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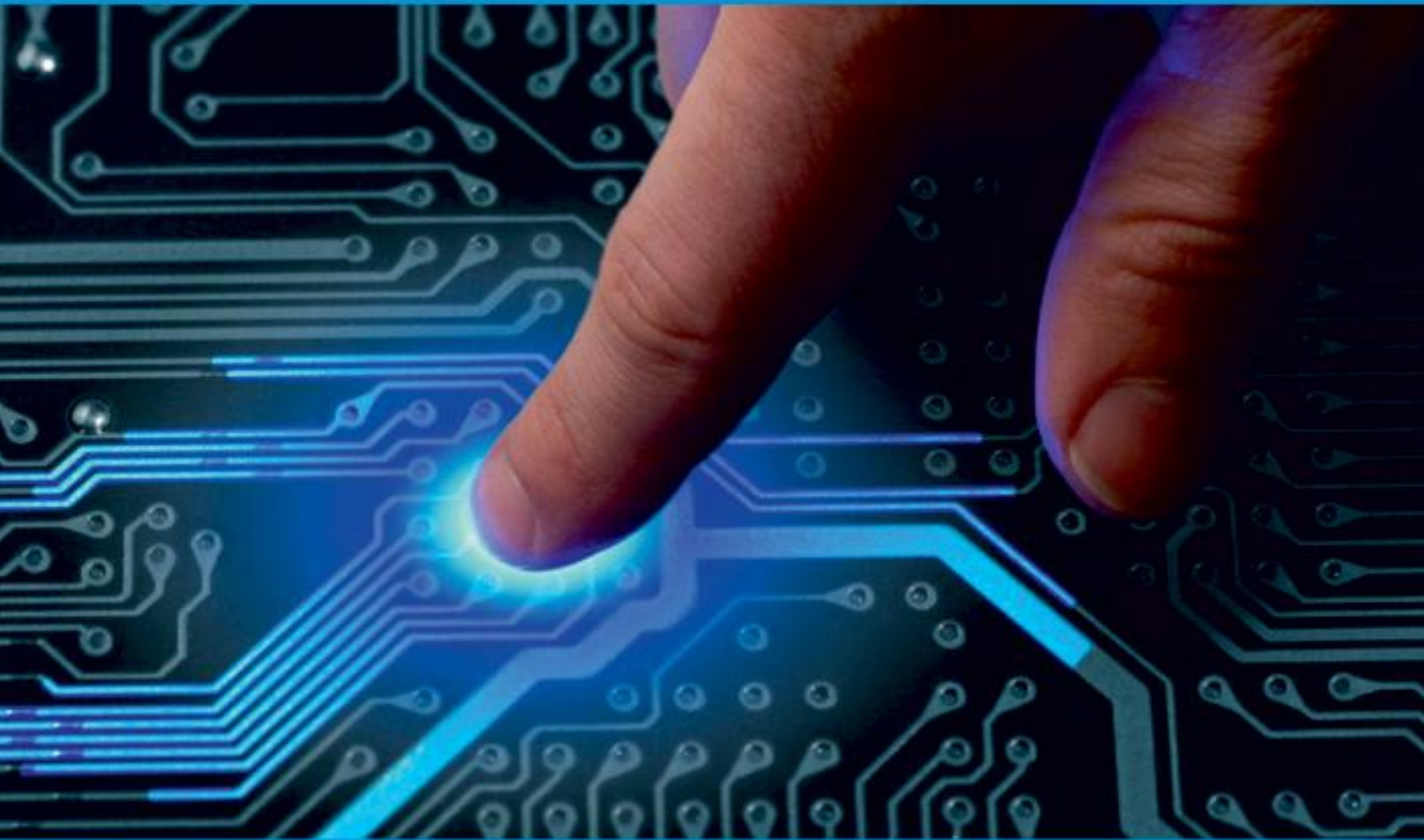

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Comparitive Analysis of Deep Learning Algorithms for Pneumonia Detection in Chest X-Ray Images

