Deep Learning Applications for Classification of Pediatric Infections

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Abstract

Pediatric infections are diseases caused by pathogenic microorganisms like viruses, bacteria, fungi, or parasites that mostly impact children. These infections, including different types of diseases , often require special diagnostic and treatment approaches because of the unique bodily and immunological appearance of children. In this paper, we proposed models for classifying pediatric infections using image datasets. Our aim is to develop and compare the performance of various deep learning models precisely for the classification of four types of pediatric infections: chickenpox, hand foot, and mouth disease, scabies, and impetigo. In an effort to achieve better performance in the infection classification, We implemented and evaluated three deep learning models: MobileNetV2, Xception, and EfficientNetV2B0. Xception achieved an accuracy of 97% , EfficientNetV2B0with 95% and third model MobileNetV2 with an accuracy o87%. The results showed that the Inception-V3 model had an accuracy of over 99% indicating that this model is better in distinguishing the tea leaf categories.The deep learning models specifically Xception can efficiently classify pediatric infections which can help in initial diagnosis and treatment.

Key Words: Deep learning, MobileNetV2, Xception, EfficientNetV2B0, Classify.

Introduction

Associated with noteworthy morbidities, skin diseases are one of the main health problems amongst children[1].As children's immunity is emerging and they are always in contact with other children mostly in schools and daycare centers, it is common for them to get infected with several microorganisms. Chickenpox, hand-foot-and-mouth disease, scabies, and impetigo are amongst the most common infections in children that may result in serious problems if not well diagnosed and treated. According to a report, hospitalization rates for chickenpox amongst children are broadly different, ranging from 1.3 to 13.0 per 10^4 cases amongst Spanish [2], Australian [3], Swiss [4, 5], and German [6,7] children. In the United States in large surveys, higher rates have been reported [8,9].HFMD (hand-foot-and-mouth disease) has been characterized as a class C notifiable disease in China since May 2, 2008. By the end of 2015, over 13 million HFMD9 (hand-foot-and-mouth disease) cases were reported, counting 123,261 severe cases and 3322 deaths in mainland China.[10].Scabies are assessed to affect over 200 million people globally [11] and the highest occurrence is thought to occur in low-resource tropical settings [12]. Bangladesh is recognized to have a high commonness of skin diseases,reported by the Directorate General Health Services (DGHS)[13].The similar report mentions skin diseases as one of the top ten leading causes of morbidity among Bangladeshis. In an earlier publication from the same base, it was defined that skin disease produced morbidity to the tune of 10.1% and 9.3% in 1988 and 1989 respectively [14].This significant factor accurately classifying pediatric infections in various models is important lies in the fact that it affects children's health outcomes by confirming timely diagnosis and proper treatment. Nevertheless, challenges including among others lack of data, imbalanced class distributions as well as clinical validation requirement does hamper the consistency and efficiency of these models in real-world healthcare situations. Developing consistent and clinically useful tools for pediatric infection classification requires striking a balance between the significance of the task.

The key contributions of this study are:

1. Developing and autonomous system to classify pediatric infections quickly and efficiently
2. Achieving higher accuracy rate in classification with a dataset.

Following the introduction other studies and researches connected with our study has been discussed on the related work section.After that, data collection,preprocessing,training models are showing in Methodology section.Accuracy rate and performance evolution of the training model,comparison between the models are discussed in Result and discussion section.Lastly,the paper is concluded in the Conclusions section.

Related Works

In order to help dermatologists, researchers have been working year after year on developing diagnostic systems that allow for automatic identification of skin disorders. Continuous improvements are needed to improve the accuracy of computer vision and image processing as these technologies continue to advance.

A Kalaivani[15] proposed the Fine-Tuned VGG-CNN model achieved 92.24% accuracy in skin disease classification outperformed other models like AlexNet ,ResNet50 , and ResNet152. The dataset is trained with 50 epochs and 0.0001 as an initial learning rate.The training data significantly improved by the data augmentation . Nevertheless, the study did not address the model's validity or important key features, which could further improve practical application.

