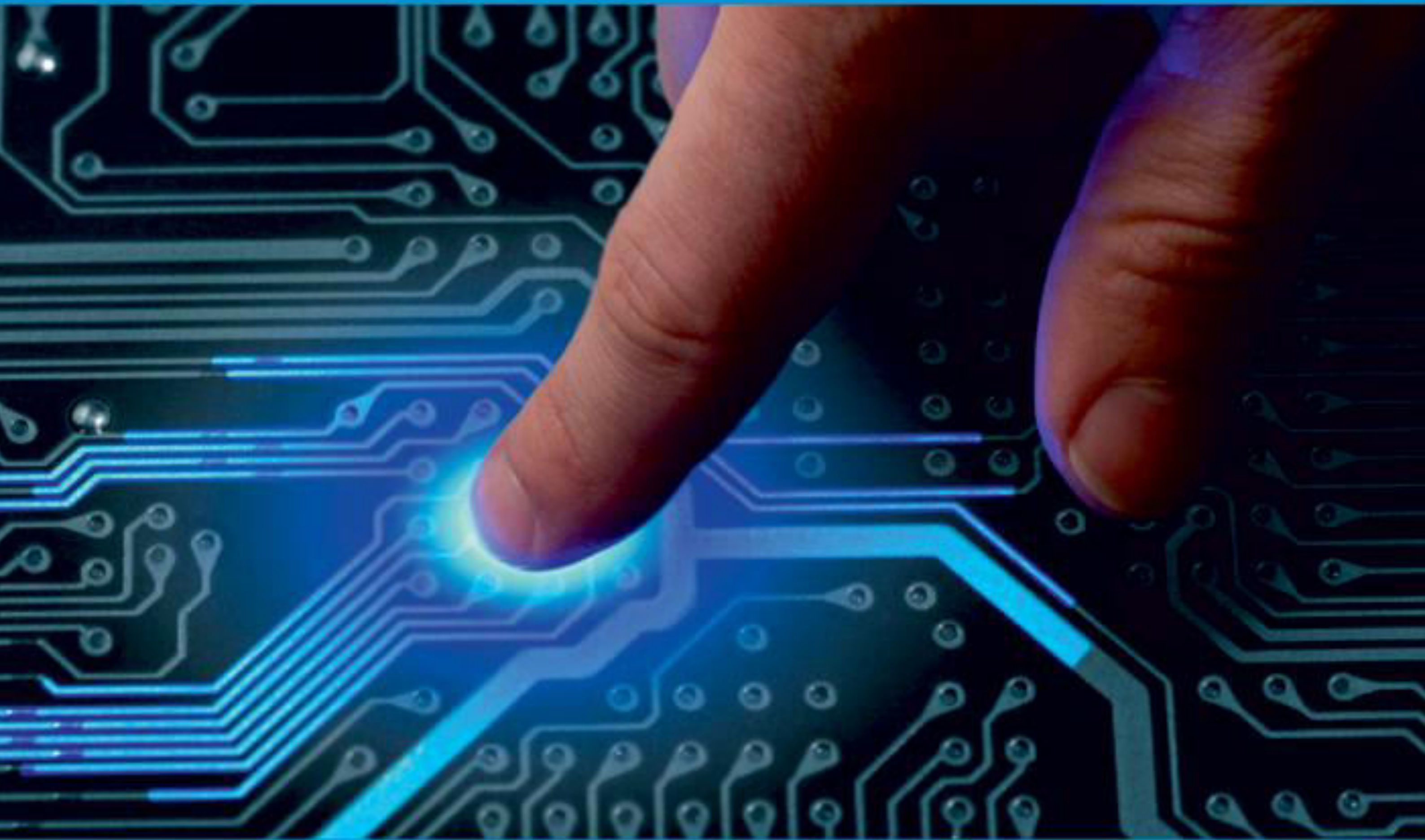
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 5, May 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005329 |

