CLASSIFICATION OF BRAIN HEMORRHAGE USING NEURAL NETWORKS AND TRANSFER LEARNING

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ABSTRACT—*Brain hemorrhage is a form of stroke triggered by a brain artery burst in the brain that leads to localized bleeding in the surrounding tissues. It is a severe medical condition that requires urgent treatment. Brain Hemorrhage, also known as Intracranial hemorrhage (ICH) is detected using CT (Computed Tomography) scan and MRI (Magnetic Resonance Imaging) scan. The manual interpretation of CT scans is a tedious task for radiologists. This work proposes two methods to identify brain hemorrhages by classifying the CT scan images into hemorrhage and non-hemorrhage images. One of the methods uses transfer learning while the other is by creating a CNN from scratch. Both methods use Convolutional Neural Network and Dense Neural Network to classify brain hemorrhages. This work will help doctors and radiologists in the early detection of acute brain hemorrhages which will help in the treatments of patients. The proposed CNN model achieved an accuracy of 80% in classifying the brain CT images. The VGG19 model performed the same classification with an accuracy of 95%.*

Keywords— *CT, Hemorrhage, Dense Neural Network, Convolutional Neural Network, Transfer Learning technique.*

I. INTRODUCTION

The internal bleeding in the brain is termed as brain hemorrhage. Often known as a brain stroke or an intracranial hemorrhage, it is a medical emergency requiring immediate treatment. This medical condition is usually triggered due to hypertension, weak blood vessels, trauma and drug abuse.

Blood leakage from hemorrhage causes brain tissue compression and damage. When the brain artery bursts or ruptures, the bleeding triggers a hemorrhagic stroke. Excess blood saturation can be so serious that oxygen-rich blood does not circulate to the brain tissue. An inadequate supply of oxygen to the brain may lead to inflammation or cerebral edema. Pooled blood can accumulate from a bleed into a lump known as a hematoma. The additional pressure will restrict oxygen from entering brain cells that can lead to death.

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This paper proposes two different approaches to detect this intracranial bleeding in the brain. One approach is to detect the bleeding using a custom Convolution Neural Network and the other is by using an existing architecture also known as Transfer Learning. This paper uses VGG19 model as the existing architecture for the transfer learning implementation.

II. LITERATURE SURVEY

Vincy Davis et al. [12] in their paper titled "Diagnosis & Classification of Brain Hemorrhage" propose a method for diagnosing brain hemorrhage where the images are subjected to morphological operations (a series of non-linear procedures linked to form or features of an image) after preprocessing. The authors use watershed algorithm for image segmentation. They employ GLCM for extraction of image characteristics which is eventually used as an input for the image classification in the artificial neural networks.The approach suggested in the paper offers an accurate brain hemorrhage diagnosis including the kind of hemorrhage with less error (0.478). However, it also suffers from being complex due to the use of multiple machine learning algorithms for image data processing.

"Monika Grewal et al. [5] have proposed a modified architecture of DenseNet called RADnet for the classification of brain images. Initially a 3D CT labeling task is modeled. This is done by the combination of CNN and Long Short Term Memory(LTSM).The authors of the paper use DenseNet architecture and bi-directional LTSM for learning slice-level features and for combining spatial dependencies between slices respectively. In addition to this, by using prior information about regions of brain hemorrhage to shift the focus of the architecture towards relevant features. They have referred to this modified architecture as RADnet. The proposed RADnet architecture resulted in classification of images with higher recall(88.64%), precision(81.25%) and F1 score(84.78%).

The research work of Qi Dou et al. [8] "Automatic Cerebral Microbleeds Detection from MR Images via Independent Subspace Analysis Based Hierarchical Features" have proposed a three stage approach to detect cerebral microbleeds (CMB). The first stage consists of candidate screening which is done based on high intensity CMB values. As a consequence, a significant number of non-microbial regions are eliminated effectively. The second stage consists of extracting dense 3D hierarchical characteristics by using a stacked convolutional Independent Subspace Analysis (ISA) network. This stage employs an unsupervised way of extracting 3D hierarchical features efficiently. Prior to this, principal component analysis (PCA) is used to reduce the overall dimensions. The final stage makes use of SVM as a classifier based on learned features from ISA. The proposed method helps in large reduction of false positives and is highly sensitive.

