MONKEYPOXHYBRIDNET: A HYBRID DEEP CONVOLUTIONAL NEURAL NETWORK MODEL FOR MONKEYPOX DISEASE DETECTION

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INTRODUCTION

The recent emergence of the monkeypox virus is one of the viruses that began to cause worry in many regions of the globe following the COVID-19 pandemic. The virus, which was well-known in earlier years and primarily seen in the western and central areas of the African continent, has lately begun to harm diverse human groups in various ways (Au et al., 2022; Durski et al., 2018, pp. 1970–2017). The virus that causes monkeypox, which is found in the bodies of rodents and other animals, is passed from infected animals to people. In the past, because transmission from wild animals to people was limited and human-to-human communication needed intensive and prolonged contact, the disease was restricted to select locations, and cases were confined to families (Sale et al., 2006; Yang, 2022). However, the recent incidence of patients with severe symptoms in more than ten nations among persons not related to the African continent, where the virus is found, has intensified study on this virus (What is the monkeypox virus?, Medical Park Hospital).

Monkeypox is a disease caused by the Monkeypox virus, a member of the Poxviridae family and the Orthopoxvirus genus. Variola virus causes smallpox, Cowpox virus causes cowpox, and Vaccinia virus is used in manufacturing the smallpox vaccine. Although the illness is called monkeypox, the virus that causes it begins in rodents (Alakunle et al., 2020). The virus, which was discovered in 1958 as a consequence of two separate smallpox-like outbreaks in colonies of captive monkeys, was dubbed monkeypox for this reason. In 1970, the first human

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infection with the monkeypox virus was detected (Fatima & Mandava, 2022; Rodriguez-Morales & Lopardo, 2022). Cases of monkeypox have been documented sporadically throughout Africa from these years until now. Monkeypox, which has been seen for many years in West and Central Africa, where tropical rainforests are extensive and restricted to this area, might seldom spread to other regions of the globe due to contamination from animals shipped from the region. However, the condition has lately grown more prevalent than it was in the past, and it has been diagnosed in various individuals from various places. Monkeypox, which is seen as a potential new viral outbreak in light of the severe impacts of the Covid-19 pandemic, has started to be closely monitored, but it has not yet spread (What is the monkeypox virus?, Medical Park Hospital).

The virus that causes monkeypox may be transferred from an infected animal or an infected person to humans. As with many viruses, there is an incubation period after exposure to the infectious agent that causes monkeypox. First, symptoms might arise between 5 and 21 days after infection (Al-Tawfiq et al., 2022). The most typical onset age is between 6 and 13 (Singhal et al., 2022). Although the symptoms are similar to those of smallpox, which caused massive epidemics in the past, the disease proceeds differently. Among the most common symptoms are a high temperature, Headache, backache, muscular aches, lymph node enlargement, Fatigue, Chilled to the bone, Similar to chickenpox, lesions on the skin that appear as little, water-filled blisters (Girometti et al., 2022; León-Figueroa et al., 2022; What is the monkeypox virus?, Medical Park Hospital).

The rash appears between 1 and 5 days after the commencement of the initial signs of monkeypox. Typically, the earliest rashes appear on the face. The disease then spreads to other body parts. Some individuals may also have lesions in the vaginal region, eyes, and oral mucosa. Due to the similarities of the rashes, the condition might be mistaken for chickenpox. The rash eventually transforms into crusty areas and begins to heal. In some people, the lesions are comprised of hundreds of blisters that spread across the body; in others, there are fewer blisters. In difficult situations, the lesions consolidate and result in widespread skin rashes (Sharma et al., 2022). Depending on the severity of the sickness, the rashes often vanish, and the patient recovers within two to four weeks. The mortality rate for monkeypox is between 3% and 6% (Girometti et al., 2022; Otu et al., 2022). Most of them are young individuals suffering from secondary illnesses (What is the monkeypox virus?, Medical Park Hospital).

The infection caused by the Monkeypox virus is infectious. Typically, the illness is spread by rodents such as mice and squirrels. Wild animals are seen as the most significant route of viral transmission to humans. Numerous events, such as being bitten by a virus-infected animal, touching the bodily fluids of these animals, their skin, or the rash induced by the sickness, ingesting the undercooked meat of an infected animal, and utilizing its fur, may be considered methods of disease transmission. This method of transmission of the monkeypox virus to humans presents the potential for an outbreak (Memariani & Memariani, 2022). The illness component is contained in the sick individual's body rashes and the fluids in these bubbles.

