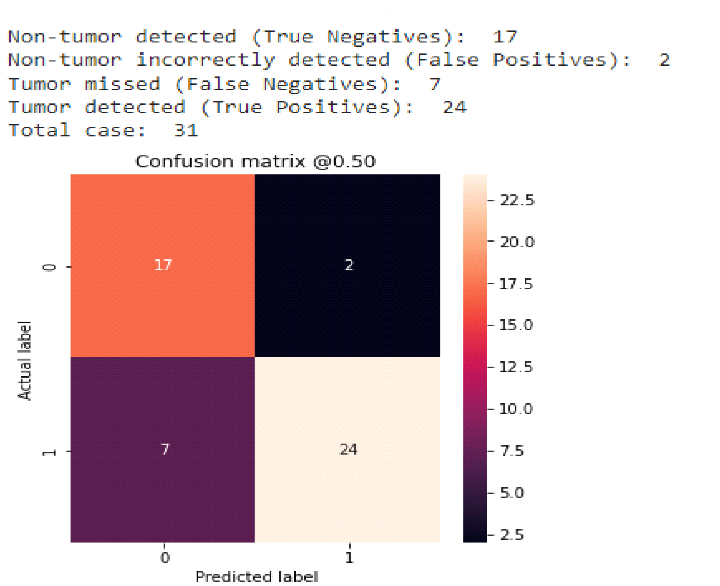

Figure 22: for 100 epochs

b. Graph

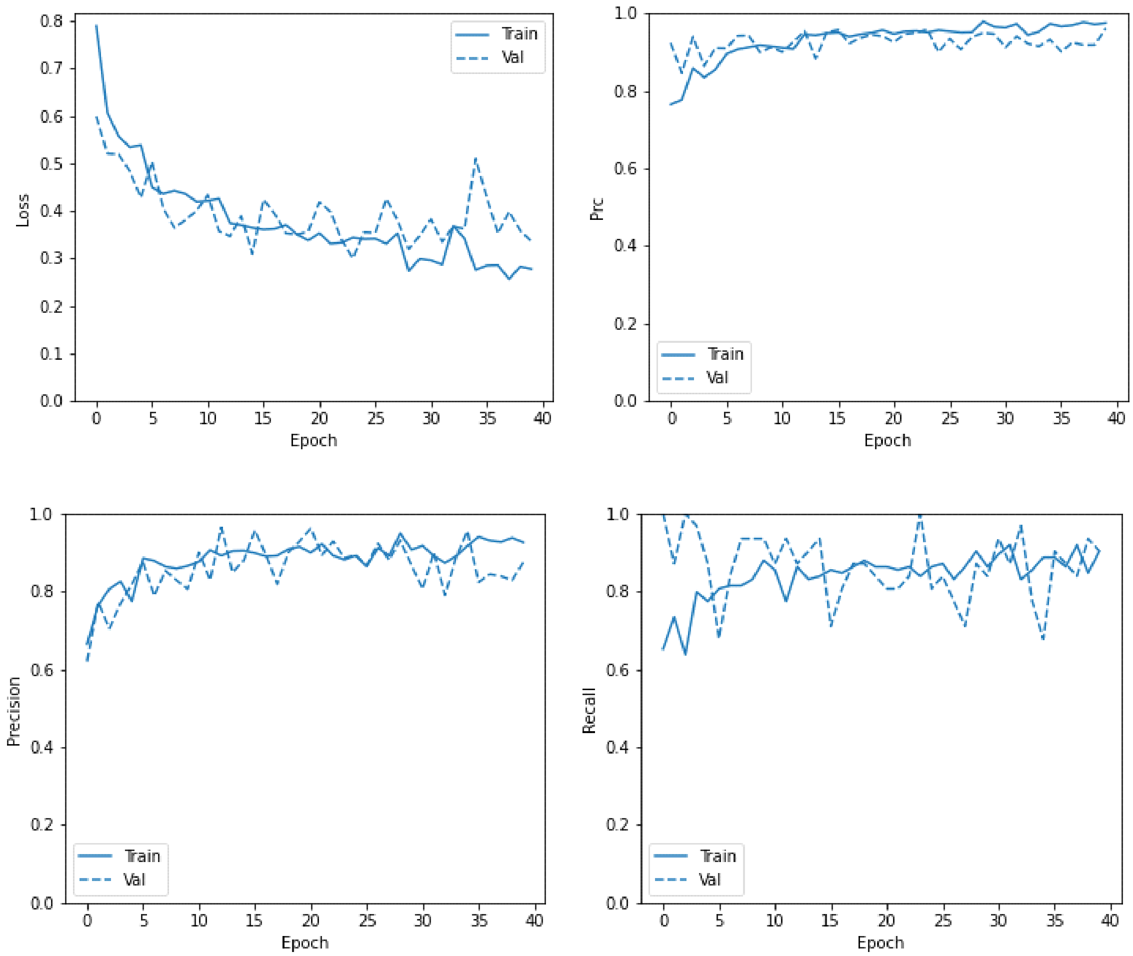

Figure 23: for 40 epochs

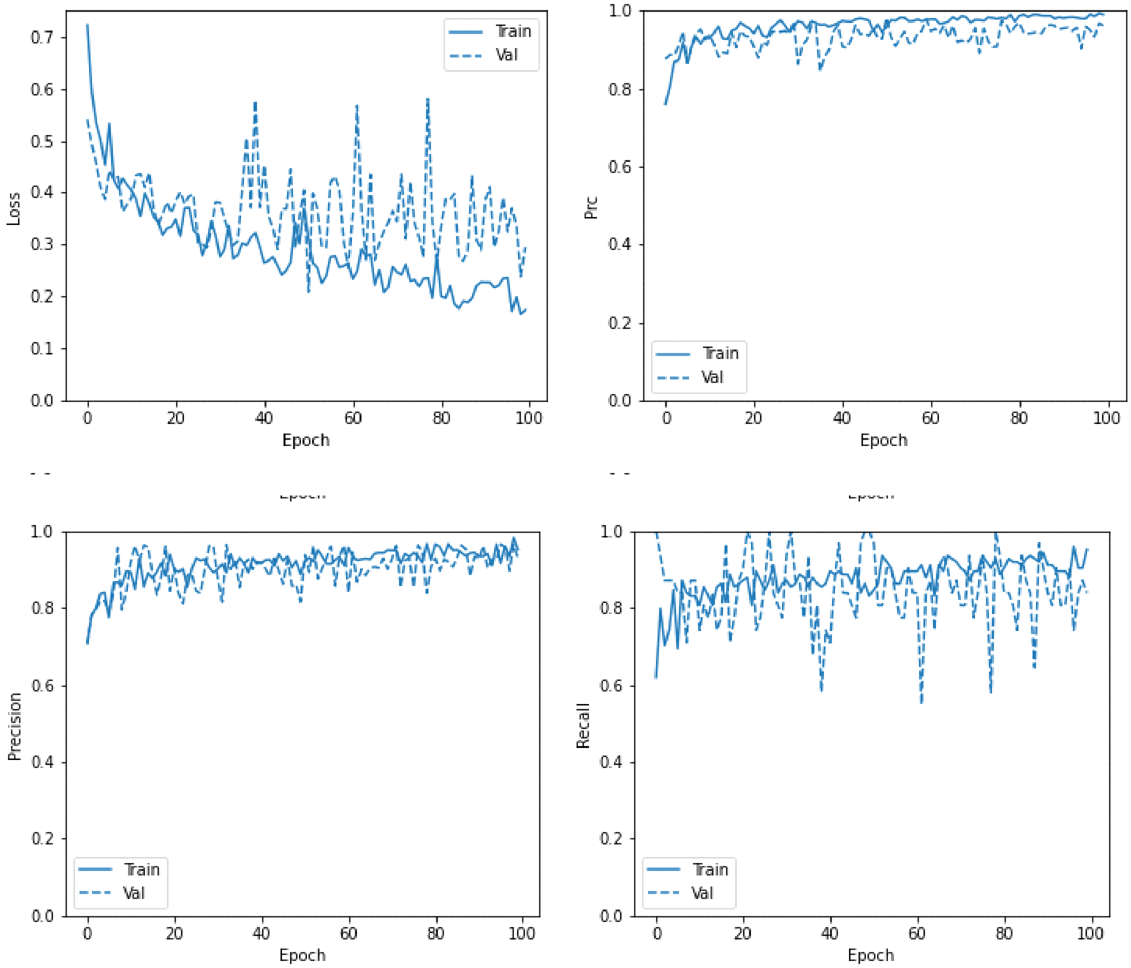

Figure 24: for 100 epochs

MobileNetV2

a. Confusion matrix

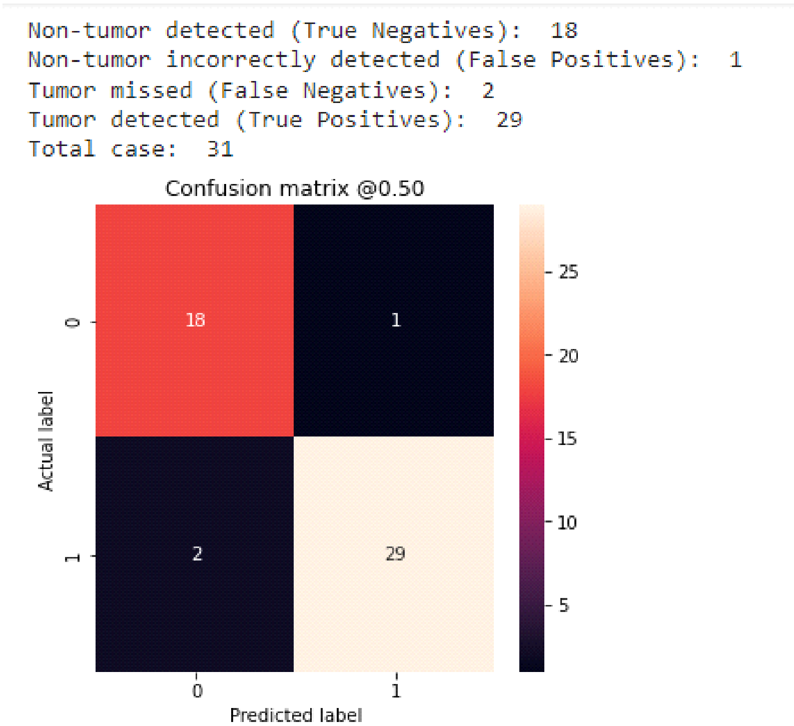