A method to classify brain images into 3 types was given by Xiahong W. et al.[13] in their work "Classification of CT brain images based on Deep Learning Network". The authors of this paper use CNN to classify the brain CT images. By employing both 2D and 3D CNN, an advanced CNN architecture was established. The 2D and 3D CNN fusion were organized based on their Softmax scores derived from both networks that combine 2D representations along the spatial axis and 3D segmented blocks respectively. Finally, the classified images were clustered into AD, Lesion and normal ageing brain classes. The proposed architecture achieved 85.2% accuracy for AD class, 80% accuracy for Lesion class and 95/3% accuracy for normal brain. The average overall accuracy was 87.6%.

Rupali Mahajan et al. [9] in their paper titled “Diagnosis of brain hemorrhage by using Artificial Neural Network” have proposed a method which incorporates machine learning algorithms and neural networks for the diagnosis of brain hemorrhage. The authors of this paper pre-process the image data prior to morphological operations. This pre-processed data is smoothened and segmented using Watershed algorithm which is followed by finding and extracting features using gray level co-occurrence matrix. The image data after it has been processed and its features extracted use an Artificial neural network for diagnosis of brain hemorrhage. This artificial neural network also uses back propagation to better initialize and alter the node weights such that the final output has less error. However, this comes at the cost of having high time complexity.

Alyaa Hussain Ali. et al. [1] have proposed image processing techniques to detect brain strokes in their contribution “Detection and Segmentation of hemorrhage stroke using textural analysis on brain CT images”. Region growing is performed on the pre-processed data. A “Region” is an area which is formed by the same intensity pixels of the brain image. This is followed by employing a median filter which helps in the removal/reduction of noise in the brain images. Threshold technique is used in these filtered images where the pixel intensity values higher than the threshold values are considered while the others are rejected. Finally, by using statistical features of images and comparing the normal images to abnormal images, the brain images are classified. The proposed method results in less noise in the image dataset.

The works of Gao Huang et al. [4] was on “Densely connected convolutional networks” which proposed a CNN architecture called DenseNet. This architecture was constructed with the main aim of increasing the flow of information between the different layers in the neural network. To accomplish this task, in the proposed CNN architecture, each layer is connected directly with every other layer with matching feature-map sizes.In addition to this, each layer gets input from the previous layers so that feed forward nature is preserved. This results in an architecture which is densely connected. Another counter-intuitive result is that the number of parameters required is smaller than the regular CNN because redundant feature maps need not be relearned. This architecture is more efficient to train and gives a higher accuracy than the traditional CNN.

“Application of Deep Learning in Neuroradiology: Brain Haemorrhage Classification Using Transfer Learning” by Awwal Muhammad Dawud et al. [2] employed a method to identify brain hemorrhage in the early stages. This proposed method uses a Deep Learning approach where it gives an evaluation of different Neural Network Learning methods. This includes creating a CNN from scratch, Alex-Net and an enhanced Alex-Net version with Support Vector Machine (AlexNet-SVM). These ANN are specialized in Brain CT classification. The main aim of this paper is to address the issue of building a CNN from scratch, where instead a Pre-trained Model with sufficient fine-tuning requires less training data and gives better accuracy. The research further supports the benefits of using SVM rather than a three-layer neural network as a classification system. The research findings indicate that the suggested pre-trained "AlexNet-SVM" model will outdo the convolutional neural network developed from scratch and the original AlexNet to detect brain hemorrhage.

P. M. Cheng et al., [7] in their contribution “Transfer learning with convolutional neural networks for classification of abdominal ultrasound images” evaluated transfer learning with deep CNN for the abdominal ultrasound sorting. Two CNN layers centered on CaffeNet and VGGNet (pre-trained model), which were retrained on the training set, were used for this analysis. The CaffeNet network correctly identified 77.3% of the test set images. The wider VGGNet network correctly categorized 77.9% of the test set. The radiologist has correctly identified 71.7% of the test sample. The results demonstrate that the use of transfer learning can be used to construct effective classifiers.

V. Desai et al. [11] have devised a method for detecting Basal Ganglia (BG) Hemorrhage in their research contribution, "Application of deep learning in neuroradiology: automated detection of basal ganglia hemorrhage using 2D-convolutional neural networks". The solution suggests two DCNNs- AlexNet and GoogLeNet that employs an untrained network and a network pre-trained on ImageNet. Classification of hemorrhage was done using both DCNNs which uses both untrained and pre-trained models. A comparison study was done. The best model was the pre-trained augmented GoogLeNet with an AUC of 1.00 in the hemorrhage classification.

