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Predicting Diseases Using Chest X-Ray Medical Images

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- Objective
- Introduction
- Brief Literature Review
- Modelling / Design
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- Experimentation / Simulation
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Objective

- Using DenseNet 201 model that accepts a patient's chest radiograph as input and classifies it as pneumonia or non-pneumonia.

- This project work, aims to solve the problem of identifying diseases in small image patches taken from larger digital pathology scans.

- DenseNet, which is a subset of the CNN model and a recently developed technology, can help us diagnose various chest diseases with higher accuracy at the primary stage using CXR images

Introduction

- Chest diseases are unique in nature and like most of the diseases if diagnosed at primary stage can either be controlled or cured. Chest X-ray is the most common imaging method for detection of this infirmity, sometimes even the most experienced radiologists may find it challenging diagnosing the diseases,

- Thus, the introduction of modern image processing in medicine is a promising strategy to reduce unnecessary manual diagnosis costs and promote disease classification and detection.

- With the help of modern computing techniques such machine learning we can create tools to increase the efficiency of such diagnosis.

Literature Survey

Serial No.	Author	Paper Title	Key Findings	Journal/ Conference
1	Zheng Wan,Xuhui Gong,Boyang Yu,Zhang Yuxiang	DenseNet model with RAdam optimization algorithm for cancer image classification	Dense Convolutional Network (DenseNet) [1] has dense connectivity which can effectively alleviate the vanishing gradient problem, reduce a lot of parameter and enhance the propagation of feature maps to compare with other models	2021 IEEE International Conference (ICCECE 2021)
2	Liang Bing-jin, Yin Jian and others	Research_and_Practice_of_X-ray_Chest_Film_Disease_Classification_based_on_DenseNet	The densenet model is basically the same as ResNet, but it establishes the dense connection between all the previous layers and the later layers	2020 ICAIE Conference

Literature Survey

Serial No.	Author	Paper Title	Key Findings	Journal/ Conference
3	Bincy Chellapandi, M.Vijayalakshmi, Shalu Chopra	Comparison of Pre-Trained Models Using Transfer Learning for Detecting Plant Disease	DenseNet model was compared in this reasearch with other machine learning models like ResNet, VGG16, VGG19, InceptionV3 and others where DenseNet was found to produce the most efficient outcomes then the rest ones	2021 IEEE International Conference (ICCECE 2021)
4	YAN QI, CHEN ZHICHAO, LUO LAN	FRUIT DISEASE IDENTIFICATION BASED ON IMPROVED DENSENET FUSION DEFOGGING ALGORITHM	DenseNet, a more efficient alternative to traditional CNNs, tackles issues like long processing times and gradient disappearance. It connects all convolution layers, preventing information loss, and transmits characteristics from both the current and previous layers, improving overall performance.	2021 18th International Computer Conference Information Processing (ICCWAMTIP)

Literature Survey

Serial No	Author	Paper Title	Key Findings	Journal/ Conference
5	Israa F. Jassam, Saleh Mesbah Elkaffas, Adel A. El-Zoghabi	Chest X-Ray Pneumonia Detection by Dense-Net	In this research, a modified deep neural network is proposed. The proposed model is based on the deep learning models followed by two stacks of two dense layer and batch normalization in the end layer of the model. The dense layer and batch normalization is used to avoid overfitting in the model.	ICCTA 2021, 11-13 December, Alexandria, Egypt
6	Parvathavarthini S, Nidhi Bohra, Sindhu S	Performance Analysis of Squeezenet and Densenet on Fetal Brain MRI Dataset	Densenet produced an accuracy of 98.7% when compared to squeezenet whose accuracy is 96.3%. The performance of densenet is high in case of various metrics like precision, recall, sensitivity and F1 Score.	ICCMC 2022) IEEE Xplore Part Number: CFP22K25-ART; ISBN: 978-1-6654-1028-1
7	Abhilash Nandy	A Densenet based Robust Face Detection Framework	ResNetarchitectures have a lot of parameters, thus increases memory usage as well as time taken for training and inference. In order to tackle this problem, we use Densenet-121 as the backbones instead. In the Densenet Architecture, a convolutional block not only receives the feature maps immediately preceding layer it as inputs, but also, it receives all other feature maps from all the layers before this layer.	2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)