Deep Learning Techniques for the Diagnosis of Brain Tumours

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ABSTRACT: Brain Tumour Detection uses a user-uploaded MRI scan image to determine whether or not a patient has a tumour. The sooner a brain tumour is discovered, the more research may be done and the patient can receive an immediate diagnosis. The Convolution Neural Network is used to implement our Brain Tumor Detection Project (CNN). VGG16 pre-trained model architecture is used to transfer-learn the CNN model of the project This project utilises Kaggle's "Brain MRI Images for Brain Tumour Detection" data set. In recent decades, medical research has made incredible progress and has become an exceptional field. The field of medicine is changing due to the advancements in technology. Fitness care has received a major boost from a slew of fresh innovations and preferences that are currently available. When cancer is mentioned, humans go into a state of hysteria. Our project's primary goal is to use CNN and VGG16 to detect brain cancers in their early stages. In the field of artificial intelligence, convolution neural networks (CNNs) are a type of deep neural network. Every image-related issue has CNN as the go-to model. This is the primary advantage of the CNN model, which is able to automatically detect the most important feature without any human intervention. VGG-16 and ResNet model are two examples of CNN models. VGG is one of the best-performing CNN models because of how straightforward it is. VGG-16 is a critical CNN model if one wants to employ an off-the-shelf model for a specific application. VGG-16, a Convolution Neural Network model architecture and weights, is used to detect brain tumours in this case. Correctness will be taken into consideration while evaluating the performance. We plan to use Brain MRI pictures for Brain Tumour Detection in our research.

I.INTRODUCTION

The skull limits the tumor's growing space, making it unique among tumours. This means that a tumor's growth might put pressure on the brain's essential organs, resulting in major health complications. A mass of tissue that develops abnormally when cells grow and divide excessively or do not die at the appropriate time. There are two types of tumours: benign (do not cause cancer) and malignant (do cause cancer) (cancer). Although benign tumours can grow to be quite large, they do not spread or infect other tissues or organs. It is possible for cancerous tumours to invade or spread to neighbouring healthy tissues. They can also spread throughout the body via the blood and lymphatic systems. Researchers and clinicians are unsure about the specific cause of brain tumours. The signs and symptoms of a brain tumour are highly variable, depending on the size, nature, and location of the tumour. Headaches and numbness or tingling in the arms or legs are the most prevalent symptoms. A person's age has nothing to do with their risk of developing a brain tumour. A brain tumour can harm anyone, regardless of age. A brain tumour can be fatal if it is not discovered early enough. Magnetic Resonance Imaging (MRI) is the most reliable and safest diagnostic technique available today among the numerous types of medical imaging. In order to detect the brain tumour, MRI scans are used. These photos reveal the aberrant brain tissue growth that has been detected. The radiologist can also benefit from these predictions by being able to make timely decisions.

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II. LITERATURE SURVEY

2.1 Bengio, Y., Lamblin, P., Popovici, D., Larochelle, H.: Greedy layer-wise training of deep networks. Advances in Neural Information Processing Systems 19 (NIPS), 153–160 (2007).

Complexity principle of circuits strongly suggests that deep architectures can be lots extra environment friendly (sometimes exponentially) than shallow architectures, in phrases of computational factors required to characterize some functions. Deep multi-layer neural networks have many tiers of non-linearities permitting them to compactly signify distinctly non-linear and highly-varying functions. However, till these days it used to be now not clear how to teach such deep networks, for the reason that gradient-based optimization beginning from random initialization seems to frequently get caught in bad solutions. Hinton et al. currently brought a grasping layer-wise unsupervised mastering algorithm for Deep Belief Networks (DBN), a generative mannequin with many layers of hidden causal variables. In the context of the above optimization problem, we find out about this algorithm empirically and discover versions to higher recognize its success and prolong it to instances the place the inputs are non-stop or the place the shape of the enter distribution is now not revealing sufficient about the variable to be expected in a supervised task. Our experiments additionally verify the speculation that the grasping layer-wise unsupervised coaching method mainly helps the optimization, by means of initializing weights in a location close to a accurate neighborhood minimum, giving upward push to inner disbursed representations that are high-level abstractions of the input, bringing higher generalization.