Pre-processing augmentation enhanced the accuracy for all networks ($p<0.001$). The pre-trained networks surpassed the untrained networks ($p<0.001$) for the un-augmented models. From this we can see that Pre-trained networks and data augmentation increased classifier accuracy.

Author & Year	**Methodology**	**Issues**
Qi Dou (2015)	Support Vector Machines	Selection of kernel function parameters is complex.
Alyaa Hussein Ali (2015)	Threshold Segmentation	Difficulty in accurately assigning Threshold value
Xiaohong W (2016)	Convolutional Neural Network	Less data used leading to a less robust model
Rupali Mahajan (2016)	Artificial Neural Network Watershed Algorithm Gray level co-occurrence matrix	High time complexity
Vincy Davis (2017)		
V. Desai (2017)	AlexNet (CNN)	Less Data Performance is relatively low as compared to newer models
Awwal Muhammad (2019)		

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Monika Grewal (2018)	RadNet (DenseNet)	High Space complexity

This paper proposes a Deep Convolution Neural network approach to classify brain CT images. VGG19 architecture is used in this work to achieve high accuracy in classifying the brain CT images as opposed to using AlexNet and CaffeNet. VGG19 model has more weighted layers as compared to the above-mentioned Networks. It uses small-size convolution filters and has fewer parameters. This helps to make a more generalized model[16].

III. METHODOLOGY

This paper deals with the issue of classifying brain CT images into hemorrhage and normal. This problem was approached using two different methods, custom CNN and VGG19.

The dataset to train the models contains 200 brain CT images. It consists of 100 images that have brain hemorrhage and 100 normal brain CT images. This dataset has been split in the ratio of 80:20 for training and testing respectively.

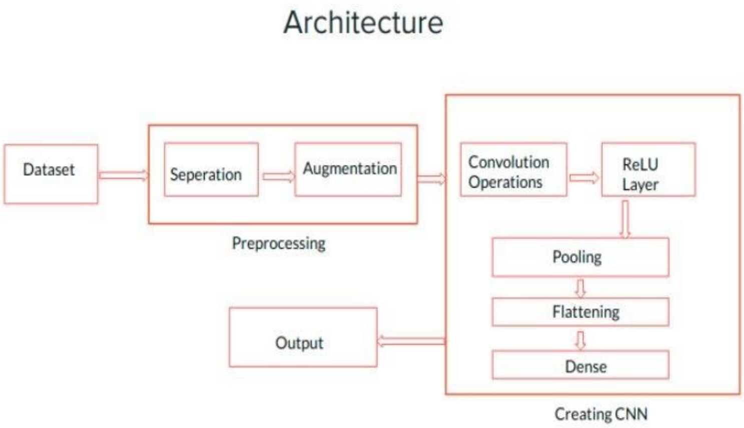

Figure 1: CNN

A. DATA AUGMENTATION

Data augmentation generates additional batches of images

Architecture and applies transformation techniques to randomly selected

images like shifting, shearing, flipping, scaling and rotating.

Since the transformations done during augmentation are random transformation, no same picture occurs twice across

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ata Augmentation is an important stage in data preprocessing. Performing data augmentation to the training

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ooling data increases classifier accuracy. This is particularly the case where the training data is very less. So as to get highly

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rained model augmentation is done.

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lly Connected Network

Data augmentation is used as an alternative to add more images in the dataset. This is because this module helps to add variety to the existing images in the currently available dataset.

Convolution Operation:

Therefore, image augmentation is a technique that enriches

In this step, filters(feature detectors) of size 3x3 matrix are the available dataset without adding more images and hence created. Each of these filters are then multiplied with the leads to good performance results with significantly reduced image to obtain a feature map, which results in multiple overfitting even with a small dataset. feature maps being obtained.

ReLU:

B. CONVOLUTIONAL NEURAL NETWORK

ReLU(Rectified Linear Unit) is an activation function that is used to introduce non-linearity. This is because images

CNN (Convolution Neural Network) is a class of deep have non-linear elements.

However, mathematical neural networks. This type of neural network is commonly operations such as the above-mentioned convolution layer applied for analyzing visual images. are linear. Therefore a ReLU function is used in the convolution operation.

The CNN architecture itself has several layers that are used for analyzing the images for its classification. They are:

- ***Pooling:***

Pooling is used for reducing the size of the intermediate representations which helps in reducing the number of parameters.