S Verma[16]developed deep learning models and achieved 85%-91.2% accuracy in classifying HFMD lesions. The MLP model achieved 99% accuracy exclusively with clinical symptoms, representing its contribution to precise HFMD detection. By integrating image data and symptoms, the Hybrid Deep Neural Networks achieved 99%-100% accuracy, effectively connecting the diagnosis gap and providing an inclusive solution for HFMD detection.

J Huang[17] has discussed the improvement of artificial intelligence technology and machine learning technology, which has promoted the development of computer vision, image processing and natural language processing. The image recognition technology based on machine learning can well identify white blood cells that are difficult to differentiate with the naked eye, so they apply image recognition technology based on machine learning to diagnose disease. The recognition rate is basically stable overhead almost 90%.

A Jain[18]have developed “Optimal Probability Based Deep Neural Network (OP-DNN),” achieving 95% accuracy in skin diseases prediction. OP-DNN outperformed existing methods in accurately predicting multiple skin diseases with a challenge by prior models .

D Aruna R[19] proposed models comparisons the accuracy of Multilayer Perceptron (MLP) , Naive Bayes, Feed-Forward Neural Network, Backpropagation Neural Network, and a combined MLP-BPNN model using a dataset of skin cancer images collected from nanosensors. The MLP-BPNN model had achieved the highest accuracy with results of 97.8% for 100 images.Limitation of this study is speed real word testing and improving the algorithm.

M Alghieth[20]developed pre-trained VGG19 model and CNN to detect skin diseases including chickenpox and impetigo among school children with achieving 99% accuracy.The dataset included 4500 images and optimized using Adamax.In this paper does not mention real world testing or deployment which is crucial validating models performance.

R Saifan[21] proposed a CNN model to classify six skin diseases with 81.75% accuracy.The dataset included 3000 images and collected from internet sources The development and a validation of a CNN model for classifying six skin diseases with high accuracy. A key gaps the need for larger, extra varied dataset to improve model performance.

R Sadik[22]Proposed CNN models,MobileNet and Xception with transfer learning to diagnose five skin diseases. These models achieved accuracy 96% and 97% .The models also created a web app for a real time diagnosis and compared their result with other CNN models but there is a lack of diverse training data

Methodology:

Proposed System Architecture

The proposed system framework is presented below in Figure:1. The sections of the proposed workflow includes dataset preparation, model training and image classification with deep learning models. This section has explained the working mechanism of the developed model for social image classification. The study has two main sectors. First is dataset preparation where the image dataset is pre-processed with auto orienting, resizing, auto adjust contrast and dataset splitting(splitting into train-valid-test along with data augmentation). And the second is the experimental models. We have chosen three models which are Xception, EfficientNetV2B0, MobileNetV2 for testing the image dataset and to see how accurately they perform image classification.