Literature Survey

Serial No.	Author	Paper Title	Key Findings	Journal/ Conference
8	Trung-Hieu Tran, Xuan-Hai Tran, Vinh-Tiep Nguyen and Khuong Nguyen-An	Building an Automatic Image Tagger with DenseNet and Transfer Learning	The motivation for skipping overlayers is to avoid vanishing gradients problem. With these skip connections, the gradients can flow backwards from later layers to initial filters. Improved from the ResNet's idea, DenseNet is made by using more skip connections. ResNet models are implemented with single-layer skips, but DenseNet models use several parallel skip connections in a dense block.	ICCTA 2021, 11-13 December, Alexandria, Egypt
9	Sanhita Basu; Sushmita Mitra; Nilanjan Saha	Deep Learning for Screening COVID-19 using Chest X-Ray Images	Three popular CNN Models,with increasing number of layers i.e AlexNet,VGGNet and ResNet are used	2020 IEEE Symposium Series on Computational Intelligence (SSCI)
10	Boran Sekeroglu and Ilker Ozsahin	Detection of COVID-19 from Chest X-Ray Images Using Convolutional Neural Networks	Chest X-ray images using ConvNets ConvNets architectures reduce the computational cost with high performance	SLAS TECHNOLOGY: Translating Life Sciences Innovation December 2020

Literature Survey

Serial No.	Author	Paper Title	Key Findings	Journal/ Conference
11	Sarah Badr AlSumairi and Mohamed Maher Ben Ismail	X-ray image based pneumonia classificatio n using convolutional neural networks	ResNet-50 and DenseNet-161 models were used to detect positive pneumonia cases, concluded that DenseNet has better efficiency and speed as per the ResNet model.	ACCENTS Transactions on Image Processing and Computer Vision
12	Pawan Kumar Mall & Pradee p Kumar Singh	BoostNet: a method to enhance the performance of deep learning model on musculoskeletal radiogr aphs X-ray images	BostNethelps in advancing the state-of-art performance of the musculoskeletal radiograph datasets.	International Journal of System Assurance Engineering and Management
13	Min SeokLeeSung WonHan	DuETNet: Dual Encoder based Transfer Network for thoracic disease classification	The Dual Encoder based Transfer Network(DuETNet) to counter the inefficiency caused. The Dual Encoder based Transfer Network(DuETNet) is compatible with various CNN architectures.	Pattern Recognition Letters

Novelty

Observations : On the basis of the studies complied

Dense Layer Advantage:
Studies show that adding a dense layer on top of convolutional layers improves accuracy and optimizes computational costs during training.

Justifiable Inclusion:
Given the observed benefits, it's justified to include a dense layer in the proposed model's architecture.

Dataset Enhancement:
Applying data augmentation enhances the dataset, contributing to model robustness.

Composite Impact:
Both the dense layer and data augmentation significantly optimize the model's performance.

Synergistic Optimization:
The combined effect of the dense layer and data augmentation enhances overall model efficiency and accuracy.

Modelling / Design

Architecture : Proposed Model using DenseNet-201

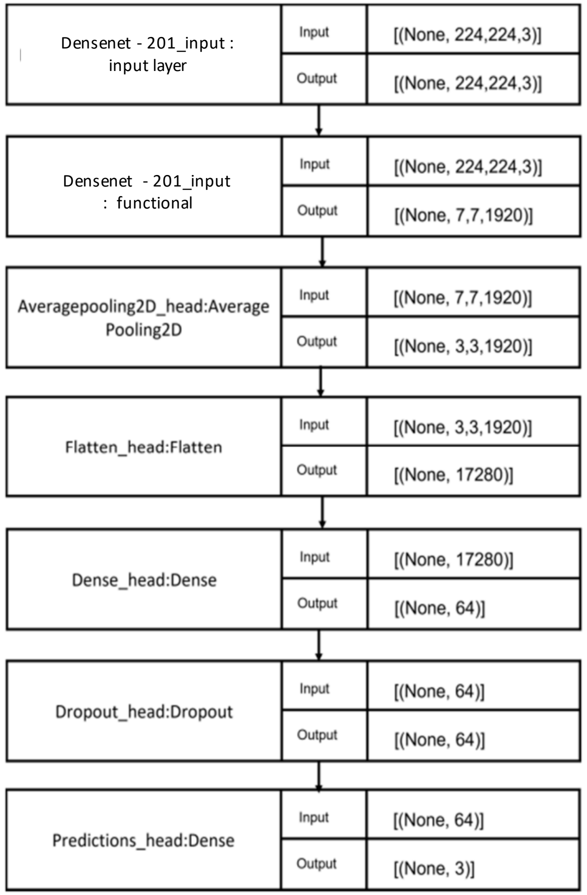


Fig. 3. Architecture of proposed model

1. Initial CNN Layers:.
- Focus on low-level features, capturing basic patterns and structures in the input data.

2. DenseNet-201 Architecture:
- Works on a dataset with three classes: Pneumonia, COVID-19, and Normal.

3. Average Pooling Layer:
- Reduces spatial dimensions of input data while preserving important features.

4. Flattening Operation:
- Converts image data into a 1D array for input in a fully connected neural network.

5. Dense Layer with ReLU Activation:
- Applies ReLU activation to introduce non-linearity, and enhances the network's capability to learn complex patterns.

6. Dropout Layer:
- Reduces overfitting errors by randomly dropping out connections during training.

7. Prediction Layer:
- Used for making predictions or classifications.
- Produces final predictions for three classes: Pneumonia, COVID-19, and Normal.

Methodology

Flow of data in Model Training

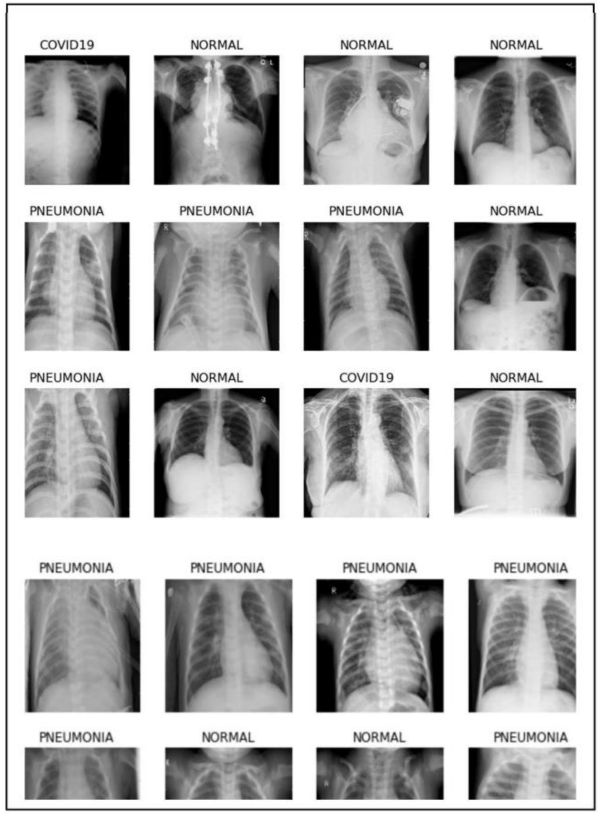


Fig. 1. CXR dataset sample consisting of both diseased and normal images

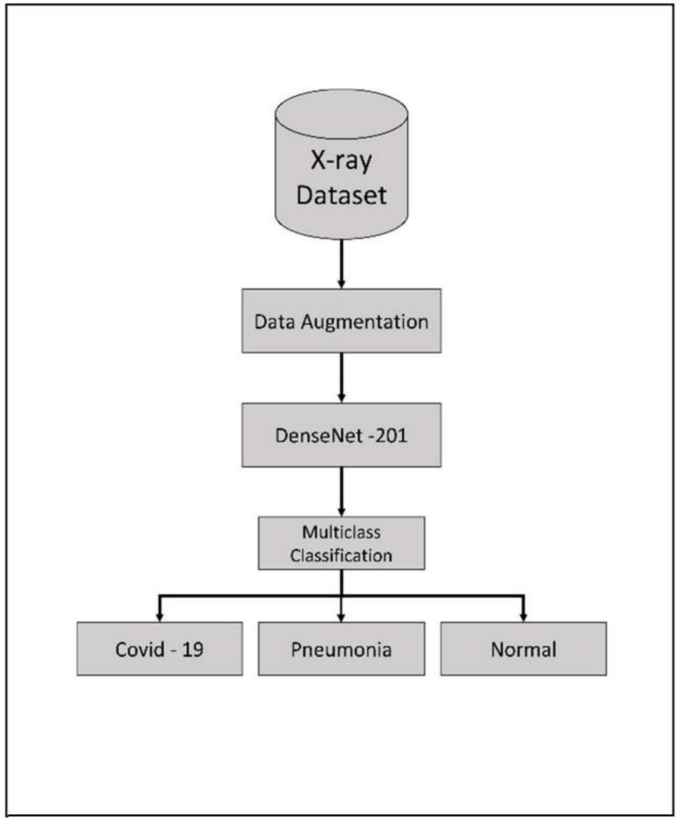


Fig. 2. Flowchart of the Proposed Model

Model Parameters:
- Total model parameters: **19,428,163.**

Training and Validation:
- Trained with **5144 i**mages of three categories (Pneumonia, COVID-19, Normal).
- **1288** images used for validation.
- Data augmentation performed using **Image DataGenerator from Keras.**

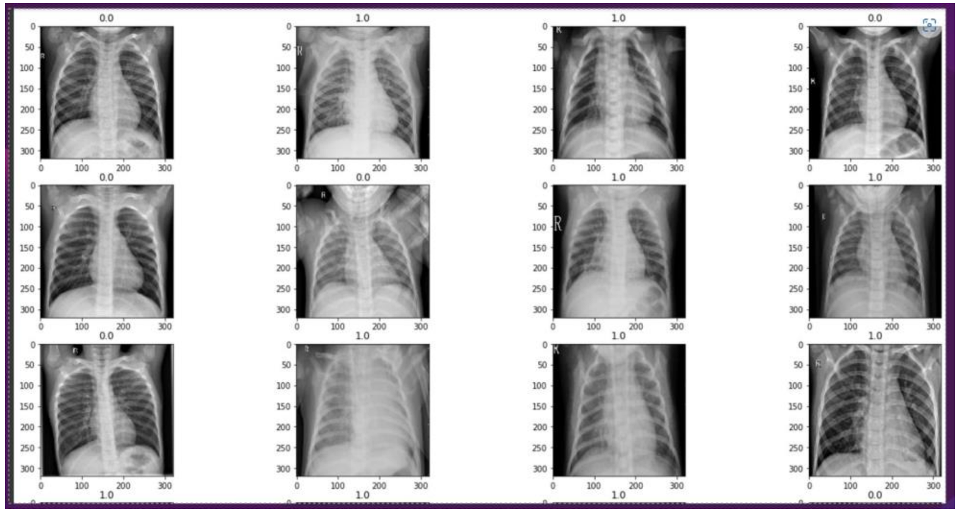
Optimization and Learning Rate:
- Adam optimizer is used.
- A specified learning rate is employed.
- Early stopping and learning rate adjustments based on validation accuracy implemented during training for 30 epochs.

Simulation / Experimental Details

Model Training and Analysis

TABLE I. DATASET COMPOSITION

Dataset	Covid-19	Pneumonia	Normal	Total
Train	460	3418	1266	5144
Test	116	855	317	1288
Sum	576	4273	1583	6432



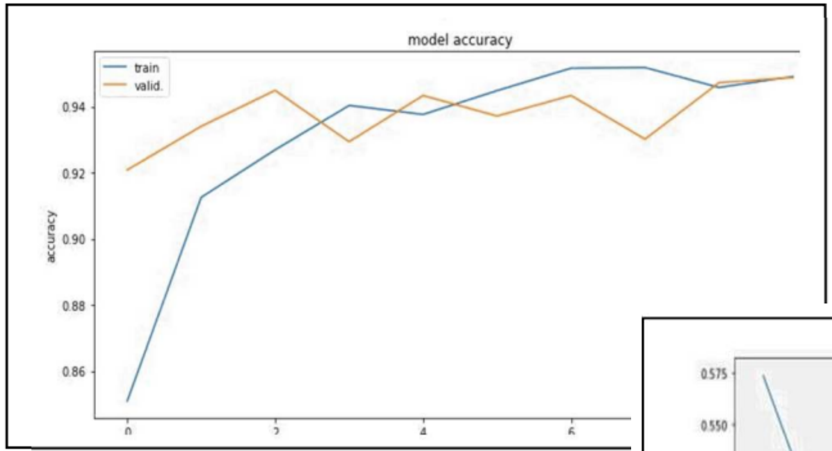


Fig. 4. Accuracy curve

The graph describes **95%** training and **validation accuracy** for 10 epochs

30 Epochs

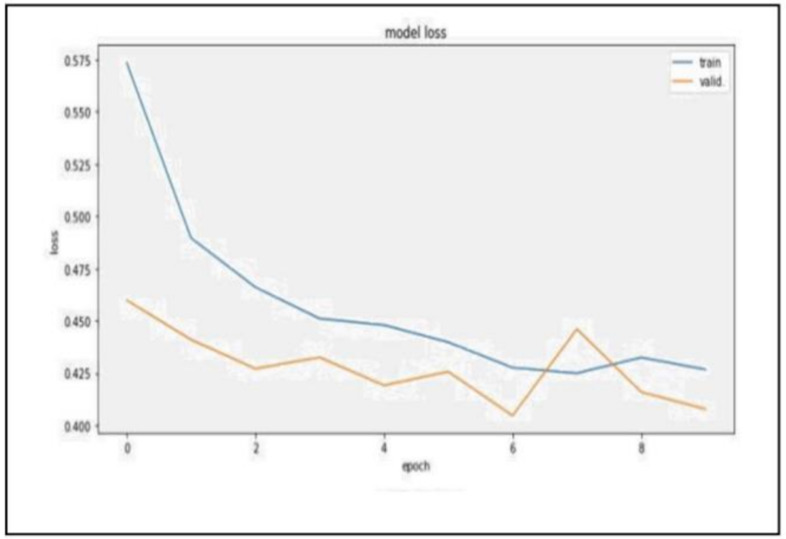


Fig. 5. Loss curve

The loss occurred in the model for **10 epoch 0.423**.

F1- score & Confusion Matrix Analysis

1) *Calculation of f1-score*

$$Recall = \frac{Tp}{Tp+Fn} \qquad Precision = \frac{Tp}{Tp+Fp} \qquad F1-Score = \frac{2*Recall*Precsion}{Recall+Precesion}$$

here, [a] Tp is True positive, [b] FP is False negative and [c] Fn is false negative

	precision	recall	f1-score	support
0	0.99	0.96	0.97	116
1	0.89	0.91	0.9	317
2	0.96	0.96	0.96	855
accuracy			0.95	1288
macro avg	0.95	0.94	0.94	1288
weighted avg	0.95	0.95	0.95	1288

Fig. 6. F1 score analysis

Trained with **5144 samples** of three categories (Pneumonia, COVID-19, Normal).
1**288 samples** used for validation.

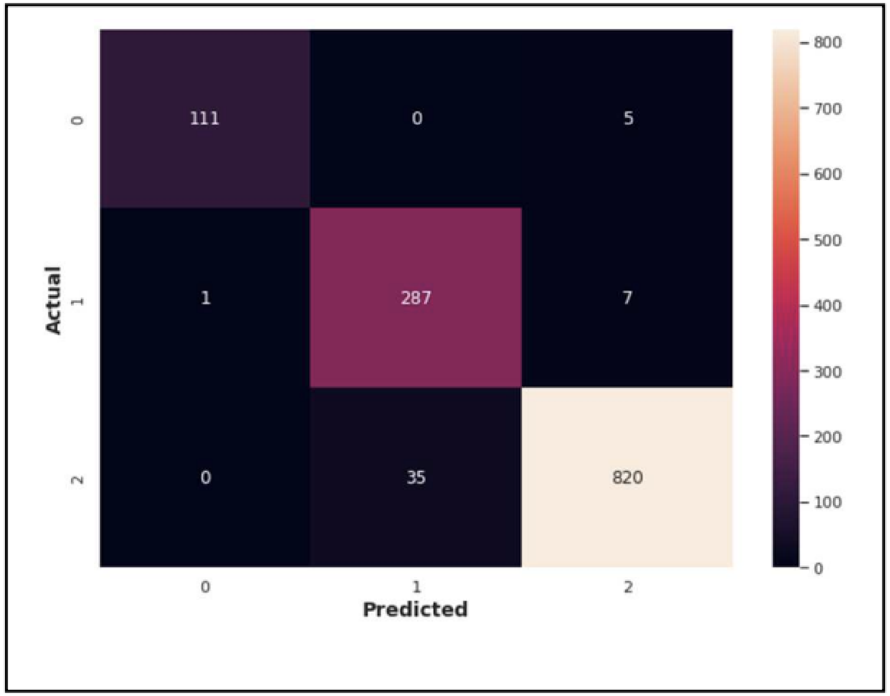


Fig. 7. Confusion Matrix

Conclusion:

The proposed model provides an accuracy of 95.96 percent, for 30 epochs. Thus, the model is liable to be used as a CAD tool to assist radiologists in examining CXR of Pneumonia & COVID-19 under the supervision of medical professionals.

Future Perspective:

Optimizing the model's training on a large scale of computing resources and implementing the proposed algorithm would potentially increase its usability and reliability for medical diagnosis.

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Thank you

Questions & Discussion