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In this paper, max-pooling was used. In max pooling, a 2x2 pixel box is used and traversed through each of the feature maps starting from the top-left corner. The maximum value in that box is identified and recorded. By taking into account the maximum value, the model is able to record the important features in the image and also account for any distortions in the images.

Pooling allows the module to be flexible in identifying features in images.

- ***Flattening:***

In this step, a feature map is flattened into a column. Each feature map is flattened and the resultant column contains the values of all the feature maps sequentially. This column is then fed as input for the fully connected layers for further processing.

- ***Fully Connected Network:***

The artificial neural network is fully linked. The entire network is split into three parts namely input layer, hidden layer and output layer.

The input is the flattened column. There is a neuron in the output layer that is used to label the image. The middle layer has neurons which are fully connected to each of the neurons in the previous and the next layer. This layer is therefore referred to as the fully connected layer. Each neuron in the hidden layer uses ReLU as the activation function which helps increase non-linearity.

IV. TRANSFER LEARNING

Transfer learning is widely used in areas where there is a lack of availability of data. It uses a pre-trained model where the weights are assigned by training the model on a

very large database. The pre-trained weights are transferred to the target model.To make use of the model for a different use case, the last few convolutional and fully connected layers are equipped with random weights and trained on the new dataset. The low level features are the same for both global dataset and local dataset. Thus, this transfer of pre-trained weights provides a powerful extraction capabilities for the target mode. Hence, through the use of transfer learning, accuracy, time for training and error rates are therefore improved[3, 6]. In this study, VGG19 was used for brain hemorrhage detection.

❑ ***VGG19***

VGGNet is a neural network that came in the classification challenge as the first runner up in ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2014. It is significantly better than ZFNet (winner in 2013) and AlexNet (winner in 2012).

The brain CT image is given as the input to the VGGNet. Image augmentation is performed on the input ct image where rescale=1./255 is done. The image is horizontally and vertically flipped. These are some of the image augmentation techniques used in this work.

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These augmented images are fed as input to the model. The images have been downsampled to 224 x 224 for it to be accepted as input for the VGG19 model. In order to translate the image into RGB format, the model requires a 3-channel system. Therefore the final pixels of the images become 224 x 224 x 3.

This model consists of 25 layers, which consists of 16

Convolutional layers, 5 Pooling layers, 1 Flatten layer and 3 Dense layers. The weights of the first 18 layers has been assigned by training it against the ImageNet database. The remaining 7 layers weights have been reassigned after training it with the brain CT dataset.

In the initial convolutional layers, low-level features like lines, points, boundaries etc. are extracted. The final few convolutional layers are used in the detection of objects.

The ReLU activation function is used for all the convolutional and dense layers with the exception of the final dense layer, which uses sigmoid activation function to get a binary output. The optimizer used in the model isStochastic Gradient Descent and the loss function employed is binary cross-entropy.