Figure 25: for 40 epochs

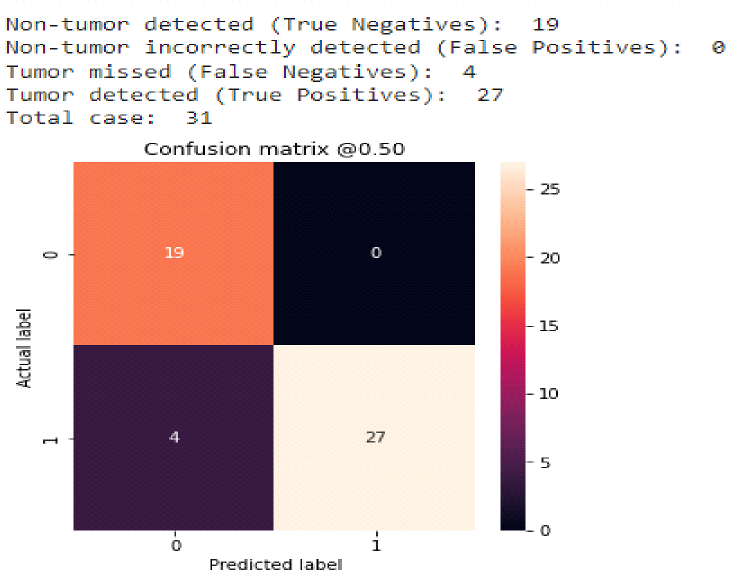

Figure 26: for 100 epochs

b. Graph

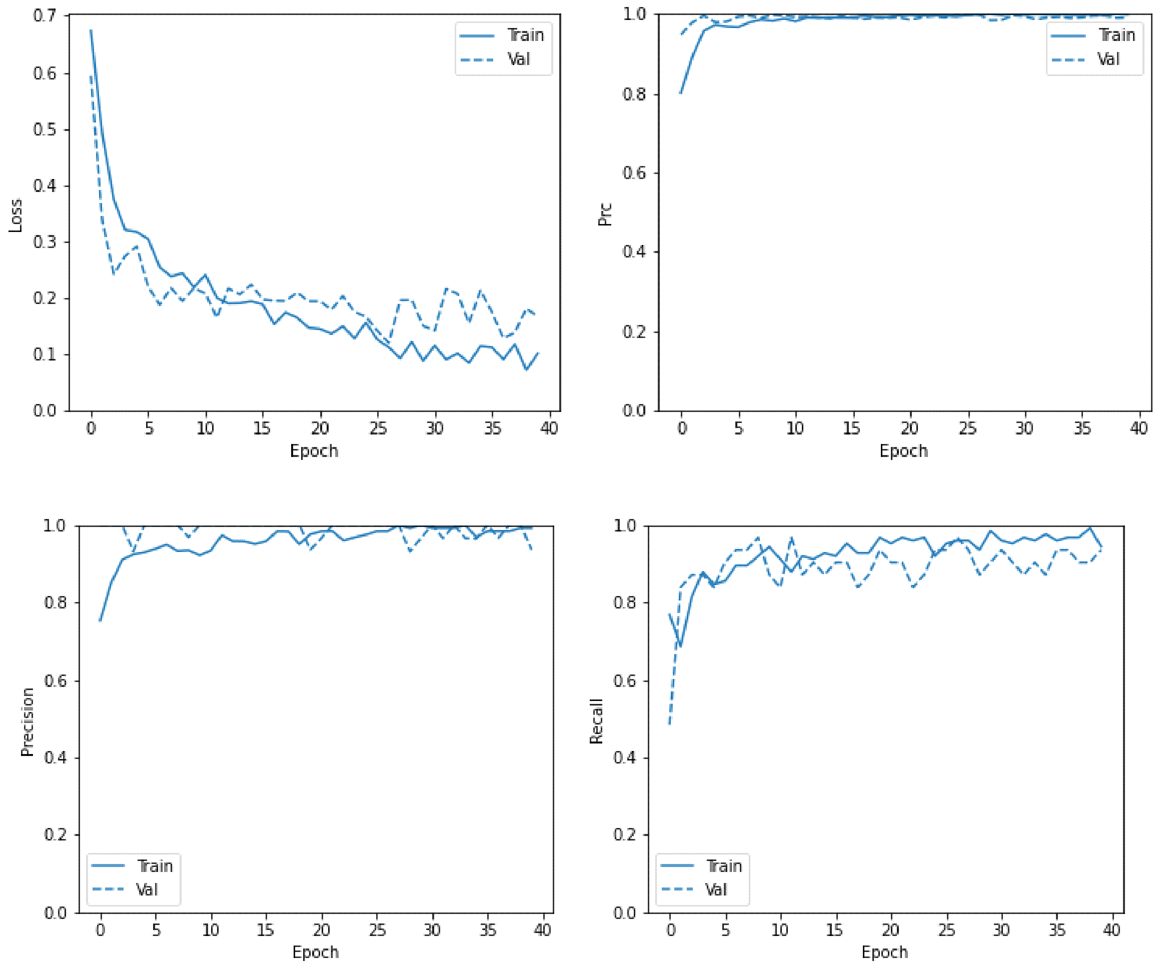

Figure 27: for 40 epochs

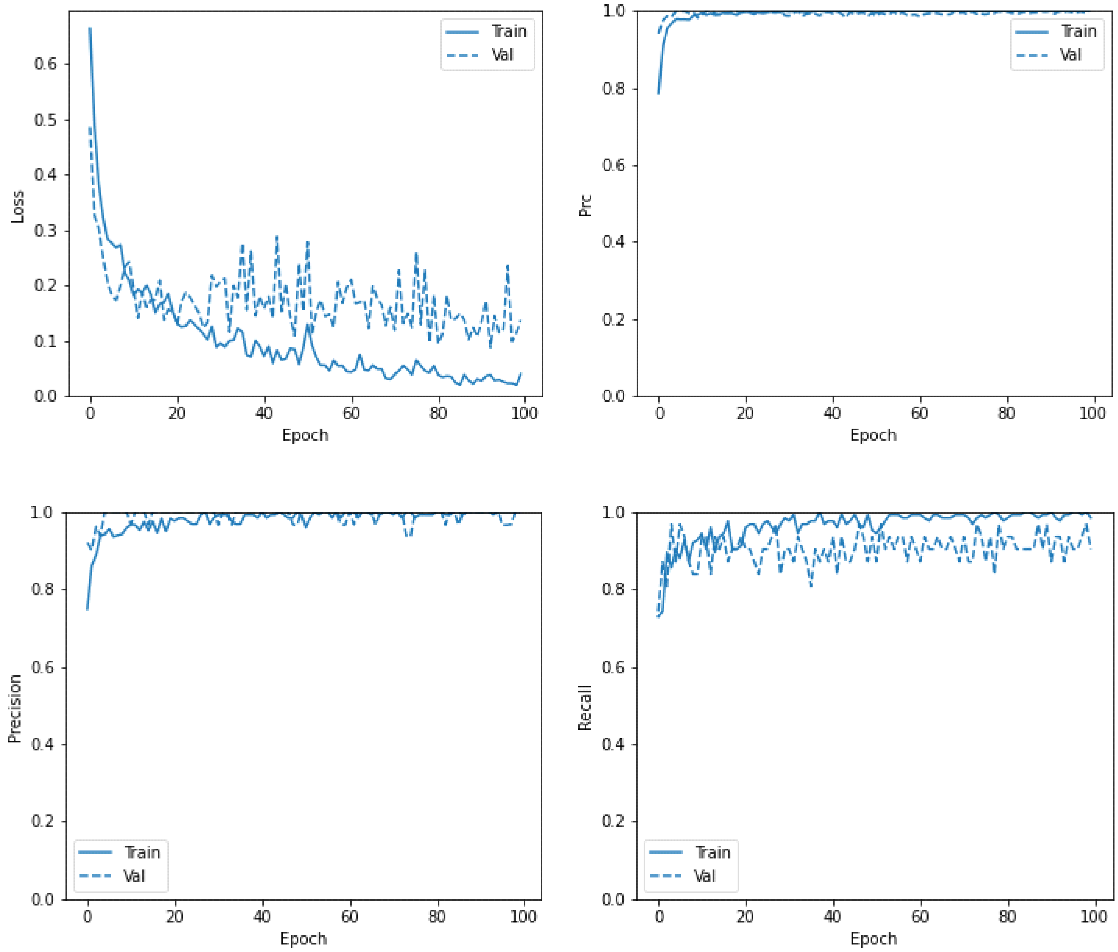

Figure 28: for 100 epochs

CONCLUSION

This study compares several CNN constructed entirely on models of transfer learning, that correctly categorize brain MRI pictures as tumors. We used Transfer Learning based different CNN models, such as VGG16, InceptionResNetV2,& MobileNetV2, to complete the picture classification technique, as well as a Simple CNN architecture that works like classifier in forecasting evaluation in tumor detection. This is the most general health problem linked with the human brain is a brain tumor. The accuracy of validation drops when the accuracy of training grows, then architecture is expected to have overfitting issues. We concluded after evaluating examination of several pre-trained CNN architecture, like VGG-16, InceptionResNetV2, and MobileNetV2, that MobileNetV2 provides greater accuracy on the trained dataset .Below you'll be able to discover desk of metrics for 100 epoch run.

