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Malaria Identification Using Neural Network

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ABSTRACT:

Malaria is a serious and sometimes fatal disease caused by a parasite that commonly infects a certain type of mosquito which feeds on humans. People who get malaria are typically very sick with high fevers, shaking chills, and flu-like illness. Four kinds of malaria parasites infect humans that is most likely to result in severe infections and if not promptly treated, may lead to death. Although malaria can be a deadly disease, illness and death from malaria can usually be prevented. Deep Learning models, or to be more specific, Convolutional Neural Networks (CNNs) models are proposed in this project A comparison of the proposed and current algorithms reveals that the accuracy of malaria disease classification based on CNNs is higher than other algorithms. It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully malaria disease on image.

Keywords: Malarai Disuse , Deep learning, Tens or Flow CNN.

Introduction:

1. Malaria is a disease caused by a parasite. The parasite is spread to humans through the bites of infected mosquitoes. People who have malaria usually feel very sick with a high fever and shaking chills.

2. While the disease is uncommon in temperate climates, malaria is still common in tropical and subtropical countries. Each year nearly 290 million people are infected with malaria, and more than 400,000 people die of the disease.

3. To reduce malaria infections, world health programs distribute preventive drugs and insecticide-treated bed nets to protect people from mosquito bites. The World Health Organization has recommended a malaria vaccine for use in children who live in countries with high numbers of malaria cases.

4. Protective clothing, bed nets and insecticides can protect you while traveling. You also can take preventive medicine before, during and after a trip to a high-risk area. Many malaria parasites have developed resistance to common drugs used to treat the disease.

II. EXISTING SYSTEM

This reports on Brain tumor segmentation, which aims at segmenting the whole tumor area, enhancing tumor core area, and tumor core area from each input multi-modality bio-imaging data, has received considerable attention from both academia and industry. However, the existing approaches usually treat this problem as a common semantic segmentation task without taking into account the underlying rules in clinical practice. In reality, physicians tend to discover different tumor areas by weighing different modality volume data. Also, they initially segment the most distinct tumor area, and then gradually search around to find the other two. We refer to the first property as the task-modality structure while the second property as the task-task structure, based on which we propose a novel task-structured brain tumor segmentation network (TSBTS net). Specifically, to explore the task-modality structure, we design a modality-aware feature embedding mechanism to infer the important weights of the modality data during network learning. Through segmenting brain tumors, the volume, shape, and localization of brain tumor areas (including the whole tumor areas, enhancing tumor core areas, and tumor core areas) can be provided, which play crucial roles in brain tumor diagnosis and monitoring.1 However, segmenting brain tumors from noisymedical images is never an easy task and many research efforts have been devoted to this area, which generally follow two main pathways. On one hand, the existing approaches consider the multi-modality brain tumor segmentation task as a common semantic segmentation problem and build their models based on the network architectures for semantic segmentation fit the data structure of the investigated multi-modality MR volumes.they proposed a novel deep neural network model to explore task structure and modality importance for multi-modality brain tumor segmentation. This is based on two findings: On one hand, the three targeted tumor areas are mutually included rather than being located separately. On the other hand, different modalities are of different importance for segmenting tumor areas.we predict the different types of brain tumor areas in different network modules. For exploring the modality importance, we introduce the modality-aware feature embedding mechanism to our network to infer the importance weights and the weighted features..

CLASSIFICATION OF MALARAI DISESES DETECTION

This section defines the various classifications used for the detection of brain by steps, namely, Pre-processing, Feature Extraction, Segmentation, Post-processing for determining the tumor area of MRI Images. Below figure is defining the feature extraction basic structure via Deep learning using tensorflow.

In pre-processing stage, the captured image is converted into gray scale and the size of the image also reduced according to the requirement. In this stage, only the irrelevant data is removed so the image became a better to operate. It is defined as the number of operations executed on the scanned input MRI brain image. It significantly improves the image rendering appropriate for segmentation of tumor. The aim of pre-processing is improving the results of the segmentation. Normally, smoothing, noise filtering and normalization need to be executed in this process. The pre-processing also explains the compact pattern representation. The linearization procedure transforms a gray scale image in binary image which helps to segment image based on the threshold value.

SEGMENTATION

In this work segmentation technique is necessary for the gray matter mask and white matter mask extraction based on the binary image. The binary image consists of information on the basis of shape and position of an object of the mask image. The benefit of binary image is that it lessens the image complexity and it simplifies the procedure. The methods of threshold detection are: Optimal thresholding, adaptive thresholding, mixture thresholding and P-tile thresholding and in this work optimal thresholding is used to segment the tumor region from the MRI brain image.

CLASSIFICATION

To detect the tumor region from the images, the classification steps plays a big and important role. For classifying the malarai region from the brain images, we have created a mask of gray and white matter based on the binary image. In the binary image, data is represented in the form of 0 and 1, and we have set threshold to create gray matter and white matter mask. In the image, the affected part represents by the white matter and on the basis of white matter, we have classified the tumor region and their volume by using different architecture such as Manual architecture, ALXENET architecture, LENET architecture.

III. PROPOSED SYSTEM

- The proposes a new and robust machine learning model based on a convolutional neural network (CNN) to automatically classify single cells in thin blood smears on standard microscope slides as either infected or uninfected.
- The proposed algorithms can automatically extract complex image malaria disease and successfully detect malaria disease in different scenes. as input, we used whole images, so it was not necessary to perform any pre-processing or the malaria , samples of more number of images are collected that comprised of different classes data. Different number of images is collected for each classes that was classified into input images

7.1 Advantages:

To identify the malaria disease

- they proposed a novel deep neural network model to explore task structure and modality importance for multi-modality brain tumor segmentation. This is based on two findings: On one hand, the three targeted tumor areas are mutually included rather than being located separately. On the other hand, different modalities are of different importance for segmenting tumor areas.we predict the different types of brain tumor areas in different network modules. For exploring the modality importance, we introduce the modality-aware feature embedding mechanism to our network to infer the importance weights and the weighted features.we proposed a Deep Learning (DL) based brain tumor prediction method to prevent disease by cultivating. The DL method used in the study is the Convolutional Neural Network (CNN). It is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully brain tumor.

To deployment this process by show the prediction result in local host web application.