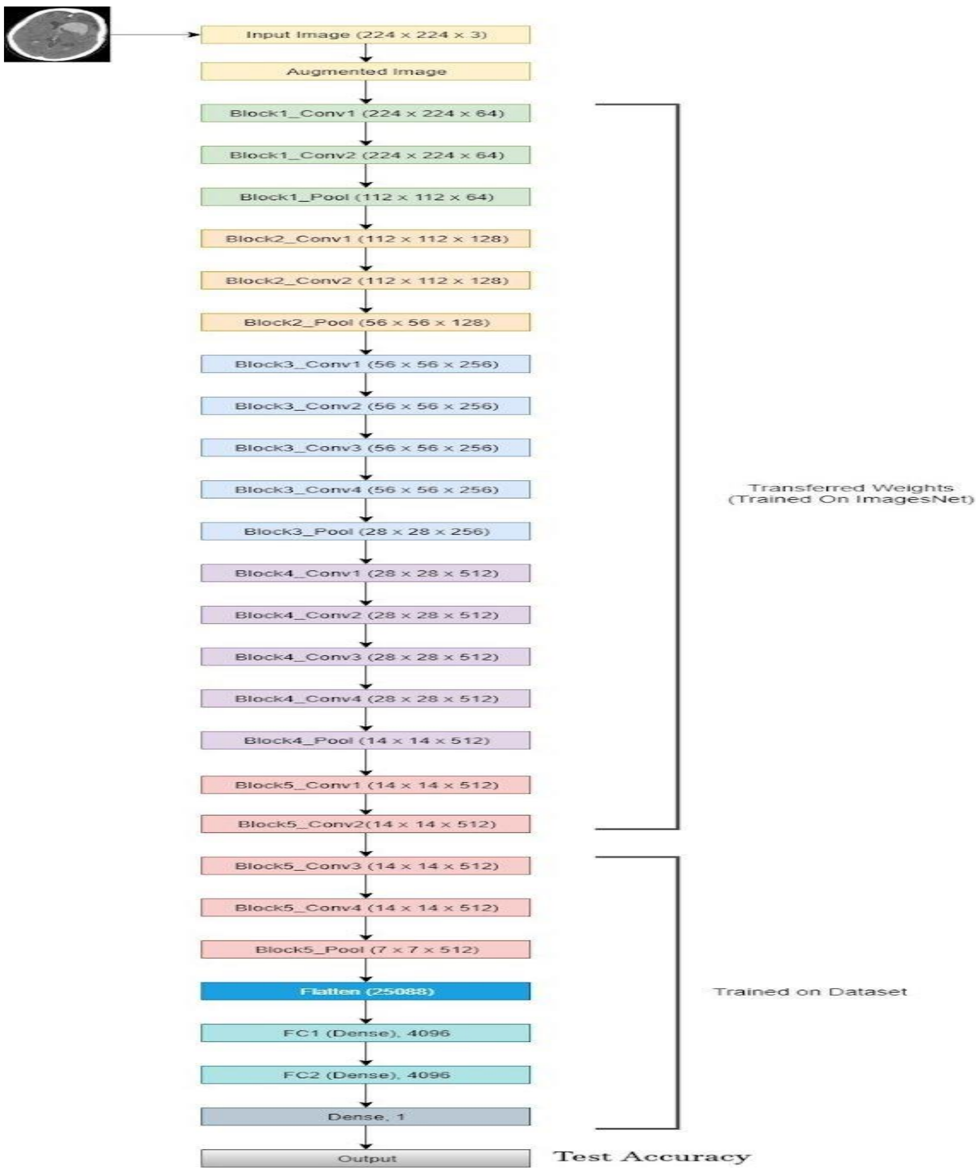

Figure 2: VGG19 Architecture

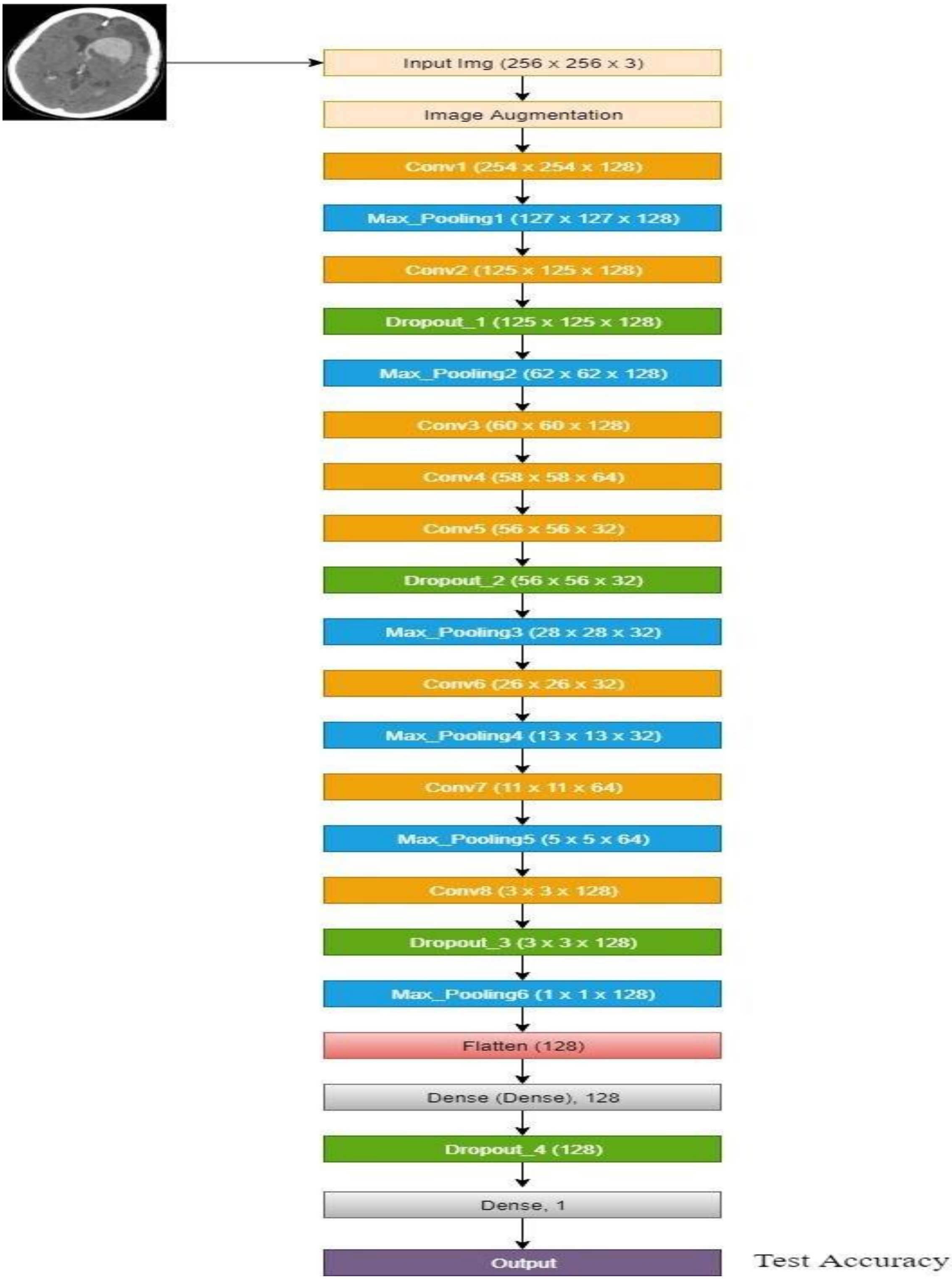

Figure 3: Proposed CNN Model

❑ *PROPOSED CNN MODEL*

The images of size 256 x 256 are taken as input for the proposed CNN architecture. In order to translate the image into RGB format, the model requires a 3-channel system.

Therefore the final pixels of the images become 256 x 256 x
3.

The model has 21 layers that are trained on the locally available brain CT dataset. These 21 layers consist of 8 convolutional layers, 6 pooling layers, 4 dropout layers, 1 flatten and 2 dense layers. The ReLU activation function is used for all the convolutional and dense layers with the exception of the final dense layer, which uses sigmoid activation function and binary cross-entropy as its loss
function.

Neural networks are prone to overfitting due to a lack of availability of data. This is reduced by the introduction of dropout layers that also leads to a more generalized model. Dropout layers randomly drop neurons, visible and hidden, including all its connections to its preceding and succeeding layer.[11] The dropout probability is set to 0.4 for the proposed CNN model.

V. RESULTS AND ANALYSIS

Both models were trained on the training dataset containing 160 CT images of the brain.
These trained models were then tested on 40 images, containing both hemorrhage and non-hemorrhage CT images of the brain equally.

Table 1: Result Analysis

	Custom CNN	VGG19
Training Accuracy	85.00 %	98.75 %
Training Loss	37.02	0.0334
Testing Accuracy	80.00 %	95.00 %
Testing Loss	48.70	26.26
No.of Epochs	100	100
Learning Rate	0.01	0.01

