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GENERATIVE ADVERSARIAL MODEL NETWORK FOR EFFECTED AREA MONITORING IMAGES BASED ON CT PATHOLOGICAL IMAGES ANALYSIS OF BRAIN

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Abstract:

Machine learning is used to analyze medical datasets. Recently, deep learning technology and abnormal patients. Then this abnormal patient data is stored into a two-dimensional array and passed to get results. The experimental result shows that the classification model achieves the best accuracy. Through experimental results, we found that deep learning models are not only used in non-medical images but also give high accurate results on medical image diagnosis, especially in brain stroke detection. gaining success in many domains including computer vision and convolutional neural networks, image recognition, natural language processing, and especially in the medical field of radiology. This project helps to diagnose brain stroke from MRI using CNN and deep learning models. The proposed methodology is to classify brain stroke MRI images into normal and abnormal images. In particular, three types of convolutional neural networks that are ResNet, MobileNet, and VGG16 are used. For classification, we passed pre-processed stroke MRI for training, trained all layers, and classify normal.

Keywords: Brain stroke, deep learning, convolutional neural network.

I. INTRODUCTION

The Term “Stroke” Encompasses Hemorrhage Disturbances Of The Cerebral Circulation Producing Central Neurological Deficits Of Acute Or Sub-Acute Onset. Ischemia Accounts For 80 To 85% Of Stroke Hemorrhage For 15 To 20%. The Effects Of A Stroke Are Unique To Every Individual, And Recovering From A Stroke Is Different For Every Person. To Diagnose Stroke Patient, Radiologist Use CT, MRI Scan But, Sometimes Radiologist Find Difficult To Identify An Abnormality In Images, Computer-Aided Diagnosis (CAD) Plays Important Role In Medical Image Analysis Which Helps Radiologists To Evaluate And Analyze Abnormalities In A Short Time. In The Last Few Decades, Machine Learning Algorithms Have Been Extensively Used In Computer-Aided Diagnosis For Image Classification Is Where A Computer Can Analyze An Image And Identify The ‘Class’ The Image Falls Under. A Class Is Actually A Label, For Example, ‘Car’, ‘Animal’, ‘Building’, And So On. For Example, You Input A Picture Of A Sheep. Image Classification Is That The Process Of The Pc Analyzing The Image And Telling You It’s A Sheep. For Us, Classifying Images Is Not A Big Deal. But It’s An Ideal Example Of Moravec’s Paradox When It Involves Machines. Early Image Classification Related To Raw Pixel Data. This Meant That Computers Would Break Down Images Into Individual Pixels. The Problem Is That Two Pictures Of An Equivalent Thing Can Look Very Different. They Can Have Different Backgrounds, Angles, Poses, And Etcetera. This Made It Quite The Challenge For Computers To Properly Deep Learning May Be A Sort Of Machine Learning; A Subset Of AI (AI) That Permits Machines To Find Out From Data. Deep Learning Involves The Utilization Of Computer Systems Referred To As Neural Networks. In Neural Networks, The Input Filters Through Hidden Layers Of Nodes. These Nodes Each Process The Input And Communicate Their Results To There Are Different Types Of Neural Networks Based On How The Hidden Layers Work. Image Classification With Deep Learning Most Frequently Involves Convolutional Neural Networks Or CNN. In A Convolutional Neural Network, The Nodes In The Hidden Layers Don’t Always Share Their Output With Every Node In The Next Layer. Deep Learning Allows Machines To Spot And Extract Features From Images. This Means They Will Learn The Features To Seem For In Images By Analyzing Many Pictures. So, Programmers Don’t Get To Enter These Filters By Hand.

