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Smart Framework for Black Fungus Detection using VGG 19 Deep Learning Approach

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***Abstract*— Black Fungus is one of the deadly infections faced during covid_19 scenario. The mucoromycetes are responsible for this fungal infection and person having any of kind trauma like cut, burn is susceptible to this deadly virus. Further, the persons having health issues such as diabetes, cancer, organ transplant are having more probability to get infected. The case study reveals 30% of covid recovered patients are infected with black fungus and 10% of them permanently lost their eye sight due to delayed detection of infection. Among them 2-3% lost their precious life. In this regard we propose a smart framework for early detection of black fungus using deep learning approach. The CNN based VGG19 architecture is capable of effectively predicting black fungus using eye image. For our experimentation we have enriched the dataset of ImageNet using data augmentation technique. Experimental results are encouraging with 80% above accuracy.**

Keywords*— *VGG19, CNN, Deep Learning, Black Fungus, Mucormycosis

I. Introduction

Fungus is detectable and harmful for human health it should cause varied grievous diseases. There are millions of different fungal species present in the environment of which few causes fungal infections which are extremely hazardous to human health. One such mycosis is "Mucormycosis", that is often referred to as black fungus, it's a really rare however a deadly mycosis caused by a bunch of moulds referred to as "mucoromycetes", that area unit gift within the atmosphere significantly in soil, plants, manure, and decaying organic matter. It's present and located in soil and air and even within the nose and secretion of healthy folks. Though the foundation causes for an individual being infected to black fungus remains unsure, in most cases folks' area unit infected there to after they get in reality with the plant spores' gift within the atmosphere particularly once an individual has any reasonably skin trauma sort of a cut, scrape, burn etc. It is also noted that this infection affects a person who is having other health issues like diabetes, cancer, organ transplants or who are using other drugs which compromises the immune system. It's a really rare mycosis however in recent times there's an incredible increase within the cases of black fungus compared to the previous couple of years or decade. Doctors and health workers recommend that it's because of the unfold of COVID-19.Varied Steroids employed in the treatment of COVID-19 scale back inflammation within the lungs and seem to assist stop a number of the harm which will happen once the body's system goes into overdrive to oppose coronavirus. However, they additionally scale back immunity and push up glucose levels in each diabetic and non-diabetic Covid-19 patient. It's thought that this call immunity may well be triggering and creating the patients additional liable to mucormycosis. Because of this the rate has additionally redoubled considerably. A number of the recognized symptoms of black fungus embrace fever, cough, chest pain, headache, swelling and redness of eyes, discoloration over eyes, nose and sides of one's face, blurred vision and in severe cases loss of vision, blood vomits, and shortness of breath. It shows severe impact on the brain and alternative internal organs if not detected and treated immediately.

The main aim of this project is to investigate and predict the chance of an individual being infected to Mucormycosis supported the black fungus symptoms with facilitate of black fungus infection detection model victimization deep neural networks. Deep Learning has proved to be a really powerful tool attributable to its ability to handle giant amounts of information particularly in pattern recognition. One among the foremost standard deep neural networks is that the Convolutional Neural Networks. It's a special style of neural network that roughly imitates an individual's brain. It takes image knowledge as input and reduces the pictures into a kind that's easier to method, while not losing any options that area unit crucial for obtaining a decent prediction. Convolutional neural networks area unit composed of multiple layers of artificial neurons referred to as nodes that could be a rough Imitation of the brain associated their area unit mathematical functions that calculates the weighted add of multiple inputs and outputs an activation worth. Once you input a picture during a CNN model, every layer generates many activation functions that area unit passed onto successive layer and therefore the output of the ultimate layer is that the chance that the image is infected to black fungus infection.