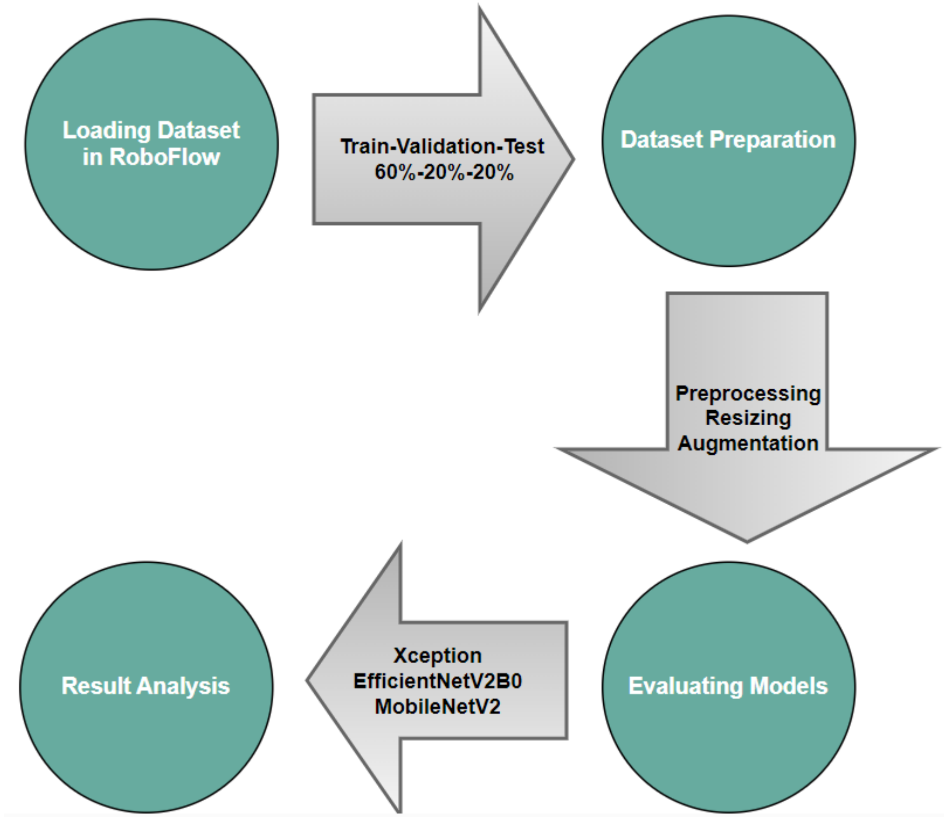

Fig 1: System Framework.

Dataset Collection

The collected image datasets for four pediatric infections are from Dermnet and Kaggle and these datasets are used for classifications using different types of efficient deep-learning models. Those four infections are chickenpox, hand foot, and mouth disease which are collected from dermnet, and the other two which are scabies and impetigo fetched from Kaggle. Although these images are collected from online resources, it is already processed but we have performed some steps to make the images more visible and to achieve perfect accuracy. All these four classes have approximately 315 images which will increase after preprocessing and augmentation.

Chickenpox

Hand foot and mouth disease

Impetigo Scabies

Figure 2: Sample images from the dataset of 4 classes

Dataset Preparation

The popular platform Roboflow is used to prepare these image datasets, dataset preprocessing, and augmentation is easy here. In objective network implementation, the 60% of training data, 20% of testing data is most suitable in this case. Besides, this dataset is validated by choosing 20% test data.

Class Name	Train (No. of images)	Test (No. of images)	Total (No. of images)
Chickenpox	18	6	24
Hand Foot and Mouth Disease	28	9	37
Impetigo	78	25	102
Scabies	64	22	86
Total	188	62	249

Table 1: Image dataset splitting

Dataset Preprocessing

Auto Orienting, resizing and auto adjust contrast(histogram equalization is used for preprocessing.

Almost all camera store image pixels are undoubtedly identical even if the camera is aligned in landscape or portrait mode. They just flip it a little to signal to the audience whether to display the pixels as is or to turn them to 90 degrees or 180 degrees when displaying an image. Regrettably, this can cause a problem if the application showing the pictures is unaware of the metadata and stupidly shows the image without showing regard to its EXIF orientation. That's why, auto-orientation is used here to get good results.
All the images are resized in 224*224 form which is ideal for this kind of classification.

Histogram equalization is used here to upgrade the contrast of an image by extending out the most repeated values permitting sectors of lower native to achieve a higher contrast. This process is also helpful in showing invisible features in both lighted and unlighted areas of the image by extending the range of magnitude values. To develop optical insight of the image, it changes the histogram of the image to be more stable. The usefulness of this technique is mainly for greater visibility in medical image processing.

Steps for histogram equalization:

Step 1:

Calculating histogram h(i) of the grayscale label of those pictures.