2.2 Bengio, Y.: Learning deep architectures for AI. Foundations and Trends in Machine Learning 2, 1–127 (2009).

Theoretical effects propose that in order to analyze the variety of elaborate features that can signify high-level abstractions (e.g., in vision, language, and different AI-level tasks), one can also want deep architectures. Deep architectures are composed of a couple of stages of non-linear operations, such as in neural nets with many hidden layers or in elaborate propositional formulae re-using many sub-formulae. Searching the parameter area of deep architectures is a challenging task, however studying algorithms such as these for Deep Belief Networks have these days been proposed to address this trouble with exceptional success, beating the latest in sure areas. This monograph discusses the motivations and standards concerning mastering algorithms for deep architectures, in unique these exploiting as constructing blocks unsupervised mastering of single-layer fashions such as Restricted Boltzmann Machines, used to assemble deeper fashions such as Deep Belief Networks.

2.3 S.-H. Hsu, Q. Peng, and W. A. Tomé, ``on the era of artificial CT for an MRI-only radiation remedy workflow for the abdomen,'' J. Phys., Conf. Ser, vol. 1154, no. 1, Mar. 2019, Art. no. 012011.

The advances in clinical imaging have led to new multi dimensional imaging modalities that have grow to be essential medical equipment in diagnostic radiology. The two modalities succesful of producing multidimensional pix for radiological purposes are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). Normally the first radiologic examination in suspicion of stroke is talent CT imaging. But MRI gives excessive decision pictures with extremely good gentle tissue characterization capabilities. A comparative analysis for the prognosis of stroke on CT and MRI photographs is presented in this paper. The algorithm proposes the use of Digital Image processing equipment for the identification of infarct and Hemorrhage in human brain. Preprocessing of clinical pics is completed by way of median filtering. Segmentation is finished via Gabor filtering and seeded location developing algorithm. The technique is established on the CT and MRI Genius photos having extraordinary sorts of infarcts. The effects of the approach are evaluated visually. The proposed technique is promising for detection of stroke and additionally establishes that MRI imaging is best to CT imaging in stroke detection.

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III. PROPOSED SYSTEM

It has been determined that the shortcomings of current applications can be addressed by the model under consideration. Brain MRI scans can be detected with this programme. It is necessary to perform "normalisation" prior to importing data. As part of data preparation for machine learning, normalisation is used. It is the purpose of normalisation to convert the values to a common scale without distorting the differences in the ranges of the values. Image input is fed into a Convolution Neural Network (CNN), which processes the image and then generates an output that classifies it. As a result, VGG-16 transfer learning is used to classify images and verify accuracy for both testing and validation datasets. Classification results show that the VGG-16 design is among the most effective at producing them

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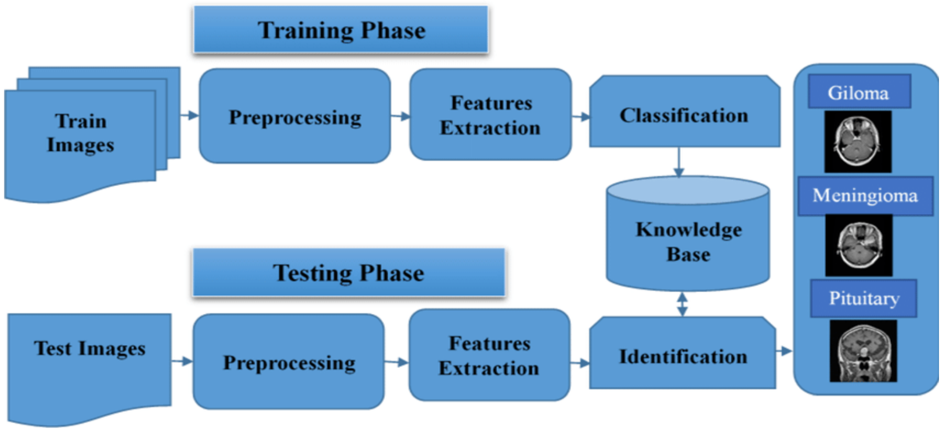

Fig 1: System architecture

3.1 CONVOLUTION NEURAL NETWORKS:

The neurons of a convolutionary neural network have learnable weights and biases, much like in a regular neural network. Dot product and non-linearity are optional features of each neuron's inputs.