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ABSTRACT: Pneumonia is a respiratory disease and its diagnosis should be made quick and accurate for managing and treating patients. The study that we carried out examines the efficacy of three convolutional neural network (CNN) models for pneumonia detection from chest X-ray images: SqueezeNet, VGG19, and the pre-trained Xception model. Since accurate diagnostic instruments are vital to the fight against pneumonia, we investigate how different training-validation split ratios (50-50, 70-30, and 80-20) affect the performance of the model. We do a comprehensive analysis of each model's capacity to correctly detect pneumonia cases across various ratios of training and validation data, using a broad dataset of chest X-ray pictures labeled for the disease. The impact of the data partitioning on the model is evaluated by looking at the important performance measures like training, validation, and testing accuracy.

The work we carried out clarifies the relationship between CNN model performance and training-validation split ratios, which helps improve techniques for detecting pneumonia. Our findings pave the way for the development of more stable and effective tools to detect pneumonia, which improves patient health. If pneumonia is not detected at the earliest, it leads to the patient's death and it will increase the mortality rate. The study also provides useful direction for researchers and medical professionals.

I.INTRODUCTION

Pneumonia is a life-threatening infection in the air sacs in one or both lungs caused due to inflammation of the alveoli.14% of all deaths of children under 5 years old, that has killed 740 180 children in 2019 due to Pneumonia. Pneumonia Identify applicable funding agency here. If none, delete this. can be caused by viruses, fungi, or bacteria such as staphylococcus aureus, and streptococcus pneumonia. Pneumonia can be prevented by immunization, adequate nutrition, and by addressing environmental factors. Pneumonia caused by bacteria can be treated with antibiotics, but only one-third of children with pneumonia receive the antibiotics they need. Deep learning is a branch of machine learning which is based on artificial neural networks. It is capable of learning complex patterns, structures, and relationships within data. In deep learning, we don't need to explicitly program everything. It has become increasingly popular in recent years due to the advances in processing power and the availability of large datasets. Epidemics and chronic diseases have claimed the lives of countless individuals throughout historical time, causing huge crises that took many years to resolve Because it is based on artificial neural networks (ANNs) also known as deep neural networks (DNNs). In disease diagnostic systems, machine learning (ML), DL, and statistical methods are extremely efficient tools They may be used to solve highly sophisticated vision tasks in the healthcare imaging sector, such as lung disease classification, lung segmentation, and many more. Recent DL advancements have helped achieve and perhaps even significantly exceed human performance in many activities. DL can also be utilized to determine the outcome of treatments, such as chevalier studies and cancer treatment. Labeled data and DL-based algorithms are linked to encouraging results in thoracic illness categorization utilizing an X-ray image modality. Deep neural network (DNN) models have traditionally been built and tested by human professionals in a continuous trial-and-error technique that takes time, resources, and expertise[1]. These neural networks are inspired by the structure and function of the human brain's neurons, and they are designed to learn from large amounts of data. The diagnosis of pneumonia requires a review of chest radiography (CXR) by a highly qualified specialist, laboratory tests, and clinical history,

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which makes its detection a difficult task. It normally presents as an area of increased opacity within the CXR.To address this issue, an innovative model is presented which utilizes DNN architecture to efficiently execute ideal classification. The proposed model is designed exclusively for the classification and prediction of pneumonia by utilizing CXR radiographs.

II. DATASET DESCRIPTION

The dataset used in this study was compiled by combining two distinct sources from Kaggle, both focusing on chest X-ray images for the purpose of pneumonia detection. To access the first dataset use this link: https://www.kaggle.com/datasets/andrewmvd/pediatricpneumonia-chest-Ray it comprises X-ray images collected from pediatric patients, the second dataset includes images from pediatric patients and to access use this link: https://www.kaggle.com/datasets/paultimothymooney/chestxray-pneumonia. By merging these datasets, we created a unified and comprehensive dataset for the study carried out. From the first dataset we took the images for the training and validation having 5856 images and from the second dataset we took the images for testing having 16 images. Using this dataset, we experimented. Various combination of training and validation split (50-50,70-30,80-20) is done for the model used i.e. pre-trained Xception ,SqueezeNet and VGG19 model.