Step 2:

Achieving cumulative distribution diffusion function:

$$C(a) = \sum_{b=0}^{a} h(j)$$

Step 4:

Normalizing cumulative distribution diffusion function:

$$C'(a) = Ca - \frac{Cmin}{N * M - Cmin}$$

N and m is the dimension and Cmin is the minimum non zero of the CDF.

Step 3:

Mapping intensities:

$$C'(a) = N * (L - 1)$$

After attaching all these steps we can complete the histogram equalization process by function T

$$T(i) = (L-1) * \sum_{b=0}^{a} h(j) - Cmin/N * M - Cmin$$

Dataset Augmentation

As the shape and condition of the pediatric infection should be visible, augmentation is used for more efficient and accurate result accuracy and confusion matrix. Besides, data augmentation is a significant approach in training vigorous machine learning models, precisely for image classification problems.
The particular augmentation methods applied for all training instances produce 3 augmented versions for every original image. In our paper from all the augmentation methods flip, 90-degree rotation, crop, rotation, noise, and cutout are used.

The images are flipped horizontally, building a mirror image to assist the model become constant in the left and right direction. To make an upside-down version images are flipped vertically which helps the model become constant to top and bottom orientation.

$$I'(x, y) = I * W - 1 - a, b$$

In this equation I is the input image, I' is output image, W is width and H is height

In 90-degree rotation clockwise rotation is used to make sure the model can acknowledge attributes anyhow of direction, Counter Clock rotation is applied to give balanced rotating variation as well as upside down rotation is also used including a different level of rotational alternative. To acknowledge those particles that are not flawlessly aligned, random rotation is also used at an angle between -20 to 20 degrees.

Clockwise Rotation(90 degree):

$$I'(x, y) = I(W - 1 - b, a)$$

Counterclock wise rotation:

$$I'(x, y) = I(y, I * W - 1 - b, a)$$

Upside Down:

$$I'(x, y) = I(W - 1 - a, H - 1 - b)$$

All of the images are cropped to the initial area and zoomed in up to 28% accomplishing diverse distances and limited views of objects in between image shapes.

$$W' = (1 - z) * W$$

$$H' = (1 - z) * H$$

Z is the zooming factor ranging from 0%-28%

$$A_{Start} = W - W'/2$$

$$B_{Start} = h - h''/2$$

The crop image equation will be:

$$I'(x, y) = I(A_{Start} + A, B_{Start} + B)$$

Salt and pepper noise is included up to 1.05% of pixels of the image so that this type of noise Modify the model to become strong undesirable features and discrepancies in the image data like sensor noise in raw images.

Wrapping 10% of the images, in three rectangular areas are randomly chosen and set to 0 so that the model can depend on adjoining context and other characteristics, diminishing overfitting particular parts of the image

After applying all these augmentation techniques, we gained a total of 693 images, 567 from the training set,63 images from the test, and 63 images from the validation.

Experimental Result

Our paper involves four infections which differs from other papers as only one pediatric infection is included there. In this section, two plots are displayed that represent the model's classification accuracy and loss with respect to epochs. For a dataset of 200 x 200 x 3 images, the plots show metrics such as training and validation accuracy, training loss, and validation loss. The plots establish the high accuracy of the models with epochs, and the validation accuracy and loss match the training accuracy and loss, respectively. We have trained the model with 500 epochs and a batch size of 4. Due to the data set, high epochs are needed to get high accuracy.