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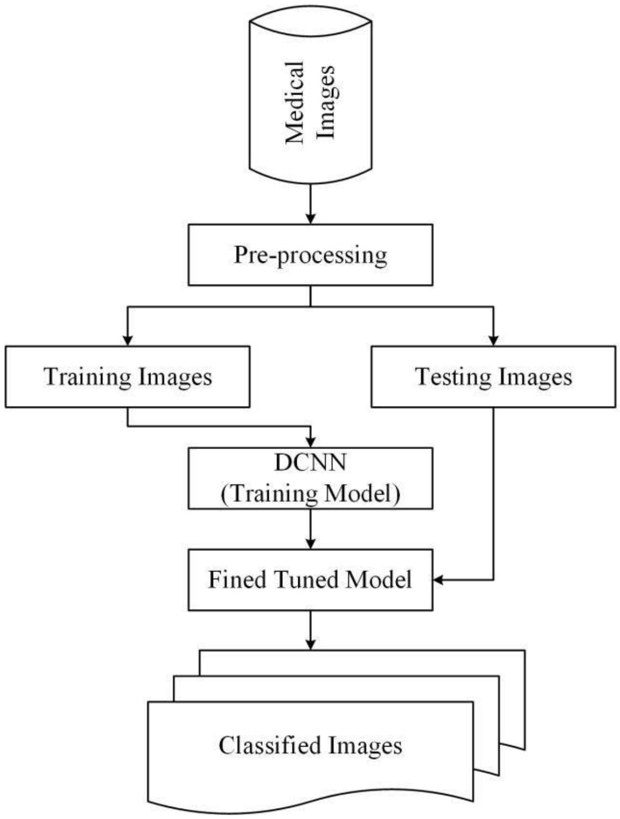
I. RELATED WORK

Two Major Approaches Are Commonly Used For Image Classification. In The First Approach, Features Are ExtractedAnd Traditional Machine Learning Approaches Are Applied For Image Classification. In The Second Approach, Features AreAutomatically Extracted By Using A Deep Cnn Through Of Hidden Layers. The Traditional Approaches Are DomainSpecific And The Performance Degrades If There Is A Change In The Domain Or Increase In The Number Of Classes.LowLevel FeaturesBased On The Method Such As Color, Texture, Shape Is Spatial Layout Are The Common Examples Of These Approaches. In The Past, Significant Research Is Performed By Using The LowLevel Visual Features And Traditional Machine Learning Approaches. The Author Applied Bag Of Visual Words (Bow) Method By Using Local Binary Pattern (LBP) And Scale Invariant Feature Transform (Sift) To Classify The Medical Images. The Feature Fusion Of Lbp And Sift Are Compared With Traditional Feature Extraction And Machine Learning Approaches.

I. PROPOSED WORK

In this work, I propose an architecture for the disease classification part of the automated system. Inspired by the work on convolutional neural networks, in this work, we have developed the deep learning approach on our rice disease dataset that we have collected over the past several months. We have used the pre-trained VGG16 model (Trained on the huge ImageNet data) and using Transfer Learning we have finetuned the fullyconnected layers so that we can accommodate our own dataset and in the end, we have done some error analysis and tried to explain the reasons for the error. We propose this application that can be considered a useful system since it helps to reduce the limitations obtained from KNNand other existing methods. The objective of this study is to develop a fast and reliable method that automatically diagnoses brain stroke and delineates abnormal regions accurately. To design an automated system, a convolutional neural network model will be used to determine. The system is developed in a Flaskbased python environment. MySQL is used for database management and the models involved in this application are ResNet, MobileNet, VGG16. A. DATASET In the proposed method, we have selected a publicly available dataset that consists of images with different classes of human body parts such as the chest, breast, etc. There is a total number of12 classes and it is important to mention that 11 classes are collected from a public dataset of cancer image archives, while12 classes are collected from Messidorthat is collected from an openaccess website of knee images. Each class contains 300images and for the whole dataset, there are 3600 images with 12different classes. We used a training-testing framework; therefore, we selected a random number of 70 percent and 30percent as a traintest ratio in our case. Therefore, 2520 images are used for training, and 1080 are used for testing. There is no common image used for both the training and testing process. In the first step, all images are converted from DICOM (digital imaging and Communication in Medicine) to JPG format. Due to the increase in variation, there can be a more complex feature matrix for the neural network to classify more accurately. To handle this issue the intensity normalization was applied before feeding the data to the convolutional neural network

colors which contrast well both on screen and on a black-and-white hardcopy, as shown in Fig. 1.



