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Application of CNN Model on Medical Images (Chest X-Rays)

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Abstract - Chest diseases encompass a range of conditions affecting the lungs, including infections caused by bacteria, viruses, or other microorganisms. These diseases can vary in severity, posing a potential threat to vulnerable individuals such as young children, older adults, and those with weakened immune systems. Detecting chest diseases involves employing diverse methods, such as physical examination, chest x-rays, blood tests, and sputum culture. During a physical examination, healthcare professionals utilize a stethoscope to listen for abnormal breathing sounds or crackling noises in the chest. They also assess factors like fever and respiratory rate. Chest x-rays provide a visual representation of the lungs, enabling the identification of areas displaying inflammation or fluid accumulation. Sputum culture involves collecting a sample of mucus expelled from the lungs through coughing and testing it for the presence of microorganisms.

***Key Words*:** Deep Learning, CNN, Chest X-Ray Images.

1. INTRODUCTION

Medical Images classification is an important research area in software engineering, which aims to identify potential lung desieses. This can help doctors take preventive measures to improve the quality and reliability of the patient. In recent years, there has been growing interest in using Neural Networks for medical images. The applications of neural networks are far reaching. They can perform tasks such as making predictions based on available data, interpreting visual data for face recognition, and other computer vision tasks, and even serve as expert systems and perform medical diagnoses

2. Literature Review

Classification of images in training often involves the use of convolutional neural networks (CNN). The latter proved their power when AlexNet won the ImageNet competition by a wide margin from other, more traditional neural networks. Since then, CNN has become one of the most promising machine learning algorithms. It is widely used to solve problems involving large-scale datasets. However, learning deep convolutional neural networks on large datasets is a highly intensive computational task and requires much time to learn. That is why the algorithm is subjected to parallelization, which reduces the load on one core, dividing the work between several [7-10]. Due to this, the use of the algorithm does not require spending days or even weeks to learn it. There are two approaches: model parallelism, i.e., the model is divided between several computing nodes and trained on the same data, and data parallelism, if the data is distributed on several nodes and the same model is used for learning. Hybrid approaches using both parallelisms have also been proposed. Examples of hybrid systems are papers [11] and [12]. In hybrid approaches, a small number of nodes are grouped to teach the model using model parallelism. The data set is divided into groups to be processed simultaneously using data parallelism. They use the master-managed model, and the main task of the server is to update parameters centrally. The disadvantage of this approach is that because all groups access the same server, which ensures their interaction, a delay is created, which reduces performance. One of CNN's most popular learning algorithms is stochastic gradient descent (SGD). It was demonstrated in the article [13]. The algorithm works iteratively: the model parameters are updated until they become optimal. Due to the dependence of the data on the model parameters between any two sequential iterations, parallel SGD can suffer due to the expensive interprocess cost of communication [14], so for many processes, this increases the learning time.4

3. Deep Learning Neural Network Models Used

Techniques in a deep learning where a model trained on one task is re-purposed on a second related task. For example, a model trained to recognize dogs could be re- purposed to recognize cats by fine-tuning the model on a dataset of cat images. Techniques can be an effective way to quickly train a high-performing model by leveraging the knowledge gained from a pre-trained model. This is particularly useful when there is a limited amount of data available for the target task.

3.1 CNN

A convolutional neural network (CNN) is a type of artificial neural network that is commonly used for image classification tasks. It can be trained to identify patterns and features in images, which makes it a good choice for detecting chest disease from medical images such as X-rays. To train a CNN for chest disease detection, you would need a large dataset of medical images the presence or absence of chest disease. You would then use this dataset to train the CNN to recognize the patterns and features in the images that are associated with chest disease. Once the CNN is trained, you can use it to classify new images as positive or negative for chest disease.

3.2 DenseNet

DenseNet is a type of convolutional neural network (CNN) that is designed to be more efficient and easier to train than other CNN architectures. It was introduced in the paper "Densely Connected Convolutional Networks" by Gao Huang et al. DenseNet is based on the idea of densely connected layers, which means that each layer in the network is connected to every other layer in a feedforward fashion. This allows the network to reuse features learned by earlier layers and helps to reduce the number of parameters in the model, which makes it more efficient and easier to train. DenseNet has been shown to perform well on a variety of tasks, including image classification, object detection, and semantic segmentation.

3.3 VGG-16

VGG16 is a convolutional neural network (CNN) architecture that was introduced in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" by Karen Simonyan and Andrew Zisserman. It is a deep CNN that was designed to be highly effective at image classification tasks. 15 VGG16 is composed of a series of convolutional and fully connected layers, and it is known for its simplicity and good performance. It has been widely used in a variety of image classification tasks, and it has been successful on benchmarks such as ImageNet. It is possible that VGG16 could be used for chest disease detection, but it would depend on the specific details of the task and the available data. In general, CNNs are well-suited for image classification tasks, and VGG16 is a strong performer on such tasks. However, there may be other CNN architectures that are more specifically tailored to the task of chest disease detection and that may perform better on that particular task.

3.4 InceptionNet

InceptionNet, also known as GoogLeNet, is a convolutional neural network (CNN) architecture that was introduced in the paper "Going Deeper with Convolutions" by Christian Szegedy et al. It is a deep CNN that was designed to be more efficient and easier to train than other CNN architectures. 17 InceptionNet is based on the idea of inception modules, which are modular blocks that can be stacked together to form a deep CNN. Each inception module consists of a series of parallel convolutional and pooling layers with different kernel sizes, which allows the network to learn features at different scales. This helps to improve the network's performance and make it more efficient. InceptionNet has been shown to perform well on a variety of tasks, including image classification, object detection, and semantic segmentation. It is possible that InceptionNet could be used for chest disease detection, but it would depend on the specific details of the task and the available data. In general, CNNs are well-suited for image classification tasks, and InceptionNet is a strong performer on such tasks.

3.5 ResNet

ResNet is based on the idea of residual connections, which are connections that bypass one or more layers and allow the network to learn residual functions. This helps to mitigate the vanishing gradient problem, which is a phenomenon that can occur in deep neural networks where the gradients of the parameters become very small, making it difficult to train the network. ResNet has been shown to perform well on a variety of tasks, including image classification, object detection, and semantic segmentation. It is possible that ResNet could be used for chest disease detection, but it would depend on the specific details of the task and the available data. In general, CNNs are well-suited for image classification tasks, and ResNet is a strong performer on such tasks. However, there may be other CNN architectures that are more specifically tailored to the task of chest disease detection and thatmay perform better on that particular task.

4. RESULT

This project has achieved to identify whether a person has chest disease or not. The training, testing and validating of the Chest X-ray images that are taken from cancer imaging archive (nbia) is achieved successfully. By using various CNN models for testing, training and validating. The images were successfully resized, rescaled and made into batches using the keras model. Further, the model was tested by giving several images which were made into batches as input. And the result shows the images as Normal or Chest disease. Therefore, at this step the completion of the basic training and testing part of the project is done.

This was done on 5 Neural Network models CNN, InceptionNet, ResNet, VGG-16, and DenseNet

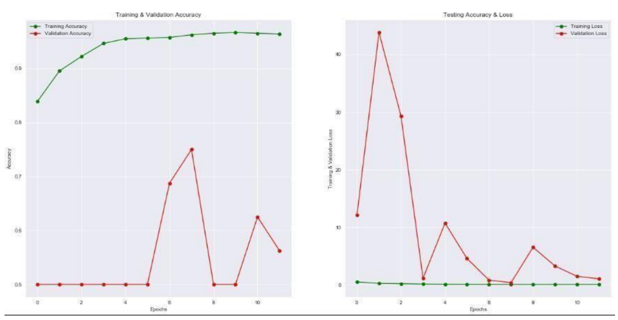


Fig. 1: CNN-Model

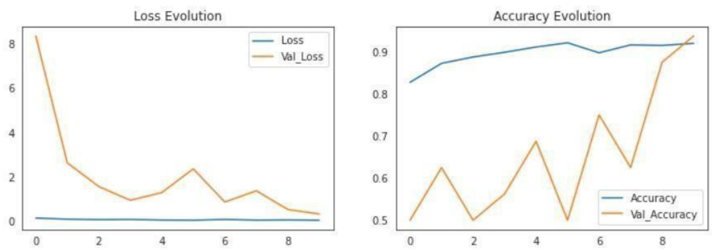


Fig. 2: DenseNet-Model

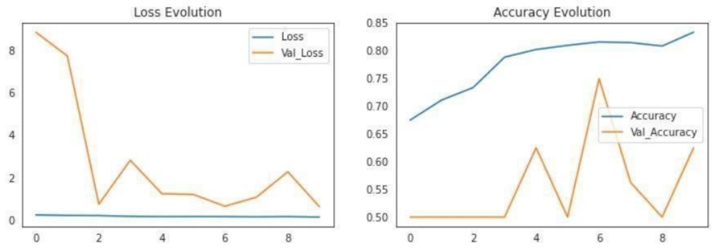


Fig. 3: **VGG-16 Model**

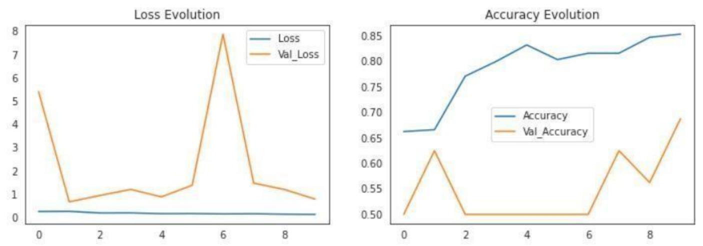


Fig. 4: **ResNet Model**

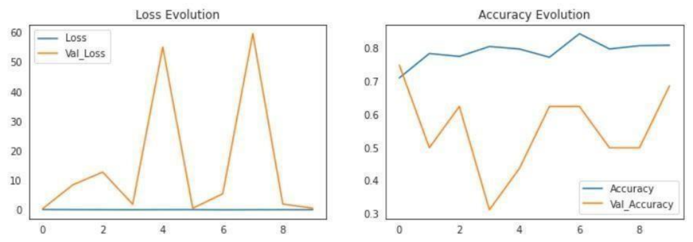


Fig. 5: **InceptionNet Model**

5. Performance Measurement

Once the predictive model has been built, it can be applied to perform a test to predict the fault modules inside the software fault datasets. In this work, we examined the ML prediction models, utilizing six classification algorithms, based on different statistical techniques such as confusion matrix (True Positive = TP, True Negative = TN, False Positive = FP, False Negative = FN), recall, precision, F1 measure, etc. Table 3 shows a quality measure of predictive model based on confusion matrix as below

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.92	0.95	0.93	390
Normal (Class 1)	0.91	0.86	0.89	234
accuracy			0.92	624
macro avg	0.92	0.91	0.91	624
weighted avg	0.92	0.92	0.92	624

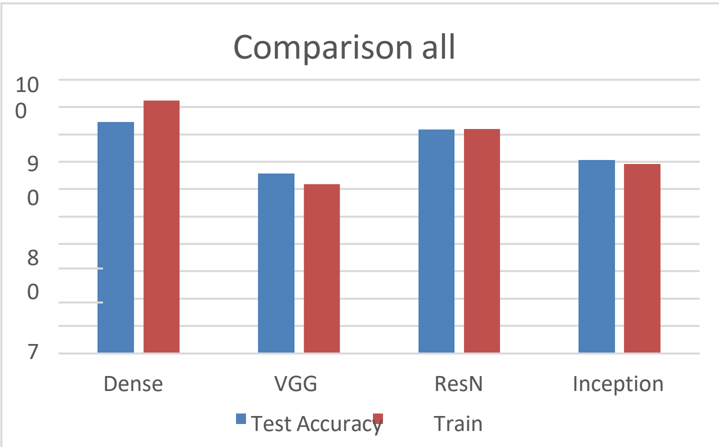
Table 1: CNN Evanluation Metrics

	0	1	accuracy	macro avg	weighted avg
precision	0.797357	0.866499	0.841346	0.831928	0.840571
recall	0.773504	0.882051	0.841346	0.827778	0.841346
f1-score	0.785249	0.874206	0.841346	0.829728	0.840847
support	234.000000	390.000000	0.841346	624.000000	624.000000

Table 2: ResNet Evaluation Metrics

	0	1	accuracy	macro avg	weighted avg
precision	0.806452	0.855037	0.838141	0.830744	0.836817
recall	0.747863	0.892308	0.838141	0.820085	0.838141
f1-score	0.776053	0.873275	0.838141	0.824664	0.836817
support	234.000000	390.000000	0.838141	624.000000	624.000000

Table 3: DenseNEt Evaluation Metrics



Graph 1: Comparison Graph

Architecture	Test Accuracy	Train Accuracy
DenseNet	84.46	92.45
VGG16	65.71	61.81
ResNet	81.73	81.96
InceptionNet	70.51	69.04

Table 4: Final Train Test Accuracy Table

Through this project, we concluded that on our set of data DenseNet performed best with 84.46% accuracy, following by ResNet(81.73), VGG-16(65.71), and InceptionNet(70.51).

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CONCLUSION

Respiratory system is one of the important parts of our body. As chest disease can be caused by various viruses and bacteria, it is very important to diagnose it as early as possible since it will lead to death. To enhance the system in chest disease detection in the underdeveloped and developing countries, such as in countries like India where we do not have expert radiologists and also the poverty that is being currently faced by rural areas, we have identified an accurate system to detect the chest disease infected individuals. This type of tool can be of immense help to the poor people who require urgent medical care.

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