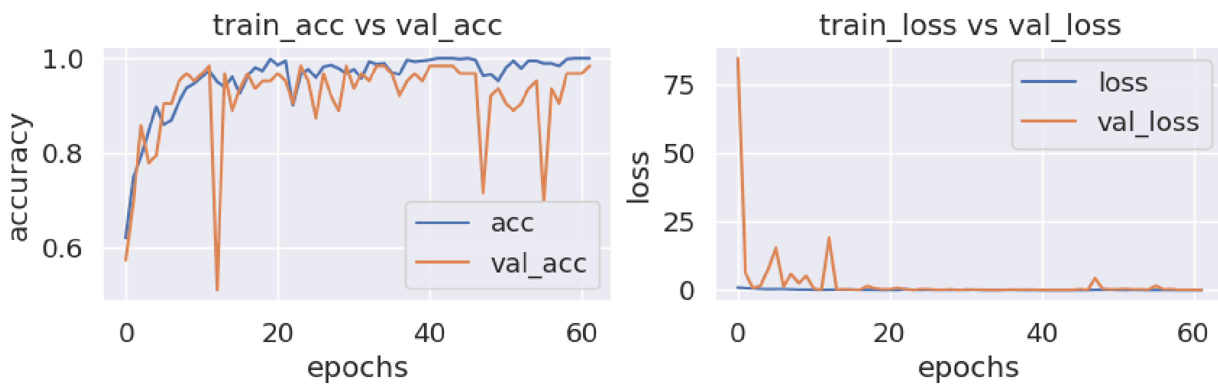

Fig 3: Accuracy and loss of Xception model.

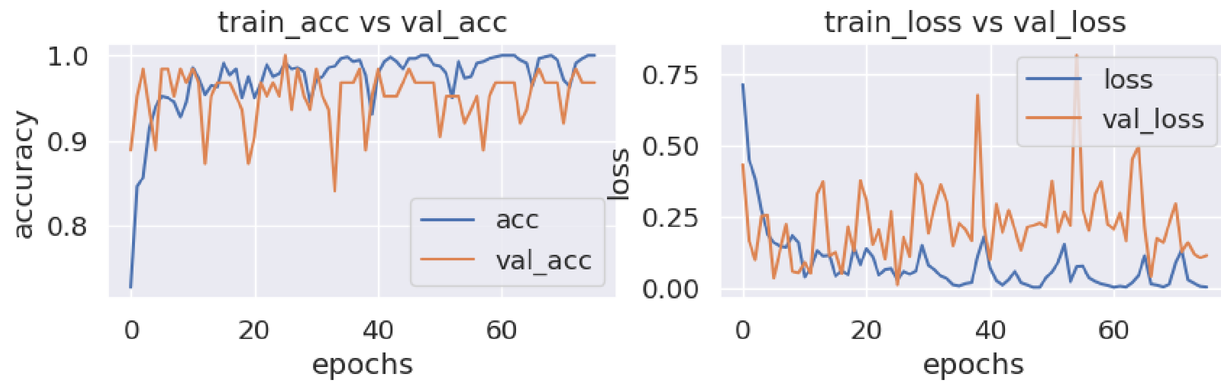

Fig 4: Accuracy and loss of EfficientNetV2B0 model.