I. METHODOLOGY

Convolutional neural networks (CNNs) are multilayered networks whose architecture determines the performance of the network. It consists of three parts namely, convolution layer, pooling layer, and fully connected layer. The first two together form the feature extractor and the third layer acts as a classifier. The pooling layer reduces the dimensionality of the features extracted by the convolutional layer. The fully connected layer followed by softmax uses the feature extracted to classify the images. The convolution layer takes the input image and extracts the features using a set of learnable filters. The dot product of each filter with the raw image pixel in a sliding window manner provides the 2D feature map. The rectified linear unit (ReLU) is one of the most popular activation functions. The maxpooling the layer is a sub-sampling layer that reduces the size of the feature map. Then the fully connected layer provides a full connection to each of the generated feature maps. Softmax assigns decimal probabilities to each class in a multiclass problem to classify the images. As shown in Figure 2, VGG16 architecture is a deep convolutional network with weights pretrained on the ImageNet Database which contains 3.2 million clearly annotated images of 5247 categories [14]. Thus knowledge in form of weights, architecture and features learnt on one domain can be transferred to another domain by Transfer Learning on such pretrained models. The features are generic in the early layers and more datasetspecific in the later layers. In our model, the initial 5 blocks of convolution layers are frozen for behaving as a feature extractor which is the advantage of CNN over traditional techniques and the last dense layer of size 128 followed by softmax layer of size 4(since a number of classes are 4) is used for classification. The pretrained VGG16 model is again trained on our dataset and finetuned to get the classifications. Keeping in mind the size of the new dataset and its familiarity with the original dataset, there can be 4 approaches to transfer learning: • New dataset is small and familiar to the original dataset. • New dataset is large and familiar to the original dataset. • New dataset is small but dissimilar to the original dataset. • New dataset is large and dissimilar to the original dataset

. IMPLEMENTATION

A. Experimental Setup The experiment was performed on a Windows 10 PC equipped with GPU card P4000, 64-bit Operating System. The CNN-based model was implemented in the Keras 2.2.4 deep learning framework with TensorFlow 1.13.1 backend and python 3.7.2.

B. Image Acquisition

The images are collected from the cultivation fields as well as from the internet. As discussed in the dataset description, data consists of 4 classes namely Leaf Blast, Leaf Blight, Brown Spot, and healthy plant images.

C. Image Preprocessing and Augmentation

The images collected are resized to 224*224 pixels and a number of augmentation techniques like zoom, rotation, horizontal and vertical shift are applied using ImageDataGenerator in Keras to generate new images.

D. CNN Model Training The image data set is loaded for the training and testing. The class labels and the corresponding images are stored in respective arrays for training. 70 percent of data is used for training and 30 percent of data is used for testing using the train_test_split function. The 70 percent data is further split and 20% of it is used for validation. The class labels are encoded as integers and then, one-hot encoding is performed on these labels making each label represented as a vector rather than an integer. Next, the VGG-16 model is loaded from Keras, and the last fully connected layers are removed. The remaining layers are made non-trainable. We have flattened the output of the feature extractor part, followed by a fully connected layer and an output layer with softmax. Then we have compiled our model using the Adam optimizer with categorical_crossentropy as the loss function for classification. We have stopped at25 epochs since after this the results were stable. Figure 3 shows the steps we have executed for the classification process.