II. Literature Review

In 2021, Mrigesh Bhatia from London School of Economics, London, UK published an article on mucormycosis in covid19 patients in India. In his article mentioned that there are over 40,000 cases of mucormycosis reported as of 28 June 2021. Mucormycosis has been declared an endemic a virus a virulent disease a pestilence in many

Indian states and has been classified as a inform disease. Early designation and prompt initiation of treatment is crucial because the condition will progress apace with fatal outcome. The treatment for this condition relies on a mixture of antifungal medication and aggressive surgical surgery of death tissue if necessary. The etiology of the explosive rise of mucormycosis in Bharat seems to be complex in nature with many hypothesis linking mucormycosis to severe Covid-19 patients UN agency area unit immune compromised and/or have associated comorbidities.For example, diabetes, which is a known risk factor for Covid, is also found to be strongly associated with risk of mucormycosis [1].

Healthy individuals have a very low risk of developing mucormycosis, however, a number of immunosuppressive conditions place a person at risk of this condition. These include uncontrolled Diabetic with or without Dehydration and Ketoacidosis, other haematological conditions, deferoxamine treatment, severe burns, acquired immune deficiency syndrome (AIDS), malnutrition and open wounds, intravenous drug abusers, prolonged neutropenia, iron overload or hemochromatosis, organ transplantation immunosuppressive and corticosteroid therapy. There are many forms of mycosis that can involve the nose, sinuses, orbits, the central nervous system (CNS), lungs, gastrointestinal tracts (GIT), the skin, jawbones, joints, the heart, kidney, and mediastinum (invasive types), but ROCM is the most common type witnessed in clinical practice across the world. As mentioned earlier, it is important to note that the term ROCM refers to the entire spectrum that takes place within this disorder, from small Sino-nasal lesions (invasion of Sino-nasal tissue into the orbit), to small rhino-orbital lesions (progression to the orbit), up to rhino-orbital-cerebral lesions (involvement of the central nervous system) [2].

According to research by Sirisatietal there have been 388 suspected or confirmed mucormycosis occurrences in India on or before the release of COVID-19 [3]. 18% of patients had diabetes with or without insulin and 57% had uncontrolled diabetes. These results are reported in Prakash et al. A study conducted in India that examined 465 cases of mucormycosis without the presence of COVID-19 found that over 60 percent of the cases had rhino-orbital symptoms, while 14 percent had pulmonary symptoms, and 12 percent had cutaneous symptoms. The most common risk factor for diabetes among Indians is the presence of diabetes, as 73.5 percent of all Indians have the disease [4].

Anaindita Roy et al., analyzed images captured with fundus photography and used Deep Learning algorithms for detecting and classifying the images. The authors propose to implement a Residual Y-net architecture which is based on Deep Residual U-net, and Residual Y-net, but in a very lightweight way. In order to improve the accuracy rate of the network, they have added residuals, which has contributed to the improvement of the accuracy rate. Taking into consideration a balanced dataset, one can compare the accuracy of the prediction to an unbalanced dataset [5].

III. PROPOSED FRAMEWORK AND METHODOLOGY

In this section we cover VGG19 Architecture, Image Net, Dataset, Data augmentation, Acquisition, Feature extraction and classification.

A. VGG19 Architecture

Karen Simonyan and Andrew Zisserman of Oxford university proposed VGGNet in 2014 as a CNN architecture that uses convolutional neural networks [6]. A primary focus of this paper is on the CNN precision in relation to its profundity. ConvNet based on VGG is comprised of an RGB image with dimensions 224*224. In the pre-processing layer, RGB pictures with pixel values in the range of 0-255 are taken and they are deducted from the mean picture values determined by running over the entire ImageNet training set. As a result of the pre-processing, following the input picture, this weight layer is applied to it. As a result of the convolution layer, training pictures are manipulated in such a way as to achieve a better outcome. A total of 13 convolution layers are accounted for in this architecture, as well as 3 fully connected layers. As compared to VGG having huge channels, they have more modest channels (3x3) that have a better depth. This has produced an open field with a similar power to that of having just one 7 x 7 convolutional layer. VGGNet is also incorporated into another model that comprises 19 weight layers, composed of 16 convolutional ones, coupled with three fully connected ones, and a similar pooling of five layers. As there are two versions of VGGNet, each has two Fully Connected layers with 4096 channels, followed by another completely connected layer with 1000 channels to ensure a total of 1000 marks are possible. In order to ensure local ordering characteristics, the final layer which is fully-connected utilizes a SoftMax layer.