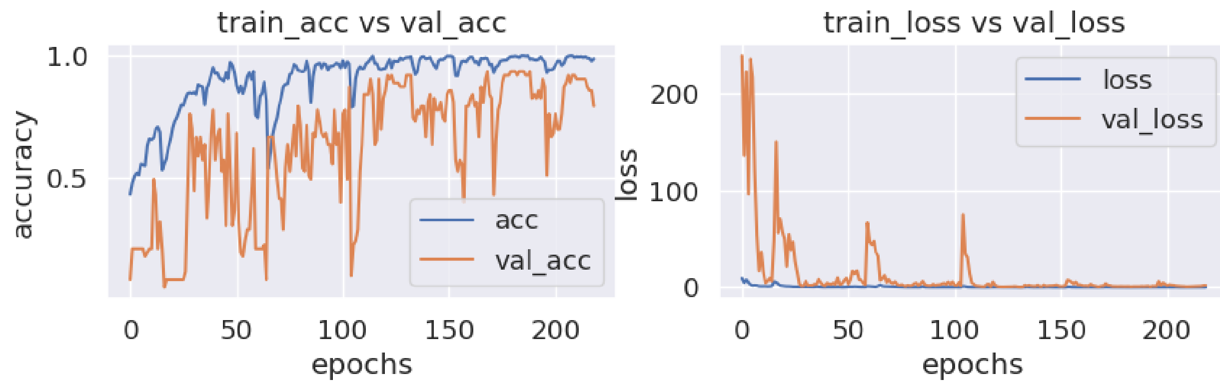

Fig 5: Accuracy and loss of MobileNetV2 model.

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In figure 6,7,8 Xception models Chickenpox, Impetigo and Scabies show higher accuracy than Hand Foot and Mouth. The EfficientNetV2B0 model almost shows the same accuracy as Xception. In the MobileNetV2 model, the accuracy of Hand Foot and Mouth is unsatisfactory.