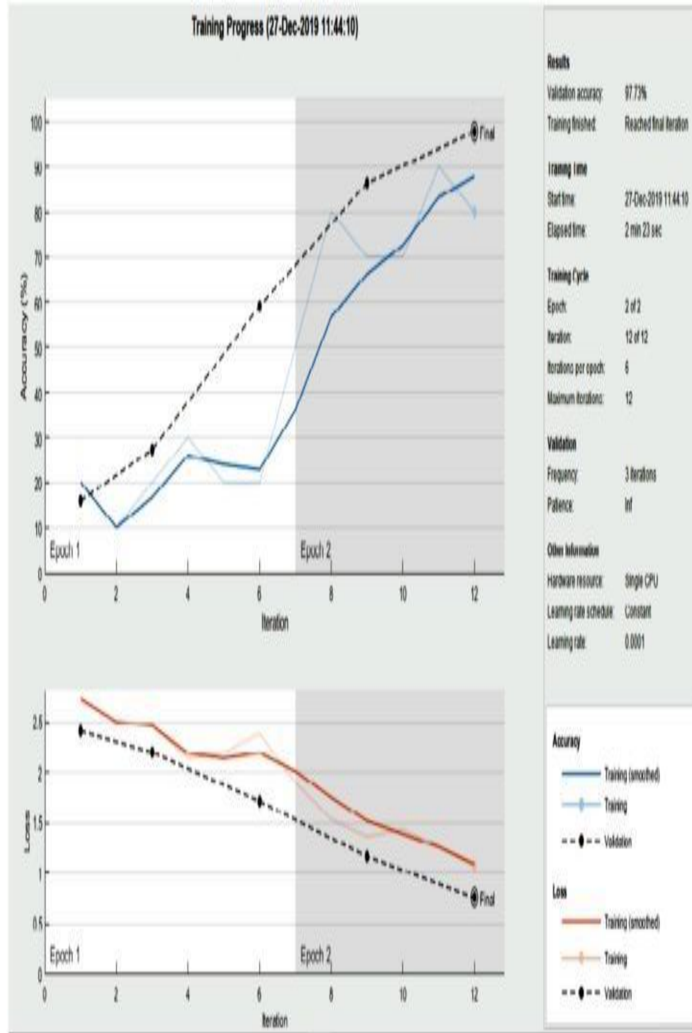
I. RESULTS

A. Calculations For classification purpose, deep learning based framework for medical image classification by training the images is proposed. In this regard, diagnosis is one of the main requirements of the existing era and investigated or examine to specific diseases. The use of computer-aided tools and reliable image analysis are the main aspects that can increase the efficiency of doctors and phycision. It is a requirement of the current era to develop such image processing methods that can help doctors in various fields of medical science. Such methods are beneficial to save human life and it is evident that diseases can be predicted before they can affect the human body. Since the last few decades, the computer vision

ABLE I. PERFORMANCE OF COMPARISON OF CNN WITH AND WITHOUT TRANSFER LEARNING

Model	***Test Accuracy***
CNN With Transfer Learning	**92.46%**
CNN Without Transfer Learning	74%

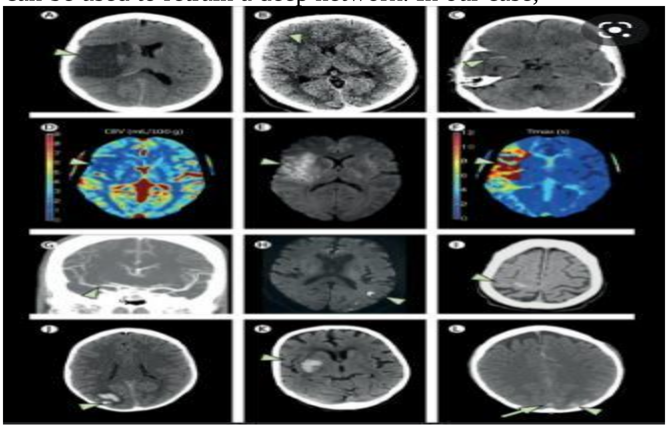
Fig. 4. Performance comparison of CNN model with and without Transfer Learning



1) B. EXPERIMENTAL RESULTS

In this manuscript, a popular and widely-used deep learning technique has been used for developing and training the proposed deep convolution neural network for classifying the medical images. In this regard, we performed image preprocessing as the first step and later performed fine-tuning to enhance the classification accuracy with reduced training time. The artifacts in the images are removed through pre-processing. Table 1 presents a short summary with a number of medical

In the training phase of transfer learning mode, we used the parameters that can avoid over-fitting of the network as classification accuracy of deep network decrease due to overfitting [54]. The techniques such as re-scaling and rotation can be used to retrain a deep network. In our case,



FUTURE ENHANCEMENT

Such methods are beneficial to save human life and it is evident that diseases can be predicted before they can affect the human body. For the last few decades, the computer vision research community is trying to reduce this gap by developing automated systems which can process medical images using machines to make decisions. They proposed a novel deep convolution network-based approach that is assists doctors and physicians in making reasonable decisions. The results obtained from the proposed method outperformed state-of-the-art methods that are reported for the same dataset. In the future, To explore large-scale image datasets for medical image classification and detection problems.

CONCLUSION

For classification purposes, a deep learning-based framework for medical image classification by training the images is proposed. In this regard, diagnosis is one of the main requirements of the existing era and investigated or examine to specific diseases. The use of computer-aided tools and reliable image analysis are the main aspects that can increase the efficiency of doctors and physicians. It is a requirement of the current era to develop such image processing methods that can help doctors in various fields of medical science.

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