Ordinary neural networks aren't very good at handling large images. How many weights does a single neuron in the first hidden layer of a typical Neural Network have? 32*32*3 = 3072 weights for a single fully-connected neuron. This is still a tolerable number, but it is evident that this fully-connected structure does not work with larger photos. As an example, if an image is 200x200x3 in size, it would result in neurons with 120,000 weights. If you're going to have a lot of these neurons, you're going to need a lot of parameters. Indeed, a large number of parameters would quickly lead to over-fitting[2] if this entire interconnectedness were implemented. This Deep Learning method, known as a Convolutional Neural Network (ConvNet/CNN), can take in an image, assign importance (learnable weights and biases) to various aspects/objects in the image, and be able to tell them apart one from the other. A ConvNet requires substantially less preprocessing than conventional classification techniques. Convolutional neural networks (ConvNets) have the ability to learn these filters/characteristics if they are given enough training. Neuronal connection patterns in the human brain are modelled on the visual cortex's arrangement in the ConvNet. The Receptive Field is a portion of the visual field in which individual neurons are responsive to stimuli.

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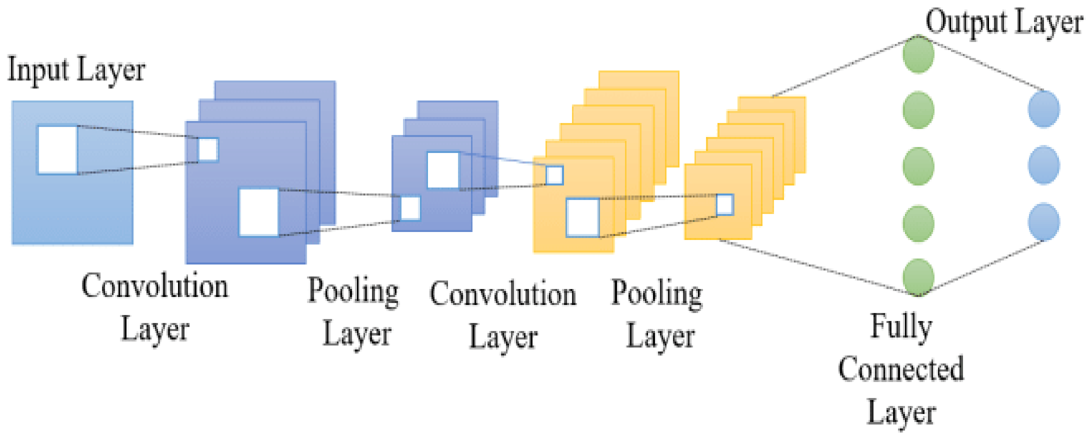

Fig 2: CNN Architecture

Due to the fact that the input is comprised of images, Convolutional Neural Networks make better use of this and constrain the design accordingly. There are three dimensions to a ConvNet: width, height, and depth.

Combining all of the above:

The first convolution layer receives an image from the previous layer. An activation map is generated as a result of the convolution. The convolution layer's filters extract important elements from the input image so that it may be passed on.

It is expected that each filter will provide a unique feature to assist in class prediction. If the image size must be preserved, the same padding (zero padding) is utilised; otherwise, valid padding is used because it aids in the reduction of features in the image.

To further reduce the number of parameters, pooling layers are implemented. Before a forecast can be formed, several convolution and pooling layers must be added.

The convolution layer aids in the extraction of characteristics from a dataset. For example, as the network gets deeper, more specialised features are recovered, as opposed to general features in shallow networks.

When the information from other levels is flattened and transferred to the output layer, the network is able to change its output into the number of classes it needs.

Errors are generated through the output layer, which generates the output and compares it to the output layer. The mean square loss is calculated using a loss function defined in the fully linked output layer. Once this is done, the error gradient is plotted out.

The filter (weights) and bias values are then updated using the error's back propagation.

A single forward-and-backward pass is required to complete a training cycle.

When it comes to picture problems, CNN is currently the go-to model because of its superior accuracy. Natural language processing, recommendation systems, and more are all examples of how it has been used successfully.

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Unlike its predecessors, CNN is able to automatically identify the most significant aspects of a situation without the need for human intervention. In the case of cats and dogs, it can recognise their individual characteristics after seeing a large number of images of each.

3.2 VGG-16 ARCHITECTURE:

Very Deep Convolutional Networks for Large Scale Image Recognition was published in 2014 by Simonyan Zisserman of the Visual Geometry Group Lab of Oxford University. The simplicity of this network is reflected in its use of only three 3x3 convolution layers stacked on top of each other. Max pooling is used to reduce volume size. A soft max classifier follows two layers with 4,096 nodes each that are fully connected. The number "16" refers to the network's total number of weight layers.