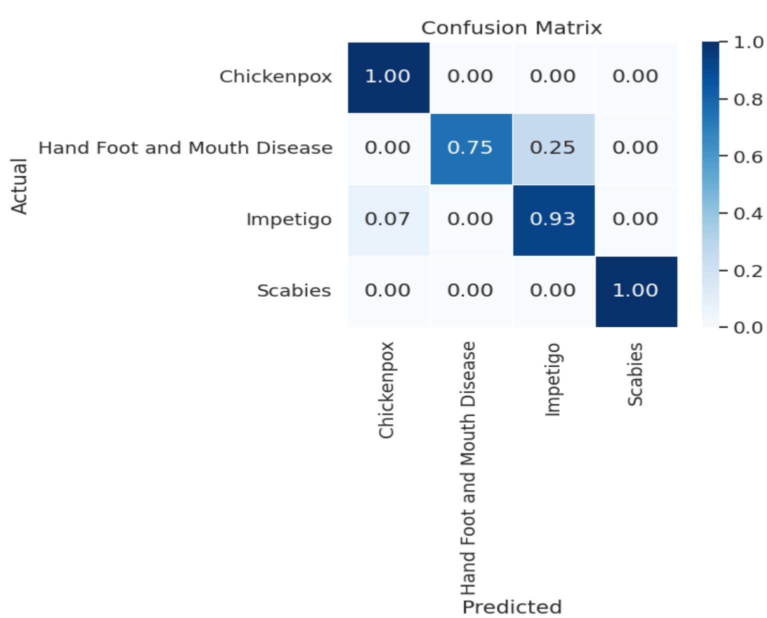


Fig 6: Confusion matrix of Xeption

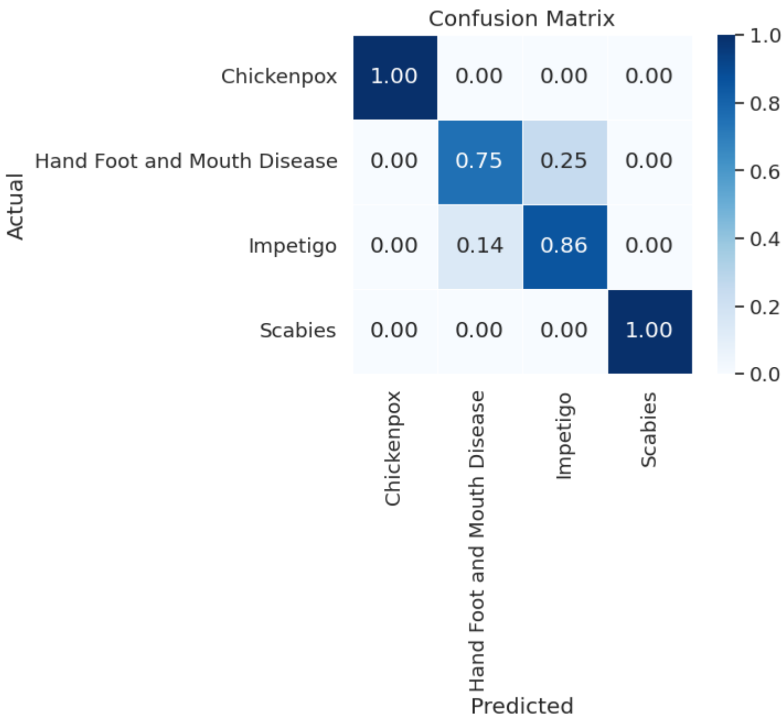


Fig 7: Confusion matrix of EfficientNetV2B0

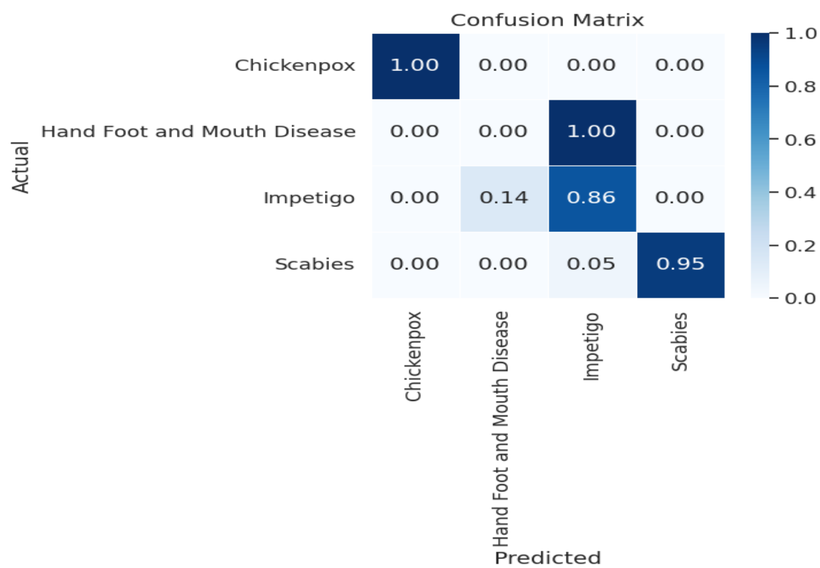


Fig 8: Confusion matrix of MobileNetV2

The performance evaluation of deep learning is a significant part of image classification. This study measures accuracy as the performance evaluation index. It is convenient for the experiments when all classes have equivalent significance. The accuracy is calculated by the ratio of the number of correct predictions and the total number of predictions.

Accuracy = TP + TN FP + FN + TP + TN

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)$$

Where, TP = True Positives, TN= True Negatives, FP = False Positives, and FN = False Negatives.

Model	Total No of parameters	Batch Size	No. of Epochs	Accuracy
Xception	20,869,676	4	500	97%
EfficientNetV2B0	5,924,436	4	500	95%
MobileNetV2	2,508,868	4	500	87%