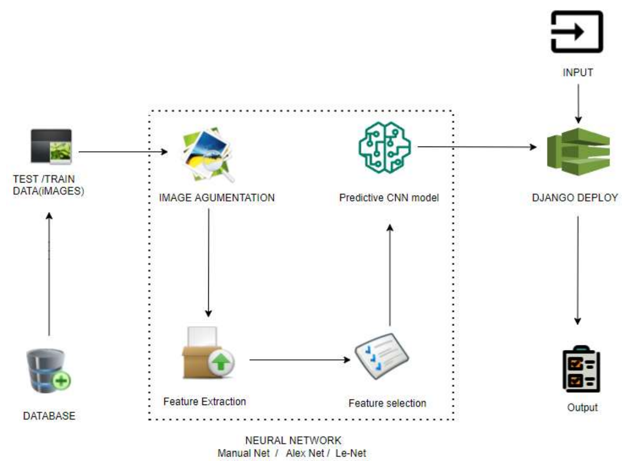


Fig 5. Proposed model overview

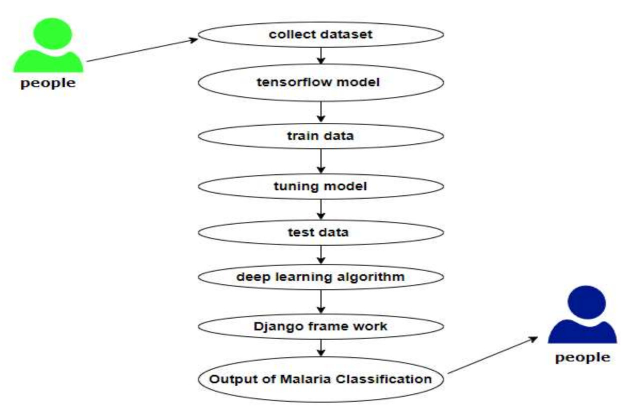
- In this paper to get truthful outcome the work is divided into four phases:
- Import the given image from dataset and training the module with manual CNN (module01)
- To train the dataset by using AlexNet (module02)
- To train the dataset using LeNet (module03)
- Deploying the model in Django Framework and predicting output (module 04)

Module 01: Import the given image from dataset:

We have to import our data set using keras preprocessing image data generator function also we create size, rescale, range, zoom range, horizontal flip. Then we import our image dataset from folder through the data generator function. Here we set train, test, and validation also we set target size, batch size and class-mode from this function we have to train using our own created network by adding layers of CNN.

Module 02: To train the dataset by using AlexNet.

To train our dataset using classifier and fit generator function also we make training steps per epoch's then total number of epochs, validation data and validation steps using this data we can train our dataset.



Module 03: To train the model using LeNet:

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. Their network consists of four layers with 1,024 input units, 256 units in the first hidden layer, eight units in the second hidden layer, and two output units.

Input Layer:

Input layer in CNN contain image data. Image data is represented by three dimensional matrixes. It needs to reshape it into a single column. Suppose you have image of dimension 28 x 28 =784, it need to convert it into 784 x 1 before feeding into input.

Convo Layer:

Convo layer is sometimes called feature extractor layer because features of the image are get extracted within this layer. First of all, a part of image is connected to Convo layer to perform convolution operation as we saw earlier and calculating the dot product between receptive fields (it is a local region of the input image that has the same size as that of filter) and the filter. Result of the operation is single integer of the output volume. Then the filter over the next receptive field of the same input image by a Stride and do the same operation again. It will repeat the same process again and again until it goes through the whole image. The output will be the input for the next layer.

Pooling Layer:

Pooling layer is used to reduce the spatial volume of input image after convolution. It is used between two convolution layers. If it applies FC after Convo layer without applying pooling or max pooling, then it will be computationally expensive. So, the max pooling is only way to reduce the spatial volume of input image. It has applied max pooling in single depth slice with Stride of 2. It can observe the 4 x 4 dimension input is reducing to 2 x 2 dimensions.

Fully Connected Layer (FC):

Fully connected layer involves weights, biases, and neurons. It connects neurons in one layer to neurons in another layer. It is used to classify images between different categories by training.

Softmax / Logistic Layer

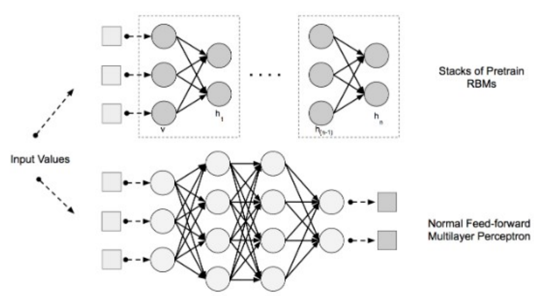
Softmax or Logistic layer is the last layer of CNN. It resides at the end of FC layer. Logistic is used for binary classification and softmax is for multi-classification.

Output Layer

Output layer contains the label which is in the form of one-hot encoded. Now you have a good understanding of CNN.

Module 04: Deploying the model in Django Framework and predicting output

In this module the trained deep learning model is converted into hierarchical data format file (.h5 file) which is then deployed in our django framework for providing better user interface and predicting the output whether the given image contain tumor or not.



IV. RESULTS AND DISCUSSION

Image Enhancement: The Image is enhanced by spatial and frequency domain approach. But based on human observation no general method is proposed to determine the quality of the image. The image is preprocessed by Gabor filter FFT and auto enhancement. Gabor filter is an outstanding multistage disintegration simultaneously localization in both domains. The multiplication of Fourier transform of harmonic and Gaussian function. The figure 7 shows the enhanced and original image using linear filter.