64 feature kernel filters are used in the first and second convolution layers, and their combined filter size is 33. When an RGB image with depth 3 (224x224x3) is passed through the first and second convolution layers, the dimensions of the input image (which is now 224x224x64) change. The output is then sent to the max pooling layer with a stride of two.

There are 128 feature kernel filters in the third and fourth convolution layers, which are 33 in size. The output will be reduced to 112 x 112 x 128 after these two levels of max pooling with stride 2.

The kernel sizes of the fifth, sixth, and seventh convolution layers are 3x3. All three make use of 256-bit feature maps. The output will be decreased to 56 x 56 x 256 when the max pooling layer with stride 2 is applied.

Between the eighth and thirteenth convolution layers, the kernel size is 3x3. 512 kernel filters are used in each of these convolution layers. Max pooling layer with stride of 2 is used to compress the output to 28x28x512 and 14x14x512, respectively.

After the fourteenth and fifteenth layers, there is a soft maximum output layer (the sixteenth layer) of 1000 units. It only has three-by-three convolutions, like AlexNet, but it has a large number of filters. For 2–3 weeks, it may be trained on four GPUs. It's currently the most used method for extracting characteristics from photographs in the community." As a basic feature extractor, the VGGNet's weight configuration has been employed in many additional applications and challenges. VGGNet, on the other hand, has 138 million parameters, making it difficult to manage. Transfer Learning can be used to accomplish VGG. As a result of this process, the model is pre-trained on a dataset, and the parameters are changed to improve accuracy.

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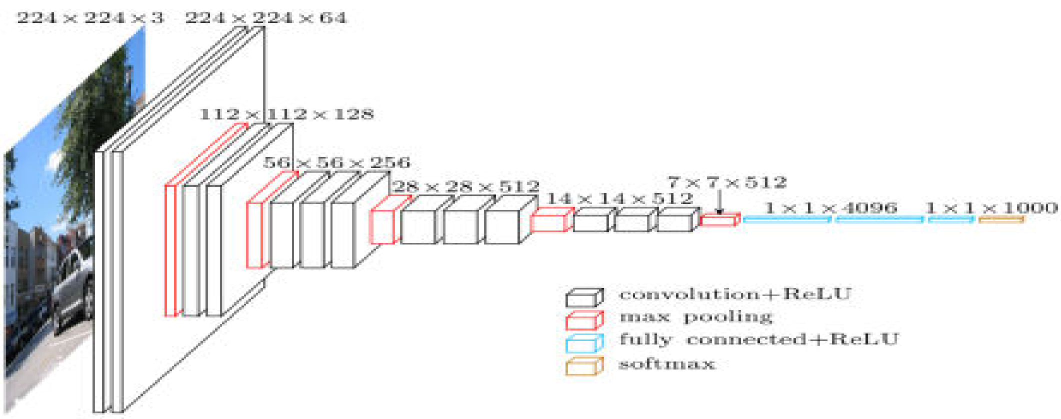

Fig 3: VGG-16 Architecture

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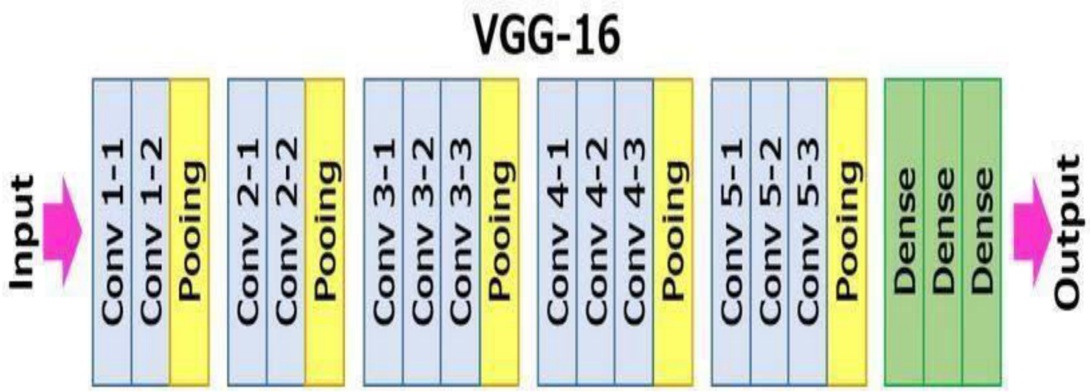