Table 2: Performance comparison of deep learning models

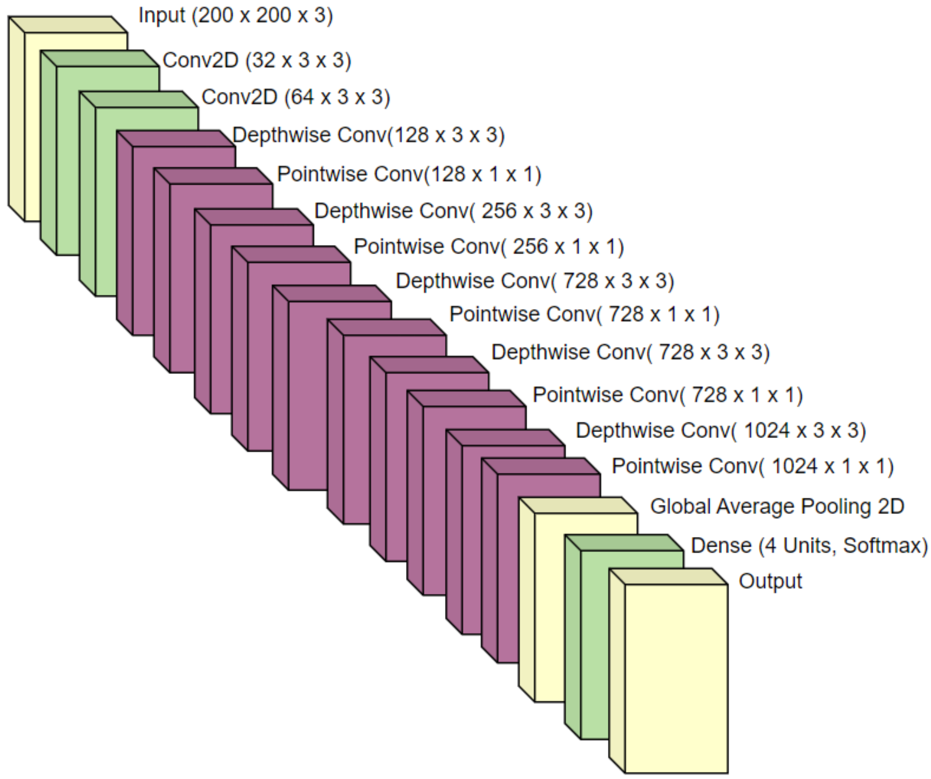
Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Xception	97%	98.71%	0.4310	0.0291
EfficientNetV2B0	95%	96.83%	0.1816	0.1130
MobileNetV2	87%	79.37%	0.8085	1.9563

Table 3: Result Analysis

Model	Accuracy
Keras Model[21]	81.75%
Xception	97%

Table 4: Result Comparison

After studying all the paper one paper is similar two our paper which use multiple disease for classification and it uses keras model[21] but it’s accuracy is 81.85% but our proposed moel Xception achieved the highest accuracy among all model which is 97%. That’s why, our paper can be used in further research for pediatric infections analysis. Almost all paper used skin disease which includes adult skin disease too but our paper studies only pediatric infections which is novelty here. As we have got highest accuracy the model architecture is given below



Xception Model Architecture

Discussion

For the classification of different pediatric infections, three models of CNN have been used and the main point of this paper is to observe which model classifies more precisely. At first, After preprocessing and augmentation of image data, MobileNetV2 was considered the best option for perfect accuracy by observing our dataset diversities but it didn't achieve the highest accuracy and it is not the best for all these infections. But then we decide to approach different models which are Xception and EfficientnetV2B0.The Xception model displays powerful prospects in the realm of pediatric infection classification providing high accuracy and vigorous attribute extraction potentiality.On the other hand, EfficientnetV2B0 provided slightly lower accuracy than Xception but it appears for remarkable development in the subject of deep learning models. Nevertheless, challenges connected to data condition, understandability, and clinical combination should be labeled to recognize its advantage in pediatric infection problems fully.Moreover Xception and EfficientnetV2B0 are considered better-fitting models for our study.

Conclusion

This research constructed the successful application of deep learning algorithms for pediatric infections. By employing three different deep learning models which are Xception, EfficientV2B0, and MobileNetV2, we achieved high accuracy rates in classifying infections based on their visual features. The Xception and EfficientNetV2B0 models surpass the

MobileNetV2 model, achieving higher accuracy rates of 97% and 95%, respectively. The results of this research focus on the perspective of deep learning algorithms to revolutionize the medical industry by improving the efficiency and accuracy of datasets. Nevertheless, there is room for improvement. For future work, we aim to work with a large image dataset and more childhood infections with a modified model architecture. This should increase the possibility of using machine learning models for classifying and detecting pediatric infections.

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Certainly! Here are the equations and processes associated with each of the data augmentation techniques mentioned: