Design of Malaria Detection Using Ensemble Techniques - A Combination of Alexnet and Densenet Algorithm

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Abstract. This paper aims to identify whether a cell is malaria infected or not by applying machine learning and Deep learning algorithms that are Alex net and Dense net. The dataset which is used for reference consists of a total 27,558 images, out of which 13,780 images are infected, and the rest are uninfected cells and is taken from the NIH Website. In the paper, the sample of that dataset is taken, and algorithms are applied to evaluate the dataset. The machine is trained to classify and detect if the cell is parasitized or uninfected. An in-breadth and depth analysis of various classifiers like AlexNet and DenseNet is done, and their performance is compared by tuning different hyperparameters. DenseNet is a deep convolutional neural network architecture developed for image classification tasks. It is characterized by densely connected layers, which enables better feature reuse and gradient flow throughout the network. AlexNet is a deep neural network that can learn complex features from images andis very effective at image classification tasks. The output is combined using an ensemble technique, and the performance of these classifiers is evaluated.

Keywords: Malaria, Ensemble Technique, AlexNet, DenseNet, Deep Learning.

1 Introduction

Effective treatment and management of malaria depends on early and precise diagnosis of the disease. Deep learning algorithms have recently shown astounding effectiveness in the detection and diagnosis of several illnesses, including malaria. This research paper, suggest an ensemble method for detecting malaria that combines the advantages of AlexNet and DenseNet. The suggested strategy beats current state-of-the-art approaches for malaria detection, according to our experimental data, displaying better accuracy and efficiency.

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2 Problem Definition

Deep learning-based state-of-the-art techniques for detecting malaria have limitations.[1] For example, a single CNN model may not capture all relevant image features. Certain techniques necessitate substantial quantities of training data and processing power. This may not be feasible in resource-limited settings. This research paper aims to propose an ensemble technique that combines AlexNet's and DenseNet's strengths for malaria detection.

3 System Overview

The project is built by combining the outputs of Densenet and Alexnet. The process involved includes the following methods

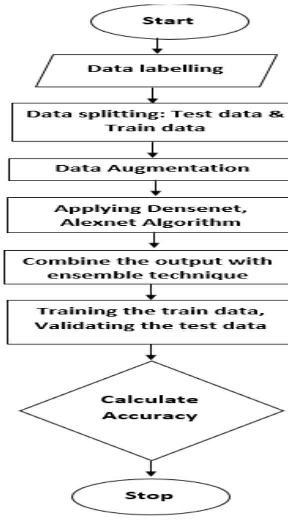


Fig. 1. System flow diagram

4 Existing System

4.1 CNN

Convolutional, pooling, and fully connected layers for classification or regression tasks make up a CNN, a deep learning algorithm used for image recognition and PC vision tasks [4]. Weights are modified during training via backpropagation.

4.2 Results

- Test data has an accuracy of 88% while training data has a 97% accuracy rate.

Table 1. The results of CNN algorithm.

Loss	Accuracy	Val_loss	Val_accuracy

0.0626	**0.9736**	**0.2463**	**0.8881**

4.3 Total Number of Images

There are 416 training data consisting of both malaria-infected and malaria-uninfected cell images, and an example of each is shown in Fig. 2

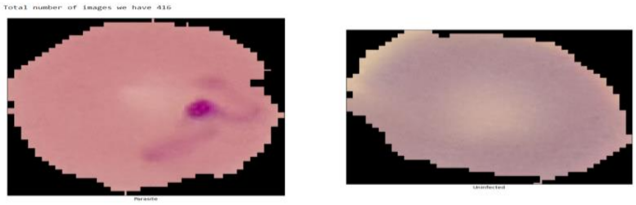
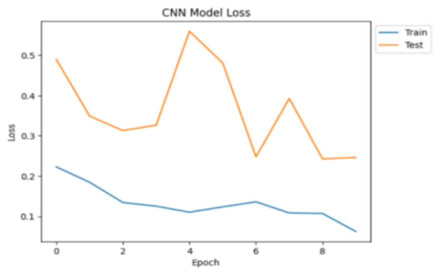


Fig. 2. Total training data present

4.4 Accuracy Reports



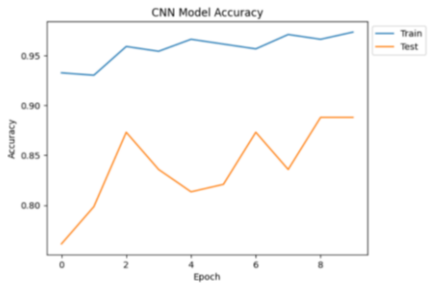


Fig. 3. Model accuracy

Fig. 4. Model loss

5 Proposed System

This research paper proposes an ensemble technique of AlexNet and DenseNet for malaria detection. AlexNet is a well-known CNN model successful in image classification tasks. DenseNet is a newer model with improved accuracy and efficiency in deep learning. The proposed technique combines the strengths of both models to enhance the accuracy and efficiency of malaria detection.

5.1 Densenet

DenseNet is a deep learning architecture designed to address the vanishing gradients issue in deep learning change layer is taken care of into the following thick block[5]. Generally, DenseNet has shown promising outcomes in different PC vision assignments, including picture grouping, object location, and division. Its novel thick availability helps battle the disappearing slope issue, prompting better assembly during preparation and further developed execution on different datasets.

5.1.1 Working

A Densenet model is built sequentially with layers like dropout, flattening, group standardization, and sigmoid/ReLU activations. It starts with a pre-trained DenseNet121 model, yielding (None, 5, 5, 1024) shape and 7,037,504 trainable parameters. Additional layers include dropout (0.5 rate), flattening (None, 25600), group standardization (102,400 params), dense layer (2,048 neurons, 52,430,848 params), and more. In total, the model has 54,587,393 trainable and 7,094,848 non-trainable parameters. Training utilizes the Adam optimizer, a learning rate of 0.001, binary cross-entropy loss for 10 epochs with train and validation data generators. Training history is stored as 'hist' for accuracy and loss curve plotting.

Accuracy = Total number of properly caTotal tegorized pictures / number of images

5.1.2 Accuracy Reports

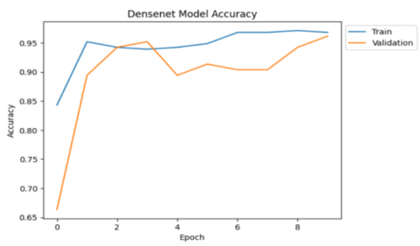


Fig. 5. Model accuracy of Densenet algorithm

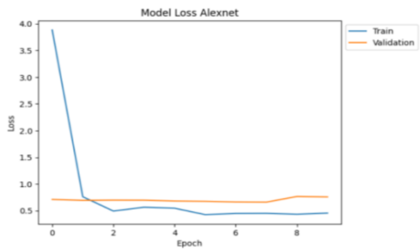


Fig. 6. Model loss of Densenet algorithm

5.2 AlexNet

AlexNet's design was historic when presented and showed profound learning viability in PC vision undertakings. Its prosperity enlivened further examination into profound brain organizations and prompted the improvement of much more perplexing and strong structures.

5.2.1 Working

A model, 'model1,' is constructed as a Sequential model based on AlexNet architecture. For binary classification, it consists of convolutional, batch normalization, max pooling, dense layers, and sigmoid activation. The binary cross-entropy loss function and Adam optimizer are used to train the model at a learning rate of 0.001, using input data in the form of 43x43 pixel RGB images. It undergoes 10 epochs of training, and the training history is visualized using 'plot' based on the 'hist' object storing historical data for accuracy and loss metrics.
Accuracy = Total number of properly categorized pictures / Total number of images

5.2.2 Accuracy Report of AlexNet

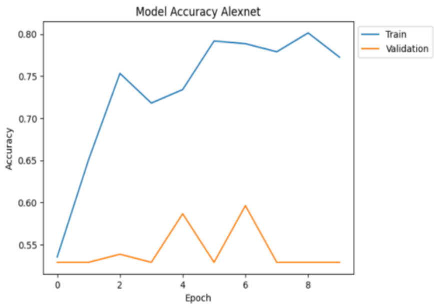


Fig. 7. Model accuracy of Alexnet algorithm

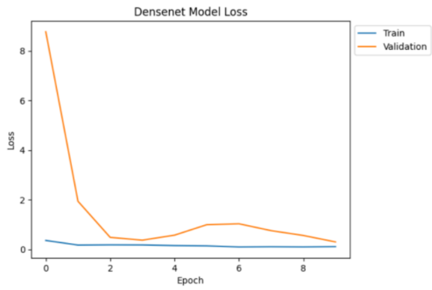


Fig. 8. Model loss of Alexnet algorithm

5.3 Ensemble Technique

Ensemble techniques in machine learning involve combining multiple models to improve overall performance and prediction accuracy. The ensemble of DenseNet and AlexNet can create a synergistic effect, enhancing the ensemble's performance by leveraging the unique strengths of each architecture.

5.3.1 Working

The code imports essential libraries such as TensorFlow and Keras for constructing and training deep learning models. It loads pre-trained models without recompiling using tf.keras.models.load_model() and assigns them names. A list called 'models' contains these models. An input tensor is created via tf.keras.Input() to specify image input shape. Model_outputs are generated by applying each model to the input, resulting in a list of output tensors. These outputs are averaged using tf.keras.layers.max() to create an ensemble model. The predict function takes an image path, loads, resizes, normalizes, and predicts its class (Parasite or Uninfected). Results are printed with the image.

6 Results

The accuracy of training data and testing data is 93% and 94% respectively which is secured by taking the maximum output using the ensemble technique.

Table 2. The result of ensemble technique.

Loss	Accuracy	Val_loss	Val_accuracy
0.1069	**0.9679**	**0.2698**	**0.9615**

6.1.1 Sample Output

Fig. 9. Sample output predicting the uninfected cell

7 Conclusion

Ensemble techniques combining DenseNet and AlexNet for malaria detection improve accuracy and robustness. These models leverage DenseNet's dense connectivity and AlexNet's convolutional layers, enhancing feature extraction and classification, resulting in improved malaria detection performance.

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