III. METHODLOGY

A.VGG19 architecture

• VGG19 Architecture: - The VGG19 model consists of 19 layers, including convolutional layers, max-pooling layers, fully connected layers, and dropout layers. - It starts with several convolutional blocks, each containing multiple convolutional layers followed by a max-pooling layer. - After the convolutional blocks, there are fully connected layers with dropout regularization to prevent overfitting. - The last layer is a dense layer with a single neuron and sigmoid activation function, producing the final binary classification output.

• Data Loading: - The data is loaded using the ImageDataGenerator class from Keras, which allows real-time data augmentation and preprocessing. - Training and validation data are loaded separately, with a validation split of 50

• Model Compilation: - The model is compiled with the Adam optimizer and binary cross-entropy loss function, suitable for binary classification tasks. - Accuracy is chosen as the metric to monitor during training.

• Model Training: - The model is trained using the fit method. - Training is performed for 20 epochs with both training and validation data generators.

• Model Evaluation: - The trained model is evaluated using the test data generator to compute the test loss and accuracy.

B. Xception architecture

• The base of the model is the Xception architecture, a deep convolutional neural network (CNN) known for its performance on image classification tasks. The pre-trained Xception model is loaded without its top classification layers. Two additional layers are added on top of the Xception base: • GlobalAveragePooling2D layer: This layer reduces the spatial dimensions of the feature maps from the convolutional base to a vector by taking the average of all values.

• Dense layer with 128 units and ReLU activation function: This layer serves as a fully connected layer to further process the features extracted by the convolutional base.

• Dropout layer: This layer helps prevent overfitting by randomly setting a fraction of input units to zero during training. Dense output layer with 1 unit and sigmoid activation function: This layer produces the final binary classification output, indicating whether an input image belongs to the positive class or negative class.

• Model Compilation: The model is compiled using the Adam optimizer and binary cross-entropy loss function. Binary cross-entropy is suitable for binary classification tasks. The accuracy metric is used to monitor the performance of the model during training.

• Data Augmentation and Preprocessing: The ImageDataGenerator class from Keras is used for real-time data augmentation and preprocessing. Data augmentation techniques such as rescaling, shearing, zooming, and horizontal flipping are applied to increase the diversity of training data and improve the model’s generalization capability. Data Loading: Training and validation data are loaded using the flow from directory method from ImageDataGenerator. The data is loaded from the specified directory (’/content/Pediatric Chest X-ray Pneumonia/train and test’) and split into training and validation sets based on the specified validation split parameter.

• Model Training: The model is trained using the fit method. The training data is fed to the model using the train generator, with the number of steps per epoch set to the train generator samples .batch-size. Validation data is provided

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using validation/-generator, with the number of validation steps set to validation-generator.samples validation-generator. batch-size. The training process is repeated for 20 epochs.

• Model Evaluation: The model is evaluated using the test data loaded from the '/content/Pediatric Chest X-ray Pneumonia/val' directory.

The evaluate method computes the test loss and test accuracy of the model. Visualization: The training and validation accuracies are plotted against the number of epochs using matplotlib. This allows visualization of the model's training progress and potential overfitting or underfitting.

C. SqueezeNet Fire Module:
The script defines a function fire module which implements the building block of SqueezeNet. A fire module consists of a squeeze convolution layer followed by expand convolution layers. It reduces the number of input channels with a squeeze convolution layer (using 1x1 convolutions) and then expands them with 1x1 and 3x3 convolutions. SqueezeNet Architecture: The SqueezeNet function defines the overall architecture of the SqueezeNet model. It consists of convolutional layers followed by fire modules and maxpooling layers. The final layers include a global average pooling layer, dropout layer, and a 1x1 convolutional layer followed by softmax activation for classification.
of primary users are assumed to cause the collisions among the transmissions of primary users and CR-Networks nodes.

V. RESULT

A.Pre trained Xception model

TABLE I
PRE-TRAINED XCEPTION MODEL PERFORMANCE

Split Ratio	Training Accuracy	Validation Accuracy	Testing Accuracy
50-50	0.9455	0.933	0.875
70-30	0.9437	0.9416	0.875
80-20	0.9517	0.9505	0.875

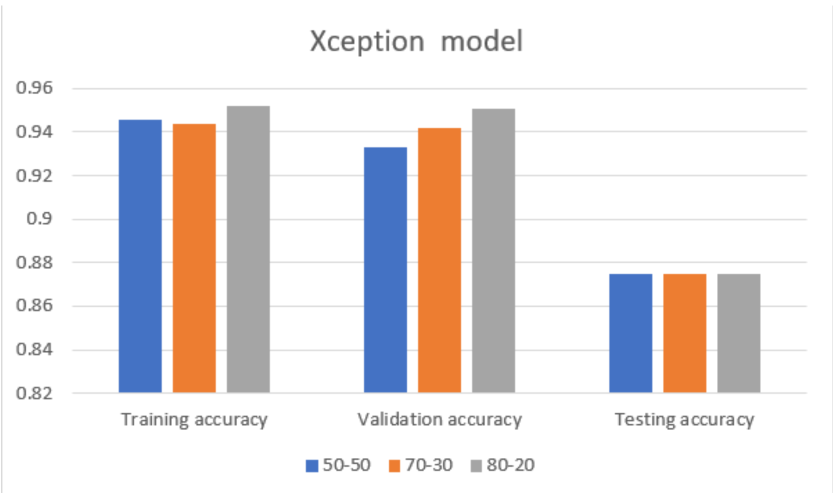

Fig. 1 Pre trained Xception model performance

The architecture, training process, and performance assessment of the Xception model are all thoroughly described in the study. The Kaggle dataset is used for the pre-trained Xception model. The study presents the experimental findings for the Xception model, which was assessed on the testing set and trained on several training/validation splits (80/20, 70/30, and 50/50). With training accuracy, validation accuracy , and testing accuracy for 80-20 training/validation split

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is 0.9517,0.9505,and 0.875,for 70-30 training/validation split is 0.9437,0.9416 and 0.875,for 50-50 training/validation split is 0.9455,0.933 and 0.875. The Xception model performs well on the Kaggle dataset. All things considered, the Xception model is a potent instrument for picture classification tasks and has found widespread use in a variety of applications, including security surveillance, medical imaging, and autonomous driving.

B.SqueezeNet

TABLE II
SQUEEZENET MODEL PERFORMANCE

Split Ratio	Training Accuracy	Validation Accuracy	Testing Accuracy
50-50	0.273	0.2679	0.5
70-30	0.7294	0.7286	0.5
80-20	0.7299	0.7292	0.5

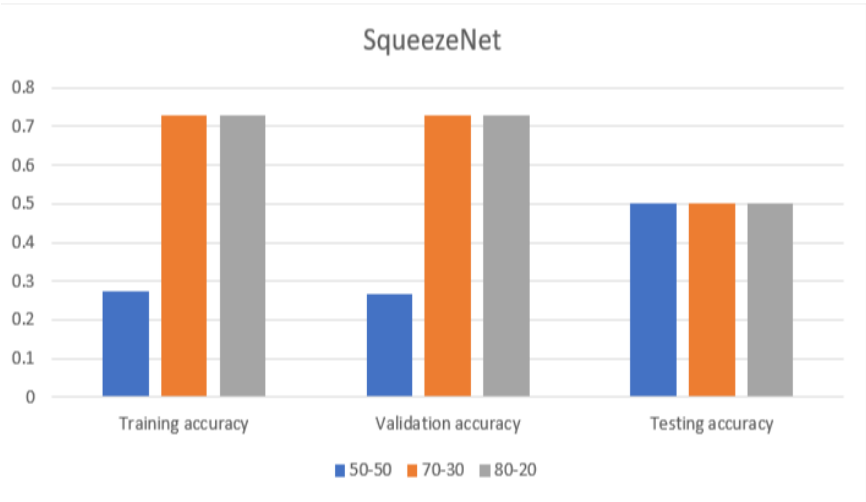

Fig. 2 SqueezeNet model performance

A brief overview of the figure, ”SqueezeNet Model.” It describes the training and assessment procedure for the SqueezeNet model. Training splits, training accuracy, validation accuracy, and testing accuracy are all covered. The model is trained with a variety of splits, including 80/20, 70/30, and 50/50 of which training accuracy , validation accuracy, and testing accuray for 80/20 split is 0.7299,0.7292 and 0.5,for 70/30 split is 0.7294,0.7286 and 0.5,for 50/50 split is 0.273,0.2679 and 0.5 respectively. The contains information on the SqueezeNet model’s performance in each of these many training scenarios, demonstrating the model’s accuracy throughout training and validation as well as its accuracy in the final test

C.VGG19

TABLE III
VGG19 MODEL PERFORMANCE

Split Ratio	Training Accuracy	Validation Accuracy	Testing Accuracy
50-50	0.7283	0.7297	0.5
70-30	0.7289	0.7315	0.5
80-20	0.7293	0.73	0.5

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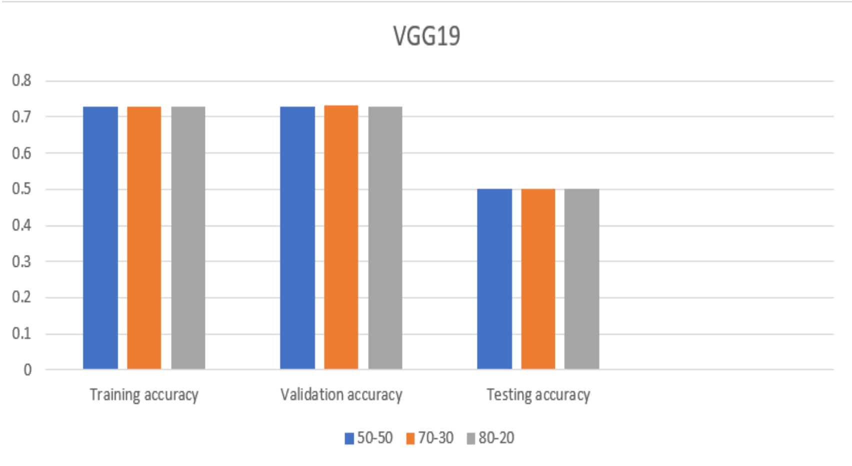

Fig .3 VGG19 model performance

A study on the VGG19 model's performance during training, validation, and testing can be found in the image description. Data on testing, validation, and training accuracy for several training splits—80/20, 70/30, and 50/50—are included in the file. The accuracy of testing for various training/validation split (80/20,70/30,50/50) is 0.5 ,training accuracy for various training/validation split (80/20,70/30,50/50) is 0.7293,0.7289 and 0.7283 repectively, and validation accuracy for various training/validation split (80/20,70/30,50/50) is 0.73,0.7315 and 0.7297 repectively.These results obtained during the experiment can be used for further study.

VI.CONCLUSION

In conclusion, the experimental results showed the robust performance of the Xception model in different training/validation separations, and showed good performance for image classification tasks in different environments. SqueezeNet and VGG19 showed high training validation accuracy but low testing accuracy. Despite exhibiting high training and validation accuracy, the SqueezeNet and VGG19 models face challenges in generalization, as we can witness the consistent low test accuracy obtained in the experiment. Further research can be carried out focusing on model refinement, regularization techniques, and data augmentation to improve the model's performance.

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