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A Survey on "Deep Learning Approach with Transfer Learning For Malaria Disease Prediction"

Seema Mahajan[1], Samar Shaikh[2], Rohit Warade[3], Sagar Sonawane[4], Milind Vaidya[5]

UG Student, Dept. of Computer Engineering, Amrutvahini College of Engineering, Maharashtra, India[1]

UG Student, Dept. of Computer Engineering, Amrutvahini College of Engineering, Maharashtra, India[2]

UG Student, Dept. of Computer Engineering, Amrutvahini College of Engineering, Maharashtra, India[3]

UG Student, Dept. of Computer Engineering, Amrutvahini College of Engineering, Maharashtra, India[4]

Assistant Professor, Dept. of Computer Engineering, Amrutvahini College of Engineering, Maharashtra, India[5]

ABSTRACT: Malaria is a life-threatening disorder due to parasites which can be transmitted to human beings through the bites of inflamed female Anopheles mosquitoes. It is preventable and curable. Malaria is due to Plasmodium parasites. The parasites are unfold to human beings thru the bites of inflamed female Anopheles mosquitoes, called "malaria vectors." There are five parasite species that purpose malaria in humans, and a couple of of those species – P. falciparum and P. vivax – pose the finest threat. In 2019, there had been an anticipated 229 million instances of malaria worldwide. Malaria deaths reached 435000 in 2017. The WHO African Region consists of a disproportionately excessive percentage of the worldwide malaria burden. In 2017, the place turned into domestic to 92% of malaria instances and 93% of malaria deaths. Where malaria isn't always endemic any more (which includes within the United States), health-care carriers might not be acquainted with the disorder. Laboratorians may also lack enjoy with malaria and fail to discover parasites whilst analyzing blood smears under the microscope. Deep Learning has proved to be great in Image Classification. Deep gaining knowledge of with switch gaining knowledge of can enhance the diagnostic accuracy and might discover the Malaria Parasites in Blood smear accurately.

KEYWORDS: Deep Learning, Transfer Learning, Malaria Disease, Vgg16, Convolutional Neural Networks, imageNet, AlexNet.

I. INTRODUCTION

Malaria is a life-threatening ailment due to parasites which can be transmitted to human beings thru the bites of inflamed female Anopheles mosquitoes. It is preventable and curable. In 2019, there had been an envisioned 229 million instances of malaria worldwide. The envisioned range of malaria deaths stood at 409 000 in 2019. Children elderly beneath five years are the maximum prone organization tormented by malaria; in 2019, they accounted for 67% (274 000) of all malaria deaths worldwide. The WHO African Region contains a disproportionately excessive percentage of the worldwide malaria burden. In 2019, the vicinity changed into domestic to 94% of malaria instances and deaths. Total investment for malaria manipulate and removal reached an envisioned US$ three billion in 2019. Contributions from governments of endemic international locations amounted to US$ 900 million, representing 31% of general investment. Malaria is due to Plasmodium parasites. The parasites are unfold to human beings thru the bites of inflamed female Anopheles mosquitoes, called "malaria vectors [1]. "There are five parasite species that reason malaria in humans, and a pair of of those species – P. falciparum and P. vivax – pose the finest threat. In 2018, P. falciparum accounted for 99.7% of envisioned malaria instances WITH INSIDE the WHO African Region 50% of instances WITH INSIDE the WHO South- East Asia Region, 71% of instances WITH INSIDE the Eastern Mediterranean and 65% WITH INSIDE the Western Pacific.

P. vivax is the principal parasite WITH INSIDE the WHO Region of the Americas, representing 75% of malaria instances [1]. Malaria parasites may be recognized via way of means of inspecting BENEATH the microscope a drop of the patient's blood, unfold out as a "blood smear" on a microscope slide. Prior to examination, the specimen is stained

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(most usually with the Giemsa stain) to provide the parasites a specific appearance [2]. This method stays the gold popular for laboratory affirmation of malaria. However, it relies upon at the exceptional of the reagents, OF THE MICROSCOPE, AND AT THE EXPERIENCE of the laboratorian. Where malaria isn't always endemic any more (which include WITHIN the United States), health-care companies won't be acquainted with the disease. Clinicians seeing a malaria affected person might also additionally neglect about to take into account malaria a number of the capability diagnoses and now no longer order the wanted diagnostic tests. Laboratorians might also additionally lack experience with malaria and fail to locate parasites whilst analyzing blood smears below the microscope. This can purpose incorrect diagnostic of the Malaria [3].

