ISSN: 2278-4632
Vol-12 Issue-12 No.02, December 2022

MALARIA DETECTION USING DIFFERENT DEEP LEARNING MODELS

Dr. G. Anitha Mary, Dean of Informatics, Loyola Academy, Old Alwal, Secunderabad-10, Telangana

Pushpa Latha Thumma, Assistant Professor, Department of MCA, St. Ann's College for Women, Mehdipatnam, Telangana

Dr. K. Vijaya Lakshmi, Dean of Research, Loyola Academy, Old Alwal, Secunderabad-10, Telangana

Y Lokesh Kumar, M.Sc. Data Science, UID: 111720720027**,** Loyola Academy, Old Alwal, Secunderabad-10, Telangana

Abstract - Malaria is a female Anopheles mosquito-borne disease that transmits a motile infective form to the host body like humans, which reproduce asexually within the blood cells of the host. The standard symptoms of malaria are fever, headache, tiredness, and vomiting. In severe cases may cause coma and death. During this research, we used deep neural networks to detect the malaria virus in human blood cells. Traditional malaria detection techniques require experts to check blood cells under a microscope. The proposed method during this research shows a system with end-to-end automated models employing a deep neural network that performs both feature extraction and classification using blood smear cell images. During this research, we got used VGG-19, ResNet-50, DenseNet, MobileNet, and a base model to suit the information to find the most effective performing model.

Keywords – Malaria, Deep Neural Networks, Feature Extraction, Classification

I. INTRODUCTION

Malaria is classified as a contagion contamination this is due to a unmarried-celled microorganism it in truth is belonging to the genus protozoan parasite of the plasmodium business enterprise in which 5 of their species can infect human beings. the disease is specifically spread via the imply of chew-inflamed girl anopheles' mosquitoes. based totally on latest information the malaria disorder puts around 40% of the planet population to danger with nearly 240 million instances pronounced yearly, Africa and specifically the sub-Saharan- Africa nations are the foremost way to malaria. typically, there are two fundamental medical strategies commonly accustomed diagnose malaria microscopy of skinny blood cells and an antigen diagnostic exam. the preceding can be a completely time ingesting operation, generally with doctors not less than 5000 cells have to be diagnosed manually to validate, the situation, although the latter is some distance quicker than the previous one, the antigen-based speedy diagnostic assessments are much less powerful.

This research focuses on designing an accurate malaria diagnosis model that may be implemented without any dependencies on skilled technicians and testing the model accuracy to induce high-quality results. Automated image analysis software could remove the foremost serious limitation of the worldwide accepted microscopy method in normal, dependency on human experts for diagnostic accuracy of the results. Automating the detection process means using the knowledge, the practice of conventional methods, and implementing it to get fast andefficient results.

Machine learning is a field of computer science where decisions are made by analyzing data and reading the info to urge the specified output. Within the past decade, the health sector has seen a big growth, lots of research is ongoing to form healthcare automated to create the method easily available to everyone.

To automate the diagnosis process, much researches are conducted on various machine learning models. Machine learning models require plenty of tuning, correlation analysis, and feature engineering. The machine learning method isn't scalable with more data provided. Machine learning requires feature engineering and have training which isn't a handy tool. Deep learning models are reliable and simply scalable with a better accuracy rate.

Currently, with the event of AI-primarily based systems which are called laptop-aided analysis or selection guide systems, malaria detection the use of blood films became extra efficient one in all of the maximum present day AI techniques is Deep learning which might be accustomed classify cellular photographs and assist to forestall incorrect diagnostic selections.

CNN is a type of neural network which is mainly used for images and a lot of improvement is going on inside the mission of DL, and it is used considerably within the situation of CV for the prognosis of clinical ailments and especially for statistics which can be supported pics.