Consequently, scenarios such as touching the rashes of a sick person and sharing clothing, sheets, towels, and other objects contaminated with these rashes may easily result in the spread of the illness. Additionally, the sickness may be transmitted by coughing and sneezing droplets. People with skin lesions like those of monkeypox should thus be sent to a medical facility quickly, focusing on hygiene. Contact with persons diagnosed with the illness should be limited; if feasible, quarantine measures should be used (Farahat et al., 2022; What is the monkeypox virus?, Medical Park Hospital).

Monkeypox is a very uncommon illness. However, in light of the recent rise in the number of reported cases and the disease's debut in unanticipated nations and populations, it is prudent to observe the virus's hygiene requirements. The most crucial step of protection is following the hygienic guidelines that aid in preventing all illnesses. For this purpose, hands should be periodically cleansed with soap and water. After handling dirty surfaces, the face or respiratory organs should never be dealt with until the hands have been cleaned. In addition, only well-cooked meat should be ingested, given that animal flesh is a significant transmission mode.

Additionally, persons who spend time in nature should be cautious. Wild and stray animals, especially deceased ones, are forbidden to be addressed. Animals seen in the wild that do not seem healthy should never be approached. Due to the importance of rodents in disease transmission, sites where animals such as mice have been seen should be thoroughly cleaned and disinfected. If foodstuffs are kept in these places, they must also be destroyed. Individuals with blisters resembling chickenpox and who exhibit indicators of infection such as fever and chills should seek medical attention and be examined. These people's clothing, towels, and bedcovers should not be handled or discontinued if they are in frequent use. However, the virus has only been detected in a few persons and has not caused any outbreaks. Nonetheless, it is prudent to take precautions against the virus since unexpectedly high numbers of infections have been recorded in many nations (Atkinson et al., n.d.; Ennab et al., 2022; What is the monkeypox virus?, Medical Park Hospital).

In addition to these, today, monkeypox is increasingly spreading in many countries. Therefore, disease detection is essential. Artificial intelligence can be used for disease detection, especially in infectious diseases. Thanks to artificial intelligence, information about the disease can be obtained without going to the hospital or laboratory. Image processing with artificial intelligence has been a modern method in recent years. Drawing conclusions from pictures and photographs thanks to deep convolutional neural networks (CNN). This method is used for many diseases. Deep CNN can be designed in many different ways (Kurmi et al., 2022). This article aims to develop a successful deep CNN for monkeypox detection.

In the literature, there are lots of research about disease or illness detection from images. However, there is not enough research about monkeypox detection from pictures because it is very newly popular worldwide.

Ahsan et al. (2019) used CNNs on a chest X-ray (CXR) dataset to determine if a patient had tuberculosis (TB). Their objective was to create a generalized model that handles all the problematic pre-processing stages performed by a traditional decision tree method. Since CNNs have several hidden layers and filters, the model attained a high accuracy level of 80% without augmenting and 81.25 % with augmenting. The achieved accuracy was equivalent to that of earlier studies on the dataset. On the other hand, CNN eliminated the need for developing complex segmentation algorithms, which might be time-consuming, needed professional skill, and was mostly specialized, rendering them inapplicable to other comparable issues.

Alanazi et al. (2021) studied a newly suggested system that employs several CNN architectures to automatically diagnose breast cancer, comparing the findings to those of machine learning (ML) methods. A substantial dataset influenced all designs. Validation tests were conducted on quantitative results using the performance metrics for each approach. The suggested approach was practical, obtaining findings with an accuracy of 87%, which might eliminate human errors in the diagnosis process. Additionally, the accuracy of their suggested approach exceeded the 78% accuracy of machine learning (ML) techniques. Consequently, the suggested approach enhanced accuracy by 9% against machine learning (ML) techniques.

Hajabdollahi et al. (2020) presented a structure with two branches, one of which did classification and the other segmentation. Initially, distinct network architectures were trained individually for each anomaly, and then the fundamental components of these networks were integrated. The bifurcated structure had a component that applied to all anomalies. One branch of the final structure had sub-networks for segmenting various abnormalities, while the other branch contained sub-networks intended to categorize a particular abnormality. The classification and segmentation results were combined to produce the classified segmentation map. The suggested framework replicates four common gastrointestinal problems and three dermoscopy lesions. The bifurcated network's minimal complexity and resource sharing make it appropriate for incorporation into portable medical imaging equipment.

Apostolopoulos et al. (2020) intended to test the efficacy of CNN architectures introduced in recent years for categorizing medical images. Specifically, the Transfer Learning approach was utilized. Using transfer learning, identifying numerous anomalies in tiny medical imaging datasets was a realistic goal that oftenyielded excellent outcomes. Their data was taken from X-ray photos found in public medical archives. The best-acquired accuracy, sensitivity, and specificity for Deep Learning with X-ray imaging were 96.78 percent, 98.66 percent, and 96.4 percent, respectively, for the Covid-19 illness.