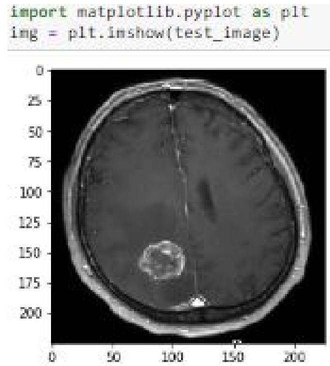


Fig 6. Original image

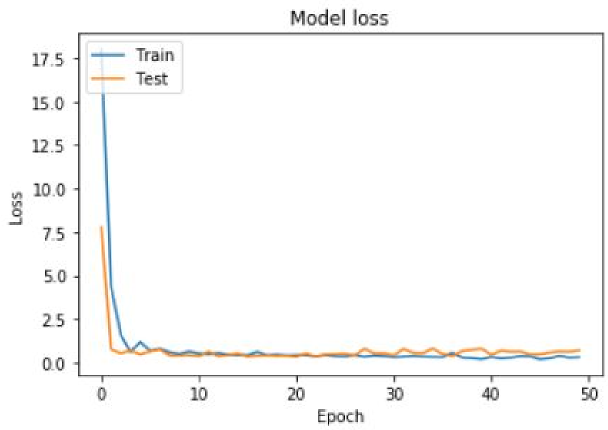


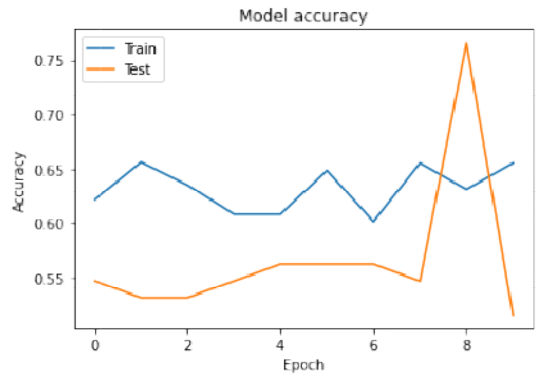
Fig 7. Image Enhanced image by a.Gabor filter b.FFT

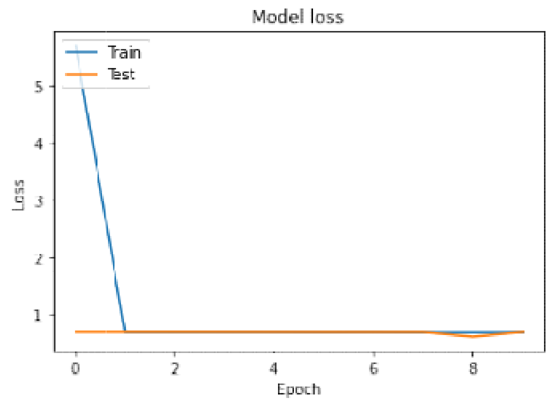
The mean and variance is statistically calculated by auto enhancement methods. It is stoutly based on subjective examination. Table 1 shows the evaluation result of the above three methods. It shows the Gabor filtering methods is powerful image enhancement. This provides high quality brightness in the enhanced image.

Table1. Comparison of three enhancement methods

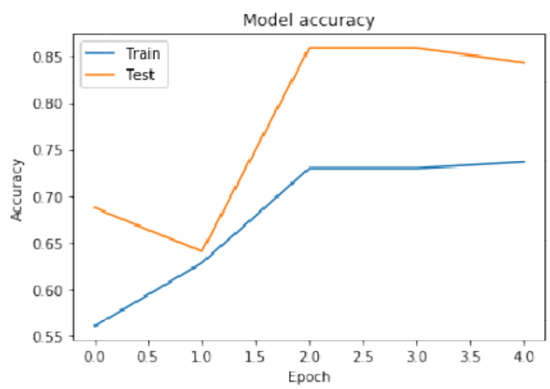
modules	**Accuracy**	**Loss**
Manual architecture	52.40%	69.21%
ALXENET architecture	52.40%	69.17%
LENET architecture	94.71%	20.78%