Deep Learning can be used along with the transfer learning for effective classification of Malaria cells into Parasitized or Uninfected. This Paper focuses on how we can use deep learning approach with transfer learning for malaria disease prediction.

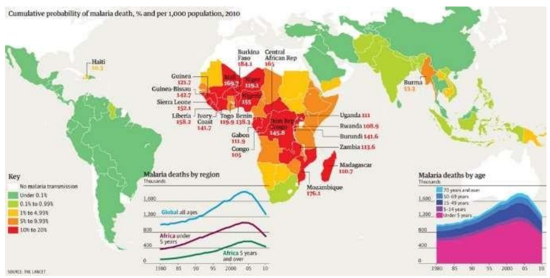

Fig. 1: Malaria Cases Worldwide

II. RELATED WORK

In [14] New method to reap correct mobileular barriers in section evaluation microscopy is provided on this paper. The use of ridge and blob measures affords a sturdy preliminary detection. The energetic contour is applied with stage set and its evolution is guided via way of means of part profiles to prevent it on the preferred barriers. The proposed approach affords an automated estimate of mobileular vicinity this is of enough accuracy to check numerous organic hypotheses. In [3] they used ResNet50 model for classification of cells whether they are parasitized or uninfected which result into 92% accuracy. In [15] they have done evaluation of white blood cell differential counts via computer aided diagnosis (CAD) system and hematology rules. In [16] they pre-trained a convolutional neural network using 1.8 million images and used a fine-tuning strategy to transfer learned recognition capabilities from general domains to the specific challenge of Plant Identification task.

III. DATA GATHERING AND DATASET

The Dataset used in this Project is collected from the official website of National Library of Medicines (NLM). The dataset contains total 27,558 images of both infected and uninfected cells. We split the dataset into 3 parts viz. Training Testing and Validation. For Training we selected 70% images which are 19291 images, for testing, we used 10% images which are 2756 images and for validation we used 20% images which are 5511 images. The reason behind splitting dataset into 3 parts is to train neural network and avoid the overfitting and Underfitting of the data.

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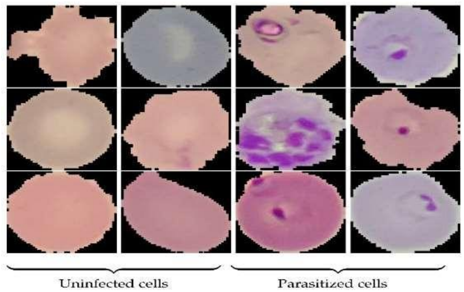

Fig. 2: Images from Dataset

IV. DEEP LEARNING

Deep learning, a subset of system learning, makes use of a hierarchical degree of artificial neural networks to perform the manner of system learning. The artificial neural networks are constructed just like the human brain, with neuron nodes linked collectively like a web [4]. Deep learning, a subset of system learning, makes use of a hierarchical degree of artificial neural networks to perform the manner of system learning. The artificial neural networks are constructed just like the human brain, with neuron nodes linked collectively like a web.

When an Artificial Neural Network learns, the weights among neurons are changing and so does the strength of the network Meaning: Given Training records and a selected task together with category of numbers, we're searching out certain set weights that permit the neural network to perform the classification. The set of weights is distinctive for each task and each dataset. We cannot predict the values of those weights in advance, however the neural network has to learn them. The manner of learning we also call as training.

There are several types of Neural Networks for different applications.