Abiyev et al. (2018) demonstrated the possibility of using chest X-rays to diagnose chest illnesses utilizing both traditional and deep learning approaches. CNNs are presented for the diagnosis of chest diseases. The notion of CNN's design and architecture was debated. Comparative backpropagation neural networks (BPNNs) with supervised learning and competitive neural networks (CpNNs) with unsupervised learning were created to diagnose chest illnesses. On the identical chest X-ray datasets, CNN, BPNN, and CpNN were all trained and tested, and their performance was analyzed. There were comparisons drawn between the networks. The experiment was successful.

Zhang et al. (2020) suggested a novel approach based on image processing for the early diagnosis of skin cancer. The method used the most suitable CNN for the task. In addition, an enhanced whale optimization technique was used To optimize the CNN. On two distinct datasets, the suggested approach was compared against other methods for assessment purposes. Simulation findings demonstrated that the proposed strategy is better than those compared.

Ali et al. (2022) created the Monkeypox Skin Lesion Dataset (MSLD), including photos of skin lesions caused by monkeypox, chickenpox, and measles. Most photographs were obtained from websites, news websites, and publicly available case reports. The sample size was increased by data augmentation, and a three-fold cross-validation experiment was designed. Next, multiple pre-trained deep learning models, including VGG-16, ResNet50, and InceptionV3, were used to classify monkeypox and other disorders. Additionally, an ensemble of the three models was created. ResNet50 scored the highest overall accuracy with 82.96(4.57%), followed by VGG16 and the ensemble system with 81.48(6.87%) and 79.26(1.07%), respectively. A prototype web application was also created as an online screening tool for monkeypox.

This paper proposes a deep hybrid CNN model called MonkeypoxHybridNet for monkeypox detection from images. The main aim is to increase the success of the network.

METHODS

Convolutional Neural Networks

Deep learning (DL) is presently the most successful solution to the issue of disease detection from images. The CNN model is very accurate and robust. In addition, the CNN model of the deep learning technique merges each link of the previous method into an end-to-end network structure for learning and training, considerably reducing the task's complications (Li, 2022).

Convolutional Layer

Convolution computation is the primary operation of a CNN and its only linear process. Multiple convolution kernels compute the convolution layer to generate various feature maps. The convolutional layer (CL) multiplies kernels with the related window. The window slides over the image or matrix. After every multiplication, the values are summed and passed to the next layer. This layer is the leading layer of CNN (Li, 2022).

Pooling Layer

The pooling layer (PL) compresses the image and reduces the feature map's file size. This layer is also known as the downsampling layer. Typically, after a sequence of convolution operations, the PL is used to lower the width and height of the feature map obtained by the CNN, hence minimizing the size of the problem. The objective of efficiently extracting feature data is to reduce computational complexity and boost computational performance. Maximum pooling and average pooling are the most often used pooling methods for picture recognition and classification applications. Maximum pooling entails selecting the most significant feature point in the area to maintain the most feature value. Mean pooling involves averaging the nearby feature points to get the feature's average value. Pooling's computational method is comparable to that of convolution. The convolution kernel traverses the feature map with a predetermined step size, and the relevant window region is pooled during pooling (Li, 2022).

Fully Connected Layer

Fully connected layers (FCL) are among the most overall layer in NN and are used in almost all topologies. Each node in an FCL is connected to every node in the preceding and subsequent layers. The primary responsibility of an FCL is to modify the feature space to make the issue more pliable. The dimension number may expand, reduce, or remain constant during this change. The new dimensions are linear combinations of the preceding layer's dimensions in each instance. Then, with an activation function, nonlinearity is introduced into the additional dimensions. FCL allows for any kind of interaction between input variables. Thanks to this structure-agnostic technique, FCL with adequate depth and breadth may theoretically learn any function. However, experience has shown that this theoretical promise is seldom achieved in practice. Researchers have developed more specialized layers, such as convolutional and recurrent layers, to overcome this issue. These layers essentially use the inductive bias based on the spatial or sequential architecture of certain data kinds, such as text, picture, and video (Kalaycı & Asan, 2022).

ResNet50

ResNet50 is the abbreviation for residual networks with 50 layers. ResNet predicts the needed delta from one layer to the next to get the final forecast. ResNet overcomes the vanishing gradient problems by enabling gradient to flow along this alternative short-cut route. ResNet's identity mapping enables the model to skip a CNN weight layer if the current layer is not required. It helps prevent the issue of the training set becoming overfitting. ResNet50 has fifty layers (He et al., 2016; Theckedath & Sedamkar, 2020).

VGG19

VGG is a model that reduces the high kernel sizes used in the previous AlexNet architecture. Kernel sizes were not fixed in AlexNet. It started with the first 11 and continued as 5 and 3. VGG fixed the kernel size. This idea was that 11x11 and 5x5 kernels could be replicated with multiple 3x3 kernels. The total number of convolutional and fully connected layers of VGG19 is 19 (Simonyan & Zisserman, 2015).

InceptionV3

InceptionV3 is the batch-normalization added to the old version inception networks. In image classification problems, the defining features can vary considerably in the image frame. For this reason, it becomes challenging to decide on fixed kernel size. Larger kernels are preferred to exclude slightly more universal features spread over large areas of images. On the other hand, small kernels enable the detection of domain-specific features in images. After all, kernels of varying sizes are needed to extract features effectively. So rather than going deeper as a layer, the main idea is to expand further. The Inception architecture does precisely that. Inception increases the mesh area by training to select the best mesh. Each Inception module can capture different levels of distinctiveness (Szegedy et al., 2015).

MonkeypoxHybridNet

For the monkeypox detection problem, a new deep CNN model is proposed. The proposed model is named MonkeypoxHybridNet. The structure of the MonkeypoxHybridNet is seen in Figure 3.

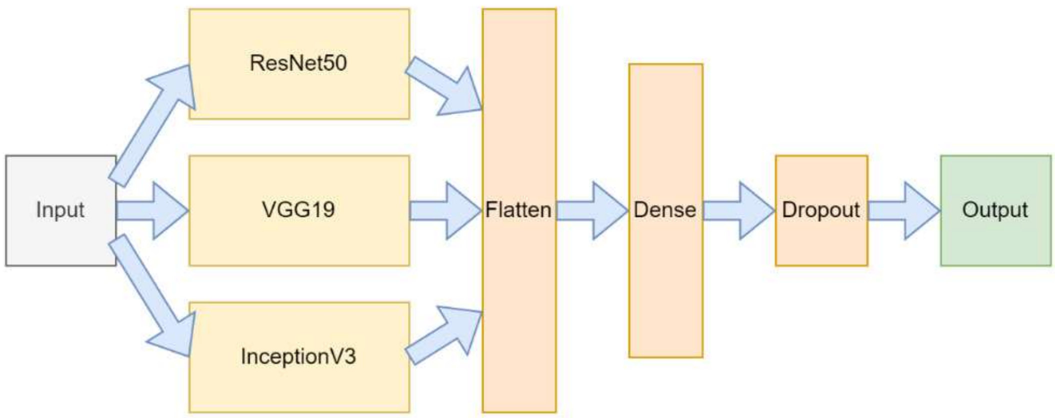

Figure 3: MonkeypoxHybridNet Structure

MonkeypoxHybridNet has three different deep CNN models. They are ResNet50, VGG19, and InceptionV3. The image input size is (224,224,3). It is widespread and used in CNN models. First, the input image goes parallel to ResNet40, VGG19, and InceptionV3 models. Next, the outputs of the three models are flatted and collected. After this stage, the information goes to the dense layer. Finally, with a dropout layer, the class is determined.

RESULTS

Dataset

The dataset used in the paper was taken from Ahsan et al. Their dataset on monkeypox skin lesions is obtained mainly from publicly accessible case reports, news portals, and websites. Their research primarily concerns identifying monkeypox patients from other cases (chickenpox, measles, normal). The dataset consists of 580 training data and 190 test data. The training data shows 210 monkeypox images, 81 chickenpox images, 69 measles images, and 1162 normal images. In the test data, there are 69 monkeypox images, 26 chickenpox images, 22 measles images, and 73 normal images. The distribution of the monkeypox dataset is seen in Table 1 (M. M. Ahsan et al., 2022; Monkeypox Skin Images Dataset (MSID)).

Table 1: Monkeypox Dataset

	Chickenpox	Measles	Monkeypox	Normal	Total
Train	81	69	210	220	580
Test	26	22	69	73	190
Total	107	91	279	293	770

Figure 4 shows sample images from the monkeypox and other classes from the monkeypox dataset.

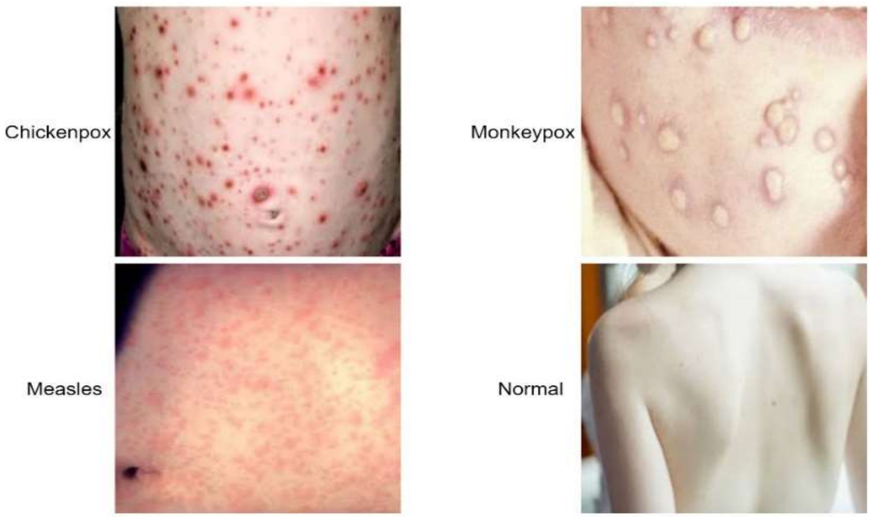

Figure 4: Sample Images From The Monkeypox Dataset

Evaluation metrics

Accuracy, precision, and F1 score are the evaluation criteria used in this research. In addition, the metrics are often used for categorization issues. The formulae for accuracy, precision, and F1 score are shown in Equations 1, 2, and 3, respectively. TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$precision = \frac{TP}{TP + FP} \tag{2}$$

$$F1\,score = \frac{2 * recall * precision}{recall + precision} \tag{3}$$

Results

This paper includes a monkeypox detection architecture for the monkeypox dataset. For this, different deep CNN models are tried. These are ResNet50, VGG19, InceptionV3, and MonkeypoxHybridNet. Figure 5 shows the main model of the problem. In the figure, a deep CNN model detects monkeypox from the images. Next, the deep CNN model is tried with the alternatives ResNet50, VGG19, InceptionV3, and the proposed MonkeypoxHybridNet model. In all models, the dropout layer is used to avoid memorization. Therefore, the commonly used Dropout (0.7) ratio is preferred.

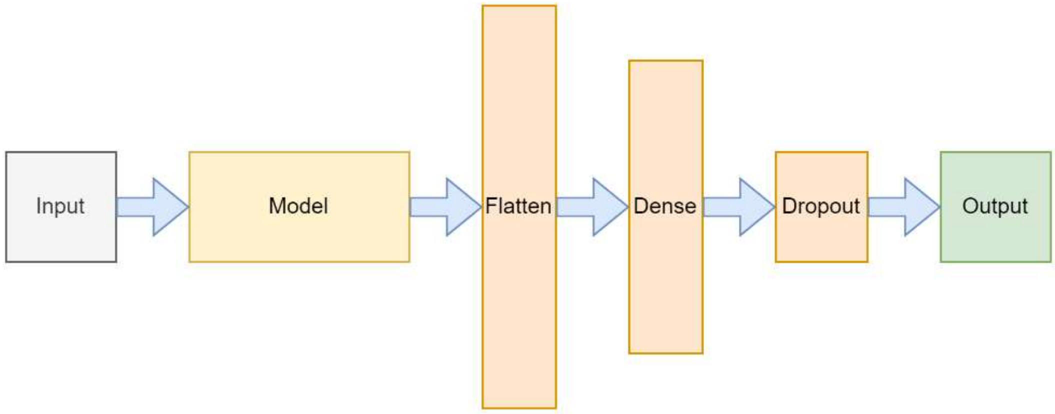

Figure 5: Main Model Of The Monkeypox Detection Model

ResNet50

When using the ResNet50 model, it initially increases as iterations progress for the training dataset for accuracy value. Then it tends to decrease. The test dataset is not regular. It is very variable. It approaches 0.60 towards the end. Figure 6 shows this situation.

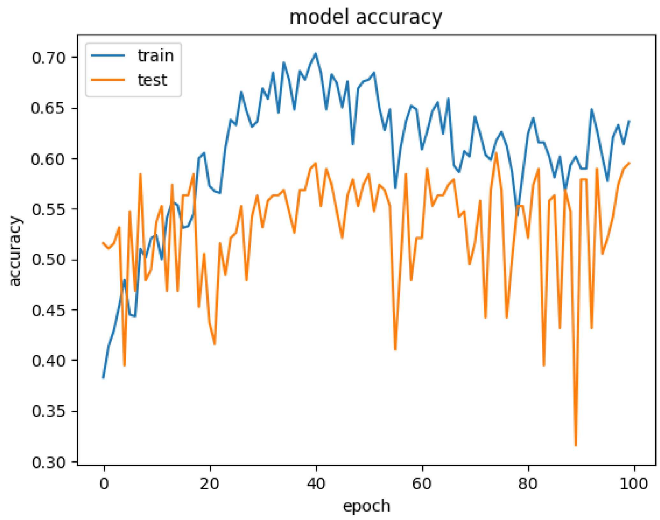

Figure 6: Accuracy Value Of Resnet50 Model

Figure 7 shows the classification results for the ResNet50 model. Considering predictions and correct results, ResNet50 model leans towards the monkeypox and normal classes. It correctly predicts 42 monkeypox, 70 normal, and 1 measles class. However, it perceives most images of chickenpox and measles as monkeypox. In this respect, it is a failed model.

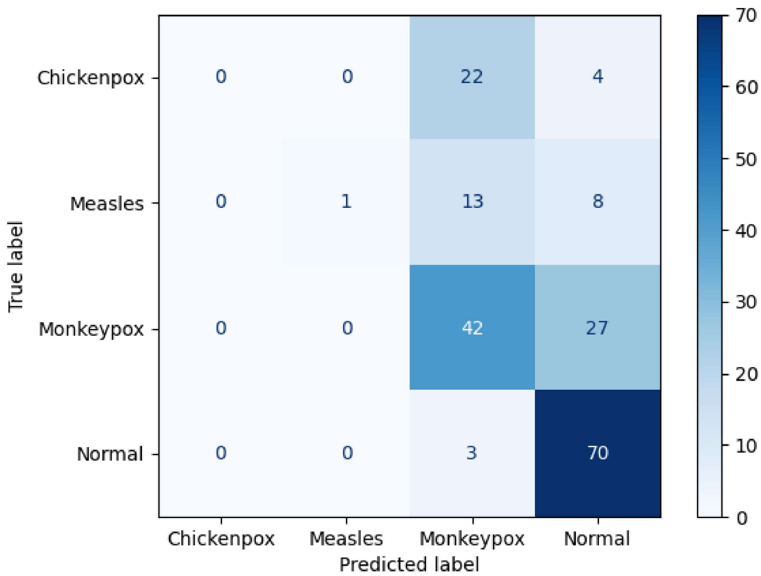

Figure 7: Classification Result For Resnet50 Model

VGG19

Figure 8 shows the accuracy value for the VGG19 model. When VGG19 model is used, the train data for accuracy values gives outstanding results and increases as the iterations increase. However, for test data, it is around 0.70.

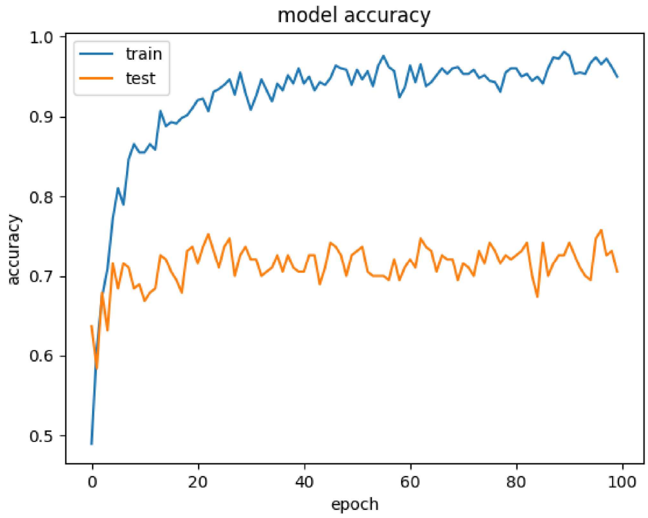

Figure 8: Accuracy Values For VGG19 Model

Figure 9 shows the classification results for VGG19. When looking at the results for the VGG19 model, 16 chickenpox, 7 measles, 44 monkeypox, and 67 normal classes are predicted correctly. There is much confusion between chickenpox and monkeypox in this model. 12 monkeypox are labeled as chickenpox. 9 chickenpox are labelled as monkeypox.

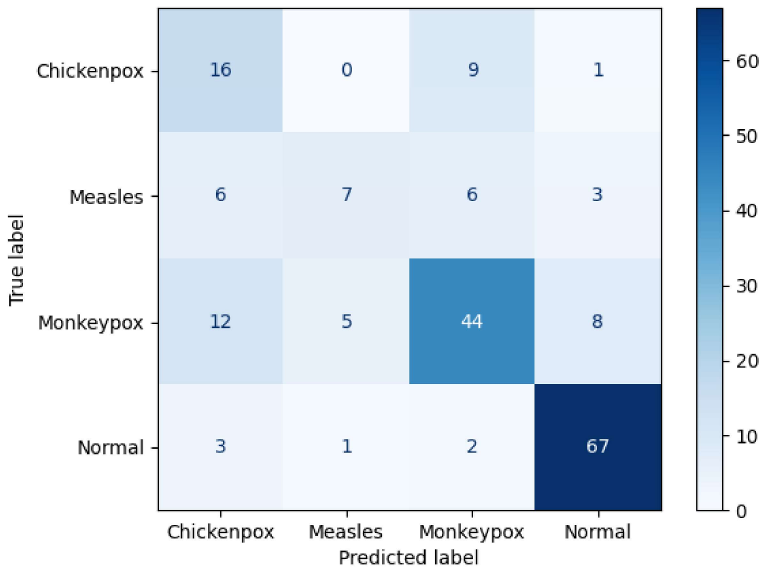

Figure 9: Classification Result For VGG19 Model

InceptionV3

Figure 10 shows accuracy for InceptionV3. Judging by the accuracy values when using the InceptionV3 model, the accuracy for the train set has increased. It is almost close to 1. The accuracy for the test set is around 0.80.

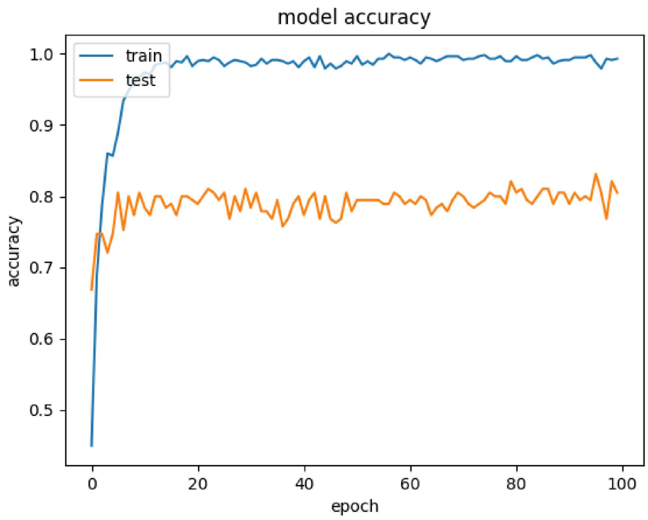

Figure 10: Accuracy Values For Inceptionv3 Model

Figure 11 shows the classification results for InceptionV3. InceptionV3 model correctly predicts 12 chickenpox, 11 measles, 58 monkeypox, and 72 normal class images. In addition, it labeled 12 chickenpox pictures as monkeypox and 11 chickenpox pictures as normal.

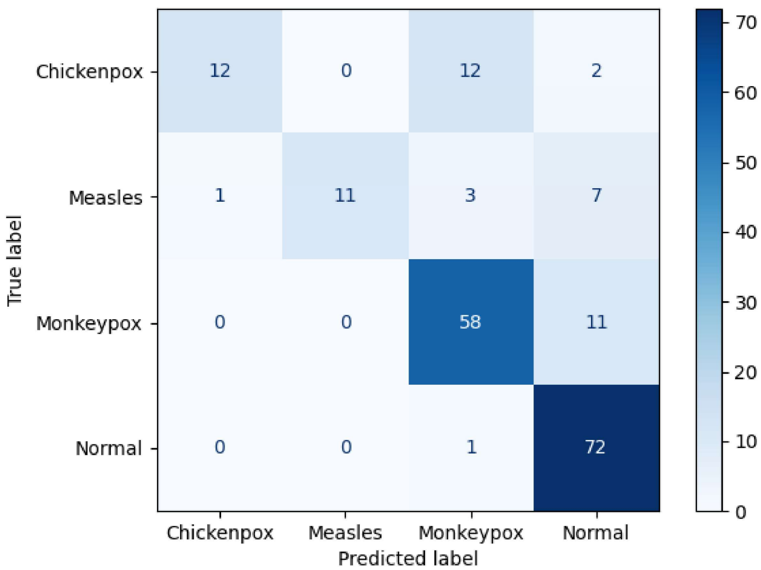

Figure 11: Classification Results For Inceptionv3 Model

MonkeypoxHybridNet

Figure 12 shows accuracy values for MonkeypoxHybridNet. When the MonkeypoxHybridNet model is selected, the accuracy value of the training dataset has reached nearly 1. However, in the test data set, it goes around 0.80 and approaches 0.85 later.