II. WORKFLOW

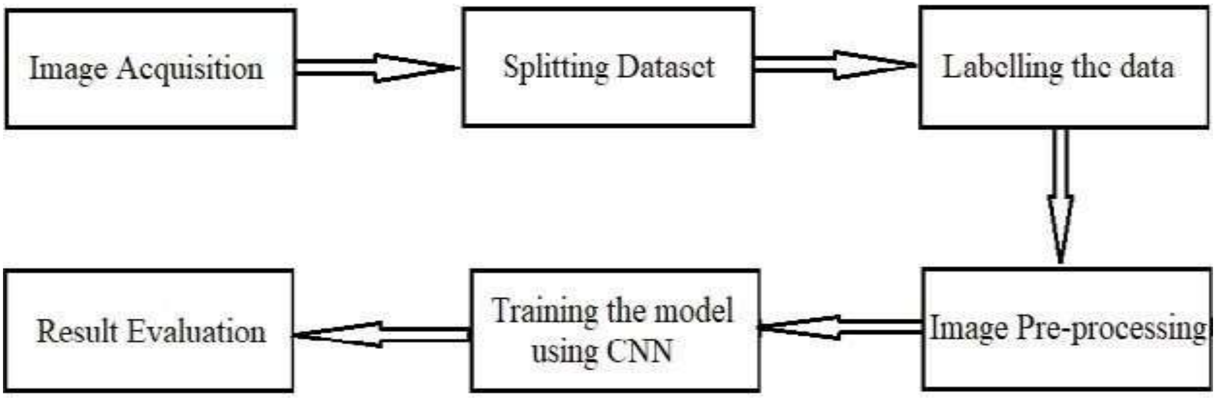

Fig. 1. Block Diagram

In the Image acquisition phase, we acquire the malaria dataset from NIH website. The dataconsists of microscopic blood cell images which consists of parasitized and un-infected images.

In the splitting dataset phase, we split the dataset into training and testing so we will fit thealgorithm on training data and evaluate the model using testing data.

In the pre-processing phase, we pre-process the image so as to suit that input image to themodel.
In the Training phase we fit different models on our data like ResNet, DenseNet, MobileNet,VGG-19 on our malaria dataset.
In the Result Evaluation phase, we evaluate the results using confusion matrix.

III. METHODOLOGY

Setting Up the Cloud

This research focuses on comparing performances of various deep Convolutional Neural Networks that need high computational power for execution. The Graphics Processing Unit (GPU) or multiple CPU computation is required to run deep neural networks. during this research, we used to google colab to perform operations on the malaria dataset.

Pre-processing

This section will help understand all the pre-processing techniques utilized in the research to record the model performance difference. The malaria dataset consists of 27,557 images of which 13,778 are parasitized images and 13,779 are non-infected images. We merged files of both non-infected images and parasitized images and labelled them as healthy and malaria for the respective files. The dataset is split into three sets for training, validation, and testing.

The ratio of a train to validation to check is 63:7:30. we decide to require only 63% of dataset as training to avoid high computational intensity because of the big dataset. The training dataset consists of 63% of the dataset with 8707 healthy images and 8653 malaria images, the validation dataset consists of seven with 1001 healthy and 928 malaria images, and therefore the testing dataset is 30% of the full dataset having 4144 and 4124 healthy and malaria images, respectively. After analyzing the dataset, images within the dataset have different dimensions varying over the dataset. Scaling images up gives a bonus in performance but also requires lots of computation time and memory space. it's better to keep up this trade-off of accuracy and computation. during this research, we decided to resize all the photographs. This resulted during a better classification score with a good processing speed. Due to the fact neural networks get maintain of inputs of the same period, all snap shots need to be resized to a hard and speedy length in advance than inputting them to the CNN. The bigger the fixed size, the much less shrinking required.Less shrinking means much less deformation of features and styles within the picture. This will mitigate the class accuracy degradation way to deformations. But, huge pictures not handiest occupy greater area within the memory however additionally cause a larger neural community. Therefore, developing each the space and time complexity.It's far obvious now that deciding on this regular size for images can be a depend of change-off amongst computational efficiency and accuracy.

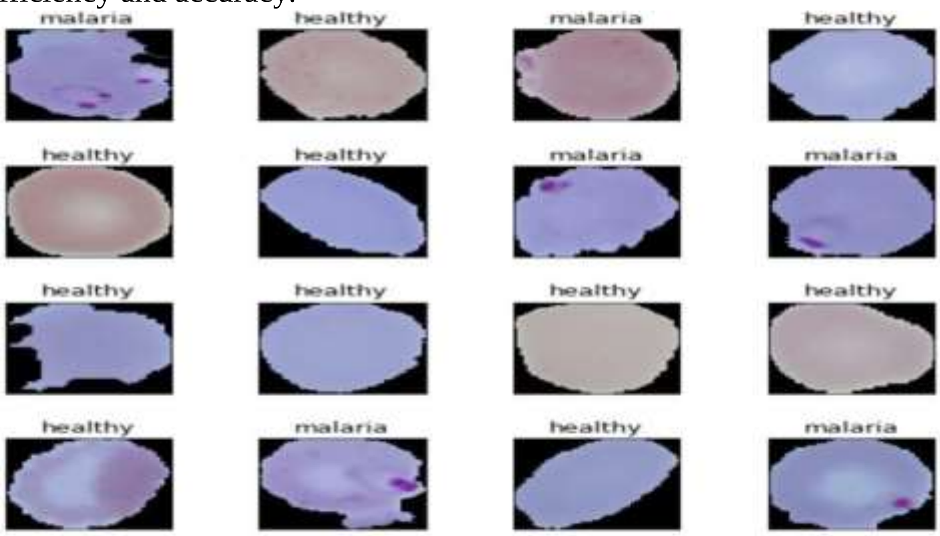

Fig.2: Malaria Dataset

Normalization

Normalization is a vital pre-processing task that minimizes the colour and variation intensity present in stained input images from different laboratories. in line with past 20 research, stain normalization has proven to significantly increase the accuracy of the unseen dataset by approximately eight percent. during this research, the pictures are collected from the pre- existing dataset of human blood cells which is ready from laboratory examination. The smear slides are prepared within the laboratory using various chemical stains which ends in colour variation thanks to the utilization of various chemicals and marking procedures. This staining leads to model learning and handling more complex models with a various set of images results in maximizing the error rate. an answer to standardize this is often normalization.

Stain Normalization could be a common pre-processing technique that attempts to cut back colour variability and improve the generalization of algorithms by transforming the input file into a standard space. In stain normalized digital pathology samples, regions of virtual tissue specimens are mapped to comparable colour characteristics irrespective of the scanning device, stain supplier, and coaching protocols. Way to the reduced variability in colour characteristics of tissues, stain normalization has established development in pc-assisted diagnostic tools.
In this research, we've got implemented stain normalization within the training and validation dataset

ISSN: 2278-4632
Vol-12 Issue-12 No.02, December 2022

while leaving the test dataset untouched. After implementation as shown in plots the range of images is transformed into a narrower range and it's evident that the semantic meaning of the pictures is preserved.

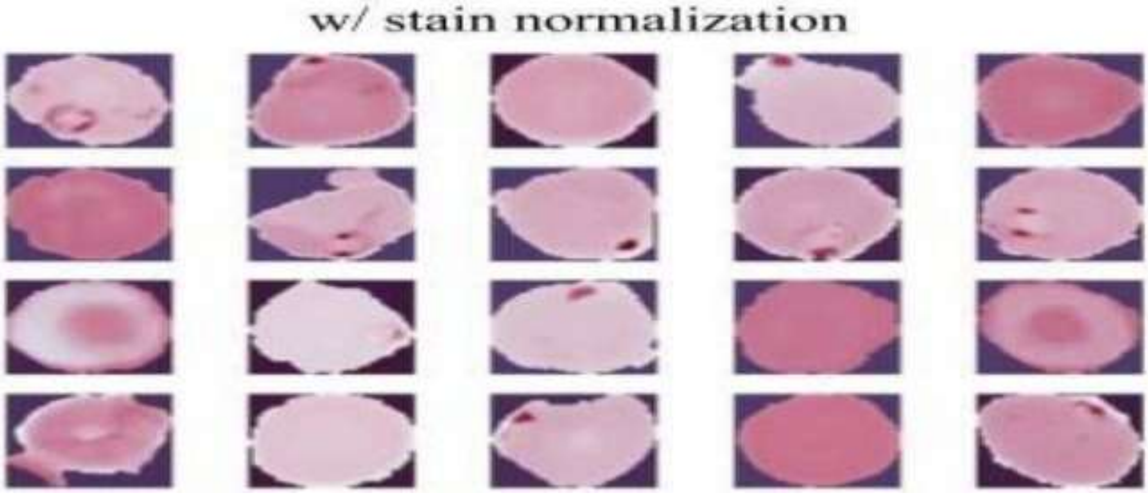

Fig.3: Cells with Stain Normalization

IV. Model Architecture and Implementation

Transfer Learning

Transfer Learning could be a feature that allows users to transfer the knowledge of pre-trained models and use it in their own problem set. rather than creating a model from scratch during this research, we used the models that are trained on large datasets like ImageNet with 100,000 data points and explored the ability of transfer learning which is proven to be significant in many image classification sorts of research.

VGG-19

vgg-19 can be a convolutional neural network it is 19 layers deep. VGG-19 is one variant of the VGG model. there are different variations of vgg like VGG-eleven, VGG- 16, and others. vgg was created by using the visual geometry group at oxford and as a result the name VGG. It uses deep convolutional neural layers to beautify accuracy. VGG-19 Architecture consists of 16 convolutional layers and three fully connected layers with five max-pool layers.

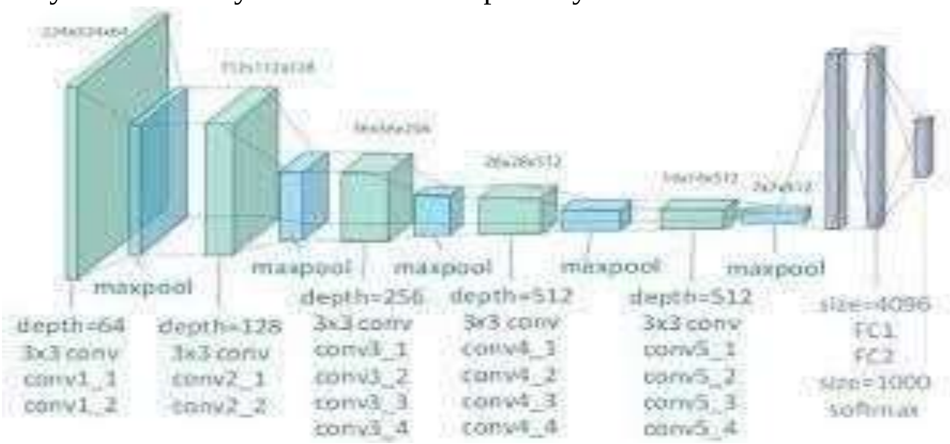

Fig 4: VGG – 19 Architecture

ResNet

ResNet-50 is a convolutional neural network which is 50 layers deep. You can load a pretrained model of the network trained on quite 1,000,000 images from the ImageNet database. The pretrained network can classify images into 1000 object categories, like keyboard, mouse, pencil, and many animals. As a result, the network has discovered rich function representations for a large variety of pics. It has an photograph length of 224 by 224.

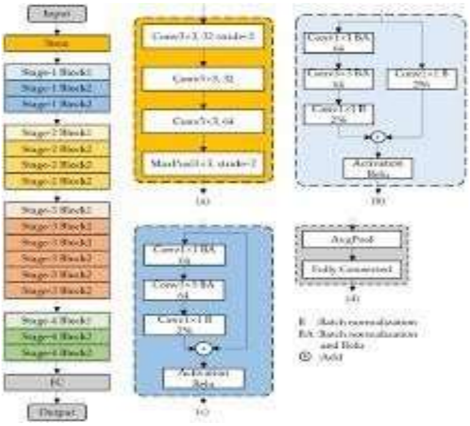

Fig 5: ResNet Architecture

DenseNet

DenseNet might be a style of network that utilises dense connections between layers, through dense blocks, wherein we connect all layers directly with each other. To hold the feed-ahead nature, every layer obtains additional inputs from all preceding layers and passeson its personal characteristic-maps to all or any subsequent layers.

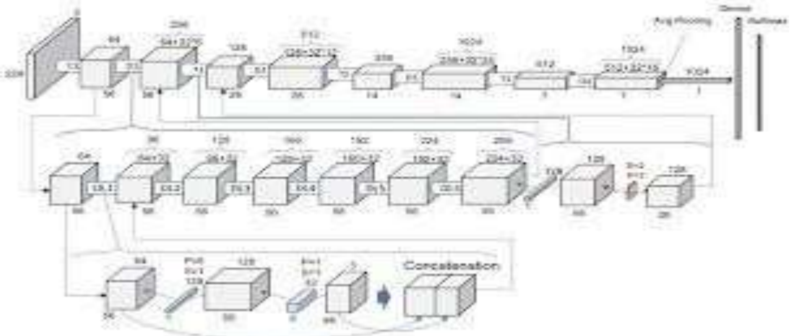

Fig 6: DenseNet Architecture

MobileNet

it is designed to be accomplished in mobile programs, and its tensor waft's first cellular imaginative and prescient version. It makes use of intensity sensible separable convolutions. it notably reduces the quantity of parameters as compared to the network with ordinary convolutions with same depth inside the nets. This leads to light weight deep neural networks.

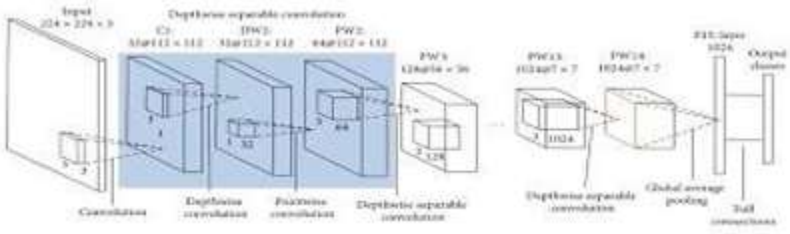

Fig 6: Mobile Architecture

V. RESULTS

Research is completed on human red corpuscle smear images to classify as infected or healthy. The research uses different pre-trained Convolutional Neural Networks with transfer learning and fine-tuning them on the malaria dataset and recording their performances.

Research reveals that after pre-processing input images and fitting the various pre-trained models on that, different models gave different results.

The ResNet model gave accuracy of 92.72% with 87% precision and 75 recall. The VGG model gave accuracy of 90.43% with 84% precision and 67% recall. The MobileNet model gave accuracy of 93.06% with 90% precision and 74% recall. The DenseNet model gave accuracy of 92.85% with 90% precision and 76% recall. The base model gave accuracy of 94.38% with 94% precision and 63% recall.

The following table shows the results of the analysis with respect to different models:

ModelName	Accuracy	Precision	Recall	F!- Score
ResNet	92.72	87	75	81
VGG	90.43	84	67	75
MobileNet	93.06	90	74	81
DenseNet	92.85	90	76	82
Proposed	94.38	94	63	85

Fig 7: Model Evaluation Results

The following image is the front-end of the malaria detection web application

Fig 8: Front End

Then we provide the positive data sample to the web application and then the following is theoutput of that data sample

Fig 9: Predicting Parasitized Image

ISSN: 2278-4632
Vol-12 Issue-12 No.02, December 2022

Then we provide the negative data sample to the web application and then the following is the output of that data sample

Fig 10: Predicting Un-Infected Image

VI. CONCLUSION

In this research, we experimented with end-to-end deep learning neural networks to boost malaria diagnosis classification performance. We showed that pre-processing techniques like normalization, standardization, and marking don't contribute much to improving performance. Instead, methods like data augmentation showed positive results by increasing the performance of the models. We also compared different models like VGG-19 and ResNet-50 and their performances. We established VGG-19 and ResNet-50 models from scratch and used transfer learning and hyper tuning the parameters. Transfer learning could be a great technique and will be wont to gain satisfactory performance compared to machine learning models that need plenty of feature scaling and engineering. In future works, we attempt to specialize in the specification of the models employed in the research to seek out the driving performance factors. We plan on finding ways to enhance the performance by manipulating the specification and hyper tuning the features to realize an excellent better-performing model.

VII. FUTURE ENHANCEMENTS

To develop a system satisfying the user needs isn't possible at one go. we want to upgrade the applying. a number of the long run enhancements of this method are:

- Optimizing the pre-trained models so as to extend its accuracy and precision.
- Deploying the online application to the 000 world where it may be utilized byanyone within the real time situation after optimizing the model.

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