International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 10 Issue: 11 | Nov 2023 www.irjet.net p-ISSN: 2395-0072

Enhancing Pneumonia Detection: A Comparative Study of CNN, DenseNet201, and VGG16 Utilizing Chest X-ray Images

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Abstract - *Pneumonia is a serious respiratory infection that can be difficult to diagnose, especially in its early stages. Deep learning algorithms have the potential to improve the accuracy and efficiency of pneumonia diagnosis. This is a binary-classification study that evaluated the performance of a custom-made CNN and two other popular deep learning models, DenseNet201, and VGG16, in classifying Chest Xray images for diagnosis of the disease into two classes: pneumonia positive and negative. The CNN model achieved the best performance, with an accuracy of 80%. This is comparable to the performance of human radiologists in diagnosing pneumonia. Overall, this study provides promising evidence that deep learning can be used to improve the accuracy and efficiency of pneumonia diagnosis.*

1. INTRODUCTION

In an age defined by technological advances, our world has undergone a remarkable transformation. Technology's widespread influence touches every aspect of our daily lives, from the way we communicate to how we work and, importantly, how we approach healthcare.

In the realm of healthcare, technology has been a catalyst for extraordinary changes. Over the years, it has evolved from the early use of electronic health records to the adoption of telemedicine, revolutionising patient care and making it more accessible. However, amidst these transformative developments, one enduring challenge in the medical field remains the need for quicker and more accurate disease detection. The ability to swiftly and precisely identify ailments, especially for critical conditions like pneumonia or cancer. Traditional diagnostic methods are often time-consuming and may lack the precision required for timely interventions.

This is where AI techniques can help us. Deep learning algorithms have intelligent and mathematically proven image classification techniques that harness the potential to revolutionise disease detection, offering a solution to the challenges of speed and precision. With its ability to rapidly analyse vast amounts of medical data, we can significantly enhance the diagnostic process, potentially saving lives through quicker and more accurate assessments.

In the context of healthcare, the fusion of AI and medicine is not just a concept; it's an ongoing reality. Researchers and healthcare professionals around the world are actively exploring how AI algorithms can be utilised to improve patient outcomes. One area of focus is the classification of Pneumonia through the analysis of X-ray images, a field of study that holds immense promise.

In this paper, we will be exploring the methodologies, challenges, and implications of employing deep learning techniques to classify X-ray images, especially in the context of Pneumonia detection. In this investigative study, we will trace out the intricacies of AI-driven X-ray image analysis, addressing both its potential and limitations and how different transfer learning models are able to handle it in terms of performance primarily focusing on accuracy and precision.

2. LITERATURE SURVEY

A survey paper by Geert Litjens et al. reviews the major deep learning concepts pertinent to medical image analysis. Since the advent of digitising medical images, researchers have pioneered automated analysis systems. Initially during the 1970s-1990s, rule-based systems with low-level pixel processing and mathematical modelling were prevalent. In the late 1990s, supervised techniques gained popularity, utilising training data for system development. The shift from handcrafted features to learned features marked a pivotal moment, leading to the rise of deep learning algorithms, particularly Convolutional Neural Networks (CNNs). The watershed moment occurred with the success of AlexNet in 2012, sparking a surge in deep learning applications to medical image analysis. Deep learning significantly impacted medical image analysis, particularly in exam classification, where small datasets pose challenges compared to computer vision.[1]

Daniel Joseph Alapat et al. explores the detection of pneumonia, an infection affecting lung alveoli, manifested with symptoms like cough and chest pain. High-risk groups, like asthma patients and people with low immunity, face the complications. Medical imaging, particularly chest X-rays, aids diagnosis, but classification still remains challenging. Deep learning algorithms promise enhanced accuracy in interpreting chest X-ray data. While neural networks assist diagnosis, they are not a substitute for physicians. Numerous neural network-based approaches successfully detect pneumonia from chest X-rays. This paper compares these approaches using the Chest X-ray 14 dataset to assess technology maturity.[2]

Study by Dimpy Varshni et al. evaluates pre-trained CNN models for classifying abnormal and normal chest X-rays, addressing challenges in pneumonia diagnosis. Combining CNN-based feature extraction and an SVM (support vector machine) classifier, it proved optimal for classifying chest X-ray images, leveraging DenseNet's substantial features. ResNet50 and DenseNets emerged as top performers, guiding their model selection. Despite the achievements, limitations include the absence of patient history and exclusive use of frontal chest X-rays. Computational power requirements and the need for expert radiologists also pose challenges.[3]

3. NEURAL NETWORKS

The concept of deep learning has advanced through the emergence of neural networks, which draw inspiration from the human brain's neurons. Artificial Neural Networks (ANNs) consist of interconnected neurons that process inputs using an objective function, producing desired outputs. In deep learning, stacked neural networks comprise multiple layers called nodes, where mathematical computations occur. Nodes, functioning as independent regression models, utilise input data, weights, a bias, and an activation function to determine signal progression, facilitating the final output or classification.

Classification of neural networks include:

- Feed Forward Neural Network (FFNN)
- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)

A feedforward neural network (FFNN) is one of the simplest types of neural networks. Despite their simplicity, they can model complex relationships in data and have been the foundation for more complex neural network architectures.

Convolutional neural networks (CNNs) are commonly applied for image and pattern recognition, utilising linear algebra principles, especially matrix multiplication, to recognize patterns in images.

Recurrent neural networks (RNNs) are characterised by feedback loops and find utility in predicting future outcomes from time-series data, such as sales forecasts or stock market predictions.

3.1 Convolutional Neural Networks (CNN):

The Convolutional Neural Network (CNN), stands among various Deep Learning algorithms. It analyses images, assigning weights or biases to classify them. CNN's goals encompass image classification, clustering based on similarities, and object recognition. The network consists of four layers, starting with the convolutional layer, the algorithm's core, which performs the primary computational work using filters or kernels. The Activation layer follows, employing the rectifier function (ReLU) for improved non-linearity. The third layer, Pooling, aids in down sampling image features, incorporating hyperparameters like the dimension of spatial extent and stride.[4]

3.2 DenseNet201:

Several researchers overlook the prerequisite for input images to adhere to specific criteria for CNN's optimal functionality. The algorithm necessitates high-quality images with a white background for efficiency. While some studies use realistic images, they neglect unforeseen consequences. To address this discrepancy, DenseNet 201 is employed to minimise errors and enhance performance. DenseNet is recognized as a top performer in image classification on popular datasets like CIFAR-10 and ImageNet. It employs a straightforward pattern, connecting layers directly in a feed-forward manner, where each layer incorporates additional inputs from preceding layers and transmits its own feature maps to subsequent layers.[4]

3.3 VGG16:

VGG16 stands out as a Convolutional Neural Network (CNN), recognized as one of the most advanced computer vision models. The model's creators enhanced its depth by employing an architecture with compact (3 × 3) convolution filters, resulting in a notable improvement over previous configuration. The depth was extended to 16–19 weight layers, totalling approximately 138 trainable parameters. A Convolutional Neural Network, also referred to as ConvNet, comprises an input layer, an output layer, and multiple hidden layers.

4. DATASET ANALYSIS

In order to perform classification, we used the Chest X-ray Pneumonia Dataset which is a hugely popular dataset available, sourced from Kaggle, a crowd-sourced and open-source platform used by data scientists and hobbyists around the world to get trained and challenged to solve numerous real-world problems. The Chest X-ray Pneumonia Dataset consists of 5863 images of X-ray images distributed over 2 different classes which are scans of normal and abnormal chests. The images are then split in the ratio as train, validation and test data. We then resized every image into 256x256 pixels for the purpose of training and evaluating our model.

5. PROPOSED METHOD

Humans are susceptible to a variety of diseases. By using deep learning algorithms, we are detecting and also classifying the presence of pneumonia. Deep learning, a vibrant research area in image classification and computer vision, employs Convolutional Neural Networks (CNN) with input and output layers and multiple hidden layers, including convolutional, pooling, fully connected, and sometimes Sigmoid layers. Utilising the New Chest-Xray-Pneumonia dataset, featuring normal and abnormal Chest X-rays, we trained a CNN with six layers, augmenting images through ImageDataGenerator to enhance dataset size.

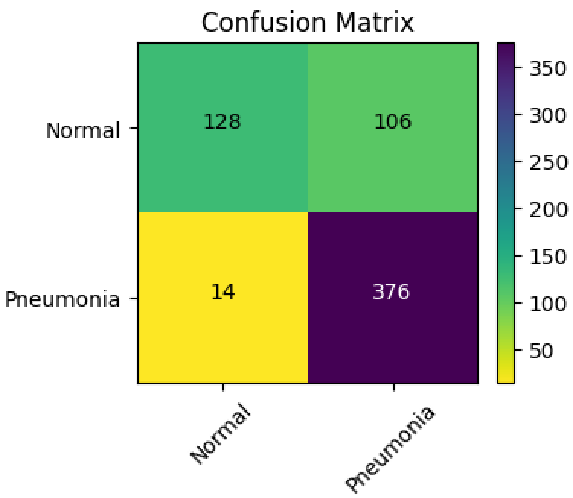
While promising, we explored alternatives like DenseNet201, a pre-trained model with 201 layers, and VGG16, which enhances depth with (3 × 3) convolution filters. Comparatively, results were more promising with VGG16, and our primary goal was to assess the accuracy and efficiency of all three models.

The models considered the background of images to evaluate performance, recognizing that the datasets with plain backgrounds lacked practical realism.