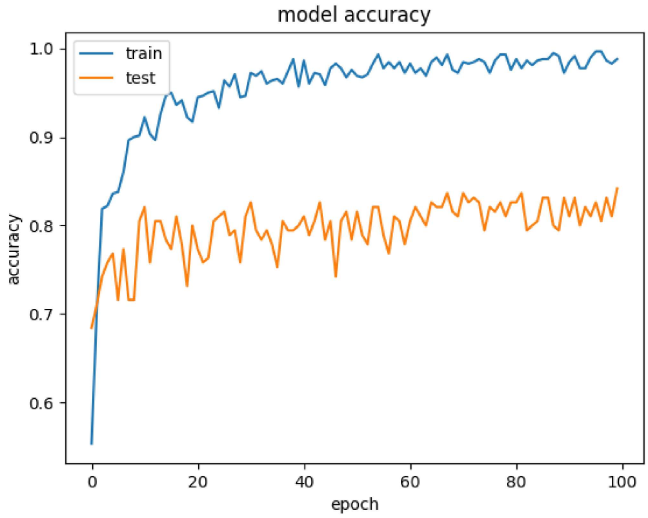

Figure 12: Accuracy Values For Monkeypoxhybridnet

Figure 13 shows classification results for MonkeypoxHybridNet. 24 Chickenpox, 13 Measles, 57 Monkeypox, and 66 normal pictures are classified correctly. The biggest mistake is that it predicts 10 normal classes as Monkeypox classes.

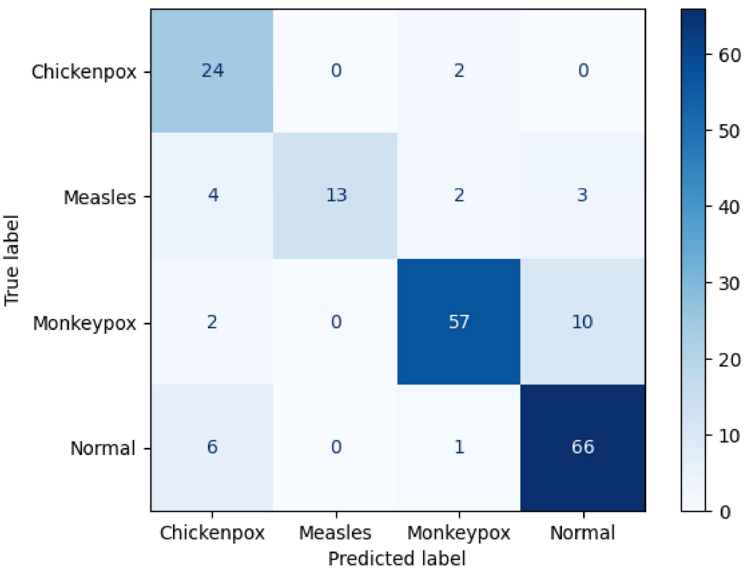

Figure 13: Classification Results For Monkeypoxhybridnet Model

DISCUSSION

Table 2 shows the comparison of the models. In the comparison, ResNet50 model gives 0.595 accuracies. VGG19 gives 0.705, InceptionV3 gives 0.805, and MonkeypoxHybridNet gives 0.842 accuracy. For accuracy, MonkeypoxHybridNet is the best. ResNet50 model gives 0.553 precision. VGG19 gives 0.709, InceptionV3 gives 0.827, and MonkeypoxHybridNet gives 0.862 precision. For precision, MonkeypoxHybridNet is the best. For F1 score, ResNet50 gives 0.510, VGG19 gives 0.700, InceptionV3 gives 0.791, and MonkeypoxHybridNet gives 0.842. Monkeypox is the best model for the F1 score. When considering the models' results, it is shown that MonkeypoxHybridNet is the best model and useful for detecting monkeypox.

Table 2: Comparison Of The Models

	ResNet50	VGG19	InceptionV3	MonkeypoxHybridNet
Accuracy	0.595	0.705	0.805	**0.842**
Precision	0.553	0.709	0.827	**0.862**
F1 score	0.510	0.700	0.791	**0.842**

CONCLUSION

Nowadays, the monkeypox virus has become very common. People fear it because of the COVID-19 experiences. Deep CNNs can be used to detect monkeypox illness. In this paper, a new deep CNN model named MonkeypoxHybridNet is proposed. It consists of ResNet50, VGG19, and InceptionV3 models. The proposed model is trained on a dataset with four classes. The classes are chickenpox, measles, monkeypox, and normal. The proposed model succeeds the other models. ResNet, VGG19, InceptionV3 models give 0.595, 0.705, and 0.805 accuracy respectively. However, MonkeypoxHybridNet gives 0.842 accuracies. It shows that MonkeypoxHybridNet is successful in detecting monkeypox illness from skin images. For future research, new models or new hybrid models can be proposed for monkeypox detection.

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