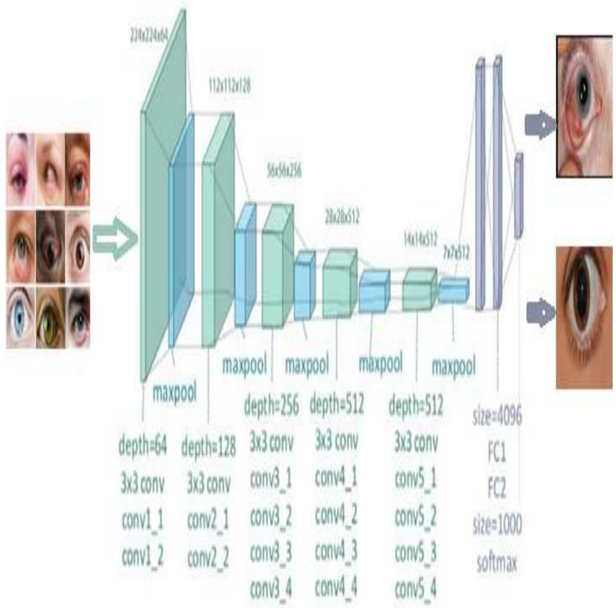


Figure 1: Architectural Framework

The 19 layers are described as follows:

- Three layers of convolutional layers are used in each of the first two layers, and the first two layers each use 64 channels, resulting in a volume of 224*224*64. There is a constant 3*3 step with the channels.
- Additionally, a pooling layer was used to reduce the height and width of the volume from 224x224*64 to 112*112*64 in the second step, which involved a maximum pool size of 2*2.
- Then two further convolution layers of 128 channels are added on top. A new depth image is generated with measurements of 112*112*128.
- The volume is then reduced to 56*56*128 after the pooling layer is utilized.
- The size is then reduced by a down inspecting layer which brings the size down to 28*28*256 and then two more convolution layers are added.
- By using a maximum pool layer between each stack, a further two stacks with 3 convolution layers are isolated.
- Following the last layer of pooling, the 7x7x512 block is transformed into a Fully Connected (FC) layer which offers 4096 channels and a SoftMax yield of 1000 classes.

B. Image Net

The ImageNet project is a collection of images that can be used for research purposes. Approximately 500–1000 image files will be used to populate 80% of WordNet's synsets. In this way, WordNet will produce tens of millions of annotated images. Also, around 1 million images are annotated with bounding boxes, which are useful in many Objects Localization tasks. There is no single standard for classification of images, except for ImageNet. Each year, millions of images are used for training to categorize images into 1,000 categories. During an ImageNet classification competition, the performance of the models is compared against each other. Therefore, it provides a way to evaluate how good a classifier is for determining the appearance of images. Often, ImageNet weights are applied to transfer learning models instead of training the network from scratch.

C. Dataset

Using a dataset that was custom-defined, we were able to accurately identify black fungus disease in this study. It is necessary for the black fungus images to be prepared independently with a dataset that includes both affected and nonaffected cases because of the lack of datasets available for black fungus images. As a result of this system, black fungus images from various perspectives were collected and organized in a machine-comprehensible manner. This allows the machine to recognize normal and affected images based on the data. CNN and VGG19 architectures, was used in the deep learning process. To create a standard learning model for black fungus disease prediction, this process was applied to our dataset and the samples were trained accordingly. As seen in Figure 2 a & 2 b , two different images are shown in graphical form: images affected by black fungus, and images unaffected by black fungus.