1. **Feedforward Neural Network – Artificial Neuron**:
   This neural network might also additionally or won't have the hidden layers. In easy words, it has the front propagated wave and no backpropagation through the use of a classifying activation function usually [7].

2. **Radial basis function Neural Network:**
   Radial fundamental features bear in mind the gap of a factor with admire to the center. RBF functions have layers, first wherein the features are blended with the Radial Basis Function in the internal layer after which the output of those functions are considered even as computing the identical output within the subsequent time-step which is basically a memory.[7].

3. **Kohonen Self Organizing Neural Network:**
   Kohonen Neural Network is used to recognize patterns in the data. Its application can be found in medical analysis to cluster data into different categories. [8].

4. **Recurrent Neural Network(RNN) – Long Short Term Memory:**
   The Recurrent Neural Network works on the principle of saving the output of a layer and feeding this back to the input to help in predicting the outcome of the layer. The application of Recurrent Neural Networks can be found in text to speech (TTS) conversion models [6].

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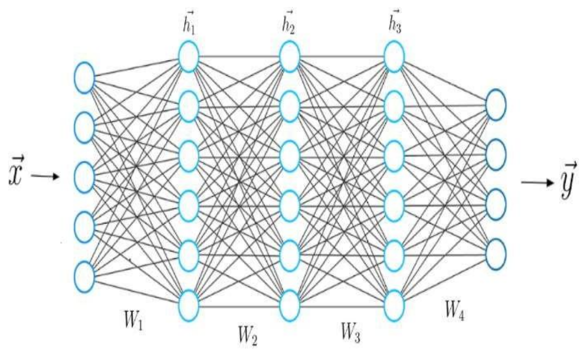
5. Convolutional Neural Network:

Its application has been in signal and image processing which takes over OpenCV in the field of computer vision. ConvNet are applied in techniques like signal processing and image classification techniques.



Computer vision techniques are dominated by convolutional neural networks because of their accuracy in image classification [5].

Fig. 3: Neural Networks

V. TRANSFER LEARNING

Transfer learning is a machine learning approach wherein a model developed for a task is reused because the place to begin for a model on a 2nd task. It is a famous method in deep learning wherein pre-trained models are used because the place to begin on computer vision and natural language processing. In transfer learning, we first train a base network on a base dataset and task, after which we repurpose the learned functions, or transfer them, to a 2nd target network to be trained on a goal dataset and task [8]. This technique will generally tend to work if the features are general, which means appropriate to each base and target tasks, in place of unique to the base task. Transfer learning has numerous benefits, however the important advantages are saving training time, higher overall performance of neural networks (in maximum cases), and now no longer wanting quite a few records. Usually, quite a few records is wanted to train a neural network from scratch however get admission to to that data is not available that is where transfer learning comes in handy. Additionally, training time is decreased due to the fact it may occasionally take days or maybe weeks to teach a deep neural network from scratch on a complicated task. There are numerous models which might be pre-trained on Image Dataset known ImageNet dataset. The ImageNet dataset encompass 14 Million images of various classes. Some of the Modules are indexed below.

A. GoogleNet (Google Inception Model):

The Inception Network changed into one of the most important breakthroughs within the fields of Neural Networks, in particular for CNNs. So a long way there are 3 variations of Inception Networks, which can be named Inception

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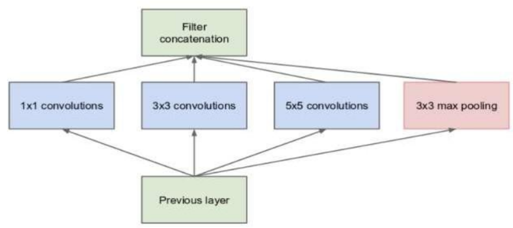
Version 1, 2, and 3. The first version entered the sphere in 2014, and because the name "GoogleNet" suggests, it changed into evolved via way of means of a crew at Google. This network changed into answerable for placing a brand new ultra-modern for classification and detection within the ILSVRC. This first version of the Inception network is called GoogleNet.

If a network is constructed with many deep layers it would face the hassle of overfitting. To resolve this hassle, the authors within the research paper Going Deeper with Convolutions proposed the GoogleNet architecture with the concept of getting filters with more than one sizes which can perform at the equal level. With this concept,



the network surely will become wider as opposed to deeper.

Fig. 4: GoogleNet Architecture

As can be seen in the above diagram, the convolution operation is performed on inputs with three filter sizes: (1 × 1), (3 × 3), and (5 × 5). A max-pooling operation is also performed with the convolutions and is then sent into the next inception module [10].

B. AlexNet:

AlexNet is one of the most popular neural network architectures to date. It was proposed by Alex Krizhevsky for the ImageNet Large Scale Visual Recognition Challenge (ILSVRV), and is based on convolutional neural networks. ILSVRV evaluates algorithms for Object Detection and Image Classification. In 2012, Alex Krizhevsky et al. published ImageNet Classification with Deep Convolutional Neural Networks. This is when AlexNet was first heard of.

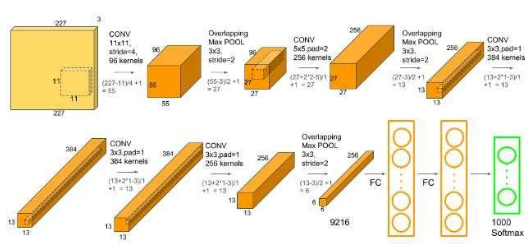


Fig. 5: AlexNet Architecture.

The input dimensions of the network are (256 × 256 × 3) that means that the input to AlexNet is an RGB (three channels) image of (256 × 256) pixels. There are greater than 60 million parameters and 650,000 neurons involved withinside the architecture. To lessen overfitting for the duration of the training process, the network makes use of dropout layers. The neurons that are "dropped out" do now no longer make contributions to the forward pass and do now no longer take part in backpropagation. These layers are present in the first fully-connected layers [11].

C. Oxford VGG Model:

VGG is a famous neural network model proposed with the aid of using Karen Simonyan & Andrew Zisserman from the University of Oxford. It is likewise primarily based totally on CNNs, and became carried out to the

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ImageNet Challenge in 2014. The authors element their work of their paper, Very Deep Convolutional Networks for large- scale Image Recognition. The network achieved 92.7% top-five test accuracy on the ImageNet dataset. The network achieved 92.7% top-five test accuracy on the ImageNet dataset. The input dimensions of the model are constant to the image size, (244 × 244). In a pre-processing step the imply RGB cost is subtracted from every pixel in an image.

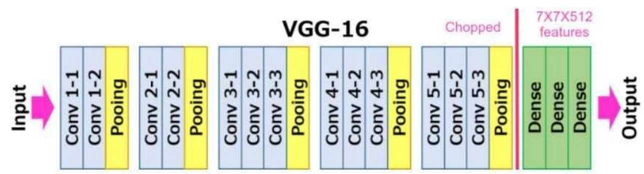

Fig. 6: VGG16 Architecture.

After the pre-processing is complete the images are handed to a stack of convolutional layers with small receptive- subject filters of length (3×3). In some configurations the clear out out length is about to (1 × 1), which may be recognized as a linear transformation of the enter channels (accompanied through non-linearity). The stride for the convolution operation is constant to 1. Spatial pooling is completed through 5 max-pooling layers, which comply with numerous convolutional layers. The max-pooling is accomplished over a (2 × 2) pixel window, with stride length set to 2. The configuration for fully-connected layers is constantly the same; the primary layers have 4096 channels every, the 1/3 plays one thousand-manner ILSVRC classification (and as a result incorporates one thousand channels, one for every class), and the very last layer is the softmax layer. All the hidden layers for the VGG network are accompanied through the ReLu activation function [12].

D. Microsoft ResNet Model:

ResNet, short for Residual Network is a particular kind of neural network that turned into delivered in 2015 via way of means of Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun of their paper "Deep Residual Learning for Image Recognition". In order to resolve the trouble of the vanishing/exploding gradient, this structure delivered the idea known as Residual Network. In this network they used a method known as skip connections. The skip connection skips training from some layers and connects directly to the output. The technique at the back of this network is in preference to layers learn the underlying mapping, we permit network fit the residual mapping. So, in preference to say H(x), preliminary mapping, permit the network fit, F(x):= H(x) – x which offers H(x):= F(x) + x [13].

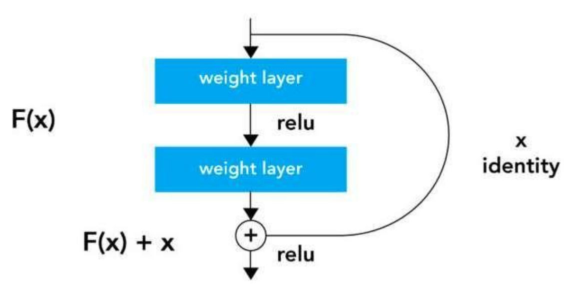

Fig. 7: Residual Learning: a Building Block.

VI. PROPOSED MODEL

The Architecture of our Model is proven in fig. 8. The input to the model can be the Microscopic image of RBC or Blood smear. This Image will input into vgg16 model layer which has pretrained weights with remaining layer

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that's fully connected dense layer with ReLu activation characteristic. Vgg16 Model has pretrained weights we'll freeze the parameters or weights of the VGG16 model after which we defined a Classifier with hidden layers (25088, 4096) (4096, 4096), (4096, 2) the output layer include 2 layers with a purpose to classify the image into Parasitized or Uninfected. We replaced the Classifier of VGG16 model with our defined Classifier. We used ReLu activation function. In a neural network, the activation function is liable for transforming the summed weighted input from the node into the activation of the node or output for that input. ReLu stands for rectified linear activation unit. It makes use of this easy formula: f(x)
= max (0, x). ReLu function is its derivative both are monotonic. The function returns zero if it gets any negative input, however for any positive value x, it returns that value back. Thus it offers an output that has a selection from zero to infinity. While training the Neural Network the Weights of VGG16 are frozen handiest the weights of dense layer are modified for the duration of the Backpropagation.

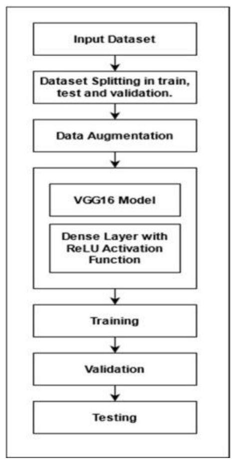

Fig. 8: Architecture of Proposed Model.

VII. EXPERIMENT

The Project is created on Jupyter Notebook IDE, in an environment of Pytorch 1.8.1. The system on which project was created runs on Windows 10 with Intel Core i5 9th gen CPU, 8GB of Ram, and NVidia GeForce GTX 1650 GPU. The training is done on GPU but for prediction we load model on CPU i.e. model uses CPU to make prediction.

A. Dataset Splitting:

The dataset incorporates overall 27,558 images of each infected and uninfected cells. We split the dataset into three parts viz. Training Testing and Validation. For Training we selected 70% images which are 19291 images, for testing, we used 10% images which are 2756 images and for validation we used 20% images which are 5511 images. The reason behind splitting dataset into 3 parts is to train neural network and avoid the overfitting and Underfitting of the data.

B. Data Augmentation and Image Processing:

The concept of data augmentation is to artificially boom the wide variety of training images our model sees via way of means of making use of random modifications to the images. In Data Augmentation phase we carry out a few image processing. During image pre-processing, we concurrently put together the images for our network and apply data augmentation to the training set. Each model could have unique input requirements, however if we read thru what ImageNet requires, we figure out that our images want to be 224x224 and normalized to a selection as VGG16 model want images to be cropped to length 224*224. To process an image in Pytorch, we use transforms, easy operations carried out to arrays. The validation (and testing) transforms are as follows:

a. Resize.

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b. Random Rotation (30 Degrees).
c. Random horizontal Flip.
d. Centre Crop (224*224).
e. Tensor.
f. Normalize with mean and Standard deviation.

The quit end result of passing thru those transforms are tensors which could pass into our network first up, we outline the training and validation transformations. Then, we create datasets and Data Loaders. By the usage of datasets.ImageFolder to make a dataset, Pytorch will routinely companion images with the precise labels provided our directory. The datasets are then handed to a Data Loader, an iterator that yield batches of images and labels.

C. Training the Model:

Before Training begins we froze all of the weights within the lower (convolutional) layers: the layers to freeze are adjusted depending on similarity of latest task to authentic dataset. VGG16 model has over 130 million parameters, however we'll train only the very last few fully-connected layers. Initially, we freeze all the model's weights. Then we defined our own custom Classifier with hidden layers (25088, 4096) (4096, 4096), (4096, 2) the output layer include 2 layers with a view to classify the image into Parasitized or Uninfected. We replaced the Classifier of VGG16 model with our defined Classifier. We used ReLu activation function.

For Training purpose we shift our model on the GPU which will improve the accuracy and also makes the training faster. Before training the model we need to set loss function and the optimizer.

The training loss function is the negative log likelihood (NLL). The NLL loss in Pytorch expects log probabilities, so we pass within the raw output from the model's very last layer. Pytorch makes use of computerized differentiation because of this that that tensors maintain tune of now no longer handiest their value, however additionally each operation (multiply, addition, activation, etc.) which contributes to the value. This means we can compute the gradient for any tensor within the network with respect to any previous tensor. We used SGD optimizer, one thing to be noted is that, as SGD is generally noisier than typical Gradient Descent, it usually took a higher number of iterations to reach the minima, because of its randomness in its descent. The model is trained for 10 Epochs. After training the model we save the model and then we can load the model later for prediction.

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Classifier(
    (hidden1): Linear(in_features=25088, out_features=4096, bias=True)
    (hidden2): Linear(in_features=4096, out_features=4096, bias=True)
    (output): Linear(in_features=4096, out_features=2, bias=True)
    (dropout): Dropout(p=0.5, inplace=False)
  )
)
```

Fig. 9: VGG16 Model with Custom Classifier.

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D. Validation:

Validation is Part of training phase. Neural Networks has tendency to work well on the trained data they after training but they fail to predict the data outside the training dataset which is new to them. In validation phase Neural Network are given with the data which is completely outside of the Training dataset. The validation phase avoids the Underfitting and overfitting of the data which improves the accuracy of Model.

E. Testing:

Testing phase is important we can say model is performing well based on the testing accuracy. In testing the data which is not from Training and validation set or we can say real world data is given to the model for prediction and then accuracy is calculated. In testing phase testing loss is calculated. Then we calculate true positive rate for Parasitized and true positive rate for Uninfected and then we calculate the average of these rates which is the testing accuracy.

VIII. MODEL DEPLOYMENT ON WEB

To deploy the model on web and to create the GUI for the model we used Flask. Flask is a web development framework developed in Python. It is straightforward to examine and use. Flask is called a micro-framework due to the fact its far light-weight and only affords components which can be essential. It only affords the important components for web development, consisting of routing, request handling, sessions, and so on. Model is hosted at the local server later we are able to deploy the model on the web using Heroku. Heroku is a cloud platform as a service supporting numerous programming languages.

IX. CONCLUSION

With the help of Transfer Learning we achieved better accuracy in predicting the Malaria Cells. Model successfully predicts the given input microscopic image is Parasitized or Uninfected with the Overall accuracy of 85%. While the accuracy for predicting the uninfected cells is 90% whereas the accuracy to predict Parasitized is 81% which is quite good and avoid the data overfitting and Underfitting. Training the model on GPU results into fast training and better accuracy. We can improve the accuracy of model by tuning the parameters of the classifier or we can train the model on TPUs for better accuracy. Besides VGG16 model we can use ResNet50 or VGG19 or Google Inception model. The Prediction time can also be reduced by loading the model on the GPU.

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