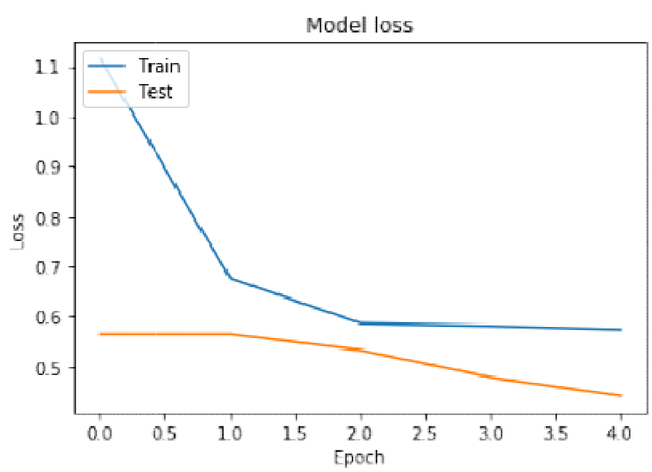
By using module 1 technique of manual architecture we get an accuracy of 65.54% and the loss is 68.70% hence, loss is very high compared due to accuracy and loss is due to layer configuration of convolutional 2d and max pooling.



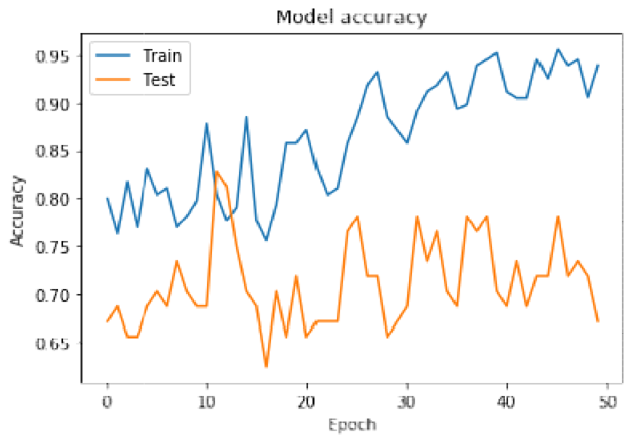


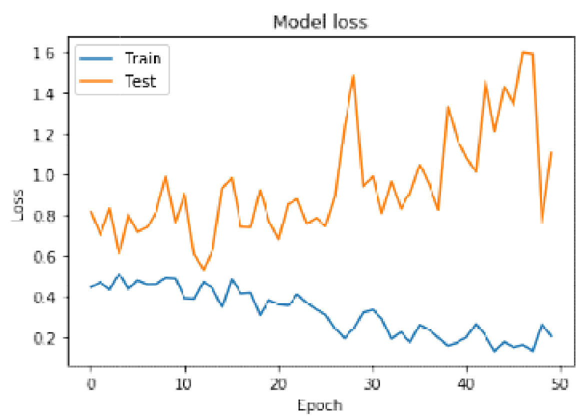
By using the Lenet architecture it is a 7 layer architecture and here the accuracy is 73.65% and the loss is 56.65%.





By Using module 3, the alxenet architecture, The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the virtual cortex.





By compared to the three modules, the ALXENET architecture is showing the best accuracy of 82.43% and less loss compared to the other modules the loss is 42.69%

CONCLUSION

It focused how image from given dataset (trained dataset) in field and past data set used predict the pattern of brain tumor using CNN model. This brings some of the following insights about tumor prediction. We had applied different type of CNN compared the accuracy and saw that ALXENET makes better classification and the .h5 file is taken from there and that is deployed in Django framework for better user interface.

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