Figure 2 a. Black fungus infected images

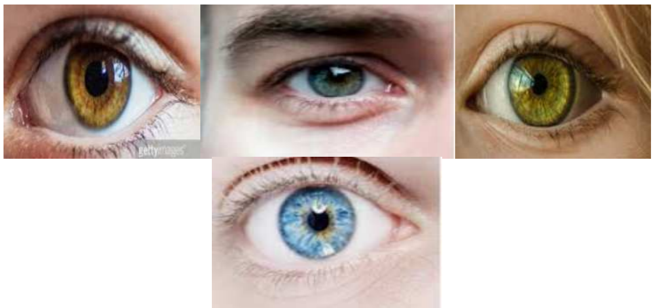


Figure 1 b. Black fungus uninfected images

D. Proposed Methodology

A number of investigational procedures can help detect the black fungus disease, such as computed tomography (CT) scanning, magnetic resonance imaging (MRI), and cell biopsy tests. However, all of these tests and investigation procedures are very expensive, and ordinary people cannot afford to pay for them; therefore, to promote a more efficient prediction process, we developed a methodology that involves traditional learning techniques, such as using convolutional neural networks, and VGG19 models new prediction algorithm. An excellent algorithm for identifying black fungus diseases is described that follows the following principles, such as data acquisition, data augmentation, data pre-processing, detection of features in images, classification, and accuracy estimations. In the case of black fungus, a real-time dataset of images was used to predict the disease based on the aforementioned procedures.

E. Data Augmentation

A technique known as data augmentation works by creating artificial images from an existing image dataset based upon existing attributes of the original image. When this process of creating artificial images happens, it does not affect any of the original images. This particular process involves deformations and rotates the original image. Each photo will have a different perspective as a result of rotating the same picture by different angles. A "hole" is created when the pattern of the image is shifted from the frame, resulting in a pattern that needs to be interpolated. In zooming, the new image will be a zoomed version of a segment of the original data [7]. Due to the lack of black fungus data available in the online platforms we used augmentation techniques to create a decent dataset for this experimentation. We have maintained 5022 Images of which 3011 infected and remaining 2011 are Normal.

F. Data Acquisition and Pre-processing

Digital images are two-dimensional representations of pictures made up of a limited amount of visual information, called pixels or bytes. An image acquisition method can be used in digital image processing and perception based on AI to obtain an image from a source. In the period between the machine's operation and obtaining a visual inspection it is most important to identify the image, since without it the machine will not be able to perform any task at all. This process describes the procedure of reformatting digital images before they are used for training and validation of algorithms. Scaling, orientation, and color corrections are included here, but are not the only ones. If unpredictability is considered as a metric of information, then these actions do not add any information to the object, instead, they remove information. During image pre-processing, undesirable abnormalities are suppressed and specific visual properties are enhanced to enhance the value of the image for later processing and decision-making. An image-processing-based learning strategy using hybrid learning and artificial neural networks is proposed in which real-time data are collected and manipulated from a set of patients. This experimentation used a target size of 224*224 training and validation purpose and the image data is processed for categorical features extraction which is a one-hot encoded.

G. Feature Extraction

Feature extraction is the process of selecting features from the data set that represent the black fungus dataset images in order to reduce the dimensionality of the pre-processed digital images. As part of this process, the raw information is divided up and reduced into much more appropriate categories of image, including normal images and those that are affected by the event. Typically, these characteristics of an image are straightforward to handle, and yet, they accurately describe and uniquely describe all the original aspects of the image. Partial face recognition using local active pixel pattern and Weighted local active pixel feature dramatically reduces computational time [8] [9]. Learning modelling techniques are more accurate if the input dataset contains image features. In this stage of the standard outline, the unnecessary information has been removed, thus reducing the complexity of the information and thus speeding up the process of training and interpretation. In this work, we extract digital image features to be used as the basis for generating new features using the traditional procedures of CNN to reduce the number of characteristics in a dataset of black fungus. The condensed characteristics produced by this analysis should also provide a comprehensive summary of the data that were included in the original feature set. The selection of features in the feature extraction process is the most important aspect of the filtering of the image, which is the process by which the extracted information is extracted. An analysis-assisted feature selection method examines the relationship or correlation between the parameters associated with a digital image input, which can then be filtered to detect those aspects that are most significant and relevant to the image's content. A feature selection process must always be explicit about the dimensions of the outputs, inputs, or standard responses' data formats prior to selecting the variables to be used. Foreground features are extracted from a black fungus image using this feature selection process in order to achieve better accuracy.