	Model Name	Precision (with Max AUC)	Recall (with Max AUC)	Max AUC	Accuracy	Mean Precision	Mean Recall	Mean AUC	Mean Accuracy
0	Simple CNN	0.857143	0.967742	0.923599	0.88	0.812170	0.842742	0.828162	0.7765
1	InceptionResNetV2	0.885714	1.000000	0.977929	0.92	0.899700	0.884677	0.939856	0.8650
2	VGG16	0.885714	1.000000	0.946519	0.92	0.858165	0.865323	0.906515	0.8200
3	MobileNetV2	1.000000	0.967742	0.996604	0.98	0.987345	0.889516	0.979775	0.9240

Figure 29: for 40 epochs

	Model Name	Precision (with Max AUC)	Recall (with Max AUC)	Max AUC	Accuracy	Mean Precision	Mean Recall	Mean AUC	Mean Accuracy
0	Simple CNN	0.878788	0.935484	0.954159	0.88	0.841914	0.870645	0.869177	0.8172
1	InceptionResNetV2	0.939394	1.000000	0.998302	0.96	0.912615	0.929355	0.955289	0.8988
2	VGG16	0.937500	0.967742	0.974533	0.94	0.898190	0.843226	0.923158	0.8396
3	MobileNetV2	1.000000	0.935484	1.000000	0.96	0.990793	0.903871	0.986358	0.9350

Figure 30: for 100 epochs

6. REFERENCES

[1]L.Guo,L.Zhao,Y.Wu,Y.Li,G.Xu,andQ.Yan,"Tumordetection in MR images using oneclass immune feature weighted SVMs," IEEE Transactions on Magnetics, vol. 47, no. 10, pp.

3849–3852,2011.

[2]R.Kumari,"SVMclassificationanapproachondetectingabnormalityinbrainMRIimages,"Inter

nationalJournalofEngineeringResearchandApplications,vol.3,pp.1686–1690,2013.

[3] J. C. Buckner, P. D. Brown, B. P. O'Neill, F. B. Meyer , C. J. Wetmore,J. H Uhm, "Central nervous system tumors." In Mayo Clinic Proceedings,Vol. 82, No. 10, pp. 1271- 1286, October 2007.

[4] Deepa , Singh Akansha. (2016). - Review of Brain Tumor Detection from tomography. International Conference on Computing for Sustainable Global Development (INDIACom)

[5] Preston, D. c. (2006). Magnetic Resonance Imaging (MRI) of the Brain and Spine from Basics. casemed.case.edu .

[6] S.U. Aswathy, G.Glan Deva Dhas and S.S. Kumar ―A Survey on detection of brain tumor from MRI Brain images‖, 7th International Conference on Cloud Computing, Data Science & Engineering –Confluence 2017.

[7]Sergio Pereira, Adriano Pinto, Victor Alves, and Carlos A. Silva ―Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images‖ IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 35, NO. 5, MAY 2016

[8] S.C. Turaga, J.F. Murray, V. Jain, F. Roth, M. Helmstaedter, K. Briggman,W. Denk, and H.S. Seung. Convolutional networks can learn to generate affinity graphs for image segmentation. Neural Computation, 22(2):511–538, 2010

[9] S. Bakas, M. Reyes, A. Jakab, S. Bauer, M. Rempfler, A. Crimi, et al., "Identifying the Best Machine Learning Algorithms for Brain Tumor Segmentation, Progression Assessment, and Overall Survival Prediction in the BRATS Challenge", arXiv preprint arXiv:1811.02629 (2018)

[10] ZeynettinAkkus, AlfiiaGalimzianova, Assaf Hoogi ,Daniel L. Rubin and Bradley J. Erickson, "Deep Learning for Brain MRI Segmentation: State of the Art and FutureDirections" J Digit Imaging DOI 10.1007/s10278-017- 9983-4, 2017.

[11] Anupurba Nandi, "Detection of human brain tumourusing MRI image segmentation and morphological operators" IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS), 2015.

[12] Swapnil R. Telrandhe, Amit Pimpalkar and AnkitaKendhe, “Detection of Brain Tumor from MRI images by using Segmentation &SVM” World Conference on Futuristic Trends in Research and Innovation for Social Welfare (WCFTR’16), 2016.

[13] G. B. Janardhana Swamy, Anusha, Lavanya, Meghashree, and Sangeetha, “Brain tumor detection using convolutional neural network,” International Journal for Research in Applied Science and Engineering Technology, vol. 8, no. VI, 2020.

[14] D. Dheeraj and H. S. Prasantha, “Study of machine learning vs. deep learning algorithms for detection of tumor in human brain,” International Journal of Computer Science and Engineering, vol. 8, no. 1, pp. 2347–2693, 2020.

[15] H. Barad and A. Patel, “Application of machine learning and deep learning methods for brain tumor identification and classification,” International Journal of Recent Technology and Engineering, vol. 86 pages, 2020.

[16] M. Talo, U. B. Baloglu, O Yildirim, and U. R. Acharya, “Application of Deep Transfer Learning for Automated Brain Abnormality Classification Using MR Images,” Cognitive Systems Research, vol. 54, 2019.

[17] A. Gudigar, U. Raghavendra, T. R. San, E. J. Ciaccio, and U. R. Acharya, “Application of Multiresolution analysis for automated detection of brain abnormality using MR images: a comparative study,” Future Generation Computer Systems, vol. 90, pp. 359–367, 2019.

[18] M. Visser, D. M. J. M¨uller, R. J. M. V. Duijn et al., “Inter-rater agreement in glioma segmentations on longitudinal MRI,” NeuroImage: Clinical, vol. 22, Article ID 101727, 2019.

[19] H. A. Khan, W. Jue, M. Mushtaq, and M. U. Mushtaq, “Brain tumor classification in MRI image using convolutional neural network,” Mathematical Biosciences and Engineering, vol. 17, no. 5, pp. 6203–6216, 2020.

[20] B. Anilkumar and P. R. Kumar, “Classification of MR brain tumors with deep plain and residual feed forward CNNs through transfer learning,” International Journal of Engineering and Advanced Technology (IJEAT) ISSN, vol. 8, no. 6, 2019.

[21] N. Abiwinanda, M. Hanif, S. Hesaputra, A. Handayani, and T. R. Mengko, “Brain Tumor Classification Using Convolutional Neural Network,” in Proceedings of the World Congress on Medical Physics and Biomedical Engineering, Springer, Prague, Czech Republic, June 2019.

[22] M. D. A. B. Siddique, S. Sakib, M. M. R. Khan, A. K. Tanzeem, M. Chowdhury, and N. Yasmin, “Deep convolutional neural networks model-based brain tumor detection in brain MRI images,” in Proceedings of the 4th International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC 2020), Palladam, India, October 2020.

[23] G. Hemanth, M. Janardhan, and L. Sujihelen, “Design and implementing brain tumor detection using machine learning approach,” in Proceedings of the 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1289–1294, Tirunelveli, India, April 2019.

[24] S. Deepak and P. M. Ameer, “Brain tumor classification using deep CNN features via transfer learning,” Computers in Biology and Medicine, vol. 111, Article ID 103345, 2019.

[25] C. Cheroni, N. Caporale, G. Testa, Autism spectrum disorder at the crossroad between genes and environment: contributions, convergences, and interactions in ASD developmental pathophysiology, Mol. Autism. 11 (2020).

[26] A. Tiwari, S. Srivastava, and M. Pant, “Brain tumor segmentation and classification from magnetic resonance images: review of selected methods from 2014 to 2019,” Pattern Recognition Letters, vol. 131, pp. 244–260, 2020. [15] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, “A Deep Learning-based framework for automatic brain tumors classification using transfer learning,” Circuits, Systems, and Signal Processing, vol. 39, no. 2, pp. 757–775, 2020.

7. APPENDICES

List of Abbreviation

Sr No.	Abbreviation	Meaning
1	CNN	Convolutional Neural Network
2	MRI	Magnetic Resonance Imaging
3	FLAIR	Fluid attenuated in version recovery weighted MRI
4	TR	Time repetition
5	TE	Pulse sequence parameter
6	VGG 16	Visual Geometry Group
7	FC	Fully connected layer
8	ReLU	Rectified linear unit
9	LRN	Local response normalization
10	KNN	K nearest neighbor
11	SVM	Support Vector Machine