Fig 4: VGG-16 Model

IV. RESULTS AND DISCUSSION

4.1 ACCURACY :

Accuracy is a way to evaluate the performance of a classification model. A percentage is the most common way to express it. Predictions in which the projected value is exactly equal to the true value can be considered accurate. For a specific sample, it's true or false. During the training phase, accuracy is commonly shown graphically and monitored, although the value is generally linked to the total or final model accuracy. Loss is more difficult to decipher than accuracy.

A metric used in classification issues to measure the accuracy of predictions is called Accuracy. To arrive at this figure, we divide the total number of forecasts by the number of right guesses.

Accuracy = Number of Correct Predictions/Total Number of Predictions

In the binary classification case, we can express accuracy in True/False Positive/Negative values.

Accuracy = (TP+TN)/(TP+FP+TN+FN)

Where

TP : True Positives

FP : False Positives

TN : True Negatives

FN : False Negatives

A **true positive** is an outcome where the model *correctly* predicts the *positive* class. Similarly, a **true negative** is an outcome where the model *correctly* predicts the *negative* class.

A **false positive** is an outcome where the model *incorrectly* predicts the *positive* class. And a **false negative** is an outcome where the model *incorrectly* predicts the *negative* class.

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Here, for our model we got the following values for accuracy -

Train Accuracy: 98%

Test Accuracy: 90%

The training accuracy graph is as follows:

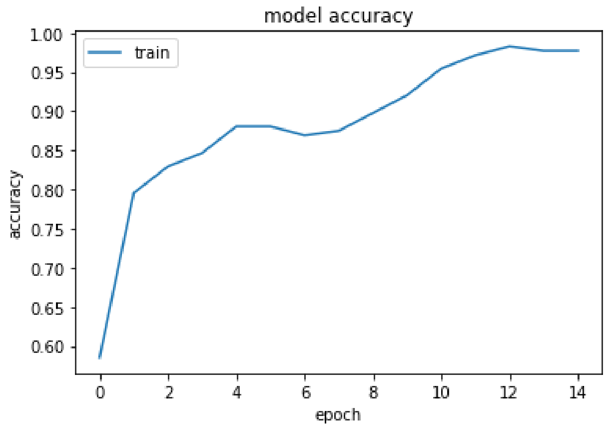

Fig 6 : Accuracy Graph

Here, we have given a comparison of accuracies of different models that are taken from different research papers and are linked in the bibliography section.

Table 1 : Performance Comparison Table

System	**Accuracy**
Model1 [4]	96%
Model2 [5]	84%
Model3 [6]	98.5%
Proposed Model	98.8%

V. CONCLUSION

There are three modules in this Deep Learning-based Brain Tumor Detection System: the first one is data refinement, followed by training and testing. Normalization, cropping, and augmentation of photos are carried out in this module. The construction of models is the focus of the second module. Using the VGG-16 algorithm and transfer learning, a CNN (Convolution Neural Network) model is constructed in the module after the second. Using the VGG-16 method, which delivered 98 percent accuracy on training set and 92 percent accuracy on test set, the model is developed to provide good results and prevent computational complexity.

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REFERENCES

[1] Learning Kinds - https://towardsdatascience.com/what-is-machine-learning-a-short-note-on-supervised-unsupervised-semi-supervised-and-aed1573ae9bb

[2] Overfitting - https://www.v7labs.com/blog/overfitting

[3] Dataset - https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection

[4] Pravitasari, Anindya Apriliyanti, et al. "UNet-VGG16 with transfer learning for MRI-based brain tumor segmentation." TELKOMNIKA (Telecommunication Computing Electronics and Control) 18.3 (2020): 1310-1318.

[5] https://ijcrt.org/papers/IJCRT2007042.pdf

[6] Muhammad Arif, F. Ajesh, Shermin Shamsudheen, Oana Geman, Diana Izdrui, Dragos Vicoveanu, "Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques", Journal of Healthcare Engineering, vol. 2022, Article ID 2693621, 18 pages, 2022. https://doi.org/10.1155/2022/2693621