H. Image classification

The classification of digital images involves both categorizing them according to their properties as well as other features such as the contours of objects, the pixel strength, and variations in the intensity of pixels in the image. As a result of this, the classification system will strive to incorporate each of these features into its classification system. Managing images in a dynamic environment can be challenging due to the unpredictable nature of such attributes. It is likely that, when transformed into knowledge, the black fungus appears identical to the human eye. Using such classification methodologies, many complex issues are resolved by distinguishing infected images from the rest that are not normal. The best match is found by selecting highest correlated Weighted Template which in term provides the class to which test probe belongs [9] [8].

IV. Experimentation

In our experimentation we have used 3011 images for training and validation.

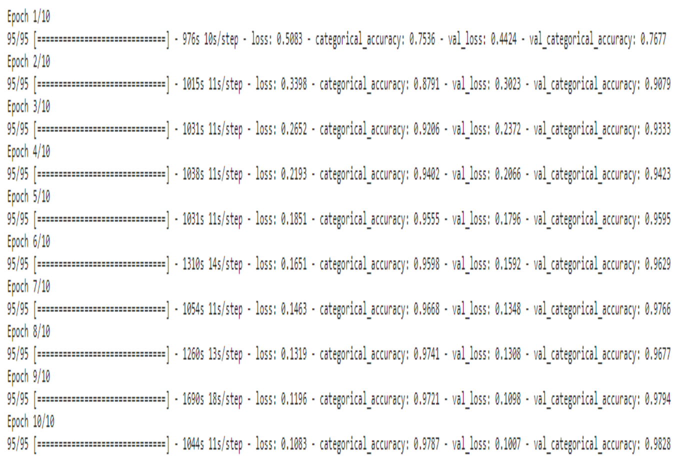
```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 2)                 50178
=================================================================
Total params: 20,074,562
Trainable params: 50,178
Non-trainable params: 20,024,384
_________________________________________________________________
```

Figure 3. VGG19 Model summary

The model is tested with 2011 images. VGG19, a deep learning based convolutional neural network, accepts relevant ImageNet weights and biases as well as distinct features to different facets of the input picture. The figure3 illustrates VGG19 model

To compile this model, Adam optimization algorithm is opted with the learning rate of 0.0001 for stochastic gradient decent (SGD) which is a combination of both the AdaGrad and RMSProp algorithms.