From the table, it can be inferred that the VGG19 model gave a higher accuracy in both training and testing when compared to the custom CNN model for 100 epochs. It can also be observed that the loss function of the

VGG19 model achieved 26.26% when compared to the custom CNN model which achieved a loss of 48.70 %. The loss function is a measure of how far the predicted value is from the true value. A lower loss value indicates a lesser difference between the predicted and true values.

With the limited amount of data available, making a generalized model is difficult when creating a CNN model from scratch.

VI. DATASET DESCRIPTION

The dataset acquired for this project is from Kaggle which contains 200 brain CT images. This consists of 100 non-hemorrhage CT images and 100 hemorrhage CT images.

VII. CONCLUSION

In this paper, we propose two methods that help radiologists to efficiently detect hemorrhage in the brain using CT images. Both methods use Deep Learning Techniques, namely Convolutional Neural Network and Dense Neural Network.

Since medical data is private and not easily available, a model is needed which can help in achieving good results even when there is a lack of data. This is satisfied by using a pre-trained model- VGG19 through transfer learning. However, the proposed CNN architecture is trained from scratch with the limited data available. Hence, VGG19 is a more generalized model and performs better when compared to the proposed CNN model.

Future work in this classification work can include a comparison study between CT scans and MRI scans to identify which can detect brain hemorrhages better.

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