These algorithms are used to adjust the weights and bias of the network to help learning and reduces the loss [10]. Categorical cross-entropy loss function is used which is generally used for multi-class classification tasks also it is designed to quantify the difference between two probability distributions..



```
Epoch 1/10
95/95 [==============================] - 976s 10s/step - loss: 0.5083 - categorical_accuracy: 0.7536 - val_loss: 0.4424 - val_categorical_accuracy: 0.7677
Epoch 2/10
95/95 [==============================] - 1015s 11s/step - loss: 0.3398 - categorical_accuracy: 0.8791 - val_loss: 0.3023 - val_categorical_accuracy: 0.9079
Epoch 3/10
95/95 [==============================] - 1031s 11s/step - loss: 0.2652 - categorical_accuracy: 0.9206 - val_loss: 0.2372 - val_categorical_accuracy: 0.9333
Epoch 4/10
95/95 [==============================] - 1038s 11s/step - loss: 0.2193 - categorical_accuracy: 0.9402 - val_loss: 0.2066 - val_categorical_accuracy: 0.9423
Epoch 5/10
95/95 [==============================] - 1031s 11s/step - loss: 0.1851 - categorical_accuracy: 0.9555 - val_loss: 0.1796 - val_categorical_accuracy: 0.9595
Epoch 6/10
95/95 [==============================] - 1310s 14s/step - loss: 0.1651 - categorical_accuracy: 0.9598 - val_loss: 0.1592 - val_categorical_accuracy: 0.9629
Epoch 7/10
95/95 [==============================] - 1054s 11s/step - loss: 0.1463 - categorical_accuracy: 0.9668 - val_loss: 0.1348 - val_categorical_accuracy: 0.9766
Epoch 8/10
95/95 [==============================] - 1260s 13s/step - loss: 0.1319 - categorical_accuracy: 0.9741 - val_loss: 0.1308 - val_categorical_accuracy: 0.9677
Epoch 9/10
95/95 [==============================] - 1690s 18s/step - loss: 0.1196 - categorical_accuracy: 0.9721 - val_loss: 0.1098 - val_categorical_accuracy: 0.9794
Epoch 10/10
95/95 [==============================] - 1044s 11s/step - loss: 0.1083 - categorical_accuracy: 0.9787 - val_loss: 0.1007 - val_categorical_accuracy: 0.9828
```

Figure 2. VGG19 Trained model

Finally, the model trained 10 epochs with 3011 images the batch size of 64 images which means for every iteration a batch of 64 black fungus images infused to the model for training purpose and validation data set is applied to validate the accuracies.

Among the 5022 images we have used 3011 images for training and validation and 2011 images are used for testing. The trained model is shown in figure.4. Authors and Affiliations.

V. Results and Conclusion

VGG19 architecture is used to test the classification and detection of black fungus. With this approach, a high accuracy rate of 98.28% of validation accuracy and 97.87% of training accuracies are achieved. The training and validation are depicted in Blue and orange in color and the training and validation losses are depicted in red and green color curves in Fig.5.In this proposed approach, the Jupiter notebook software is used to develop the code needed for the prediction of the black fungus infection, and this is done using a free, open-source programming language called Python. Using real-time datasets as training norms, the resulting scenarios are able to identify the disease in an appropriate and intelligent manner. The infected images are detected as 0 and normal images are detected as 1 which is shown in figure.6.

A black fungus called mucormycosis is particularly prevalent in patients affected with Coronavirus and treated with steroids. The panel of federal Coronavirus experts has released a statement despite no significant outbreak being reported. Several promising areas of research have been identified this disease like WHO and the Clinical Infection research society.

Figure 5. Fungus and normal detection output images

Since people throughout the world have been financially and psychologically affected, it is vital to take this matter seriously to prevent further trouble.

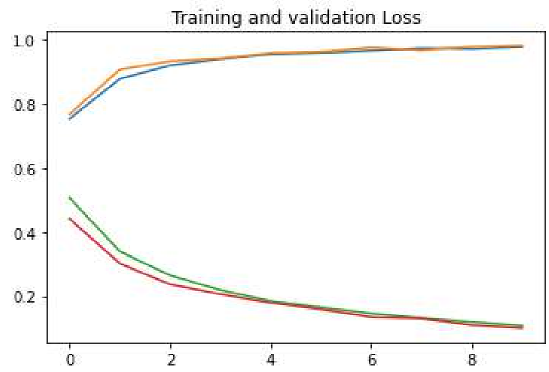


Figure 6. Training and validation accuracy.

A global effort to eliminate mucormycosis will benefit from additional studies on this subject. The proposed model is evaluated in this study in relation to its ability to predict black fungus disease. By using this classifier, expensive investigations such as MRI or CT can be avoided in order to quickly detect the black fungus disease.

In the future, the work can be further enhanced using additional data and different deep learning architectures to train and test the model in a more efficient way also there is a great scope for IoT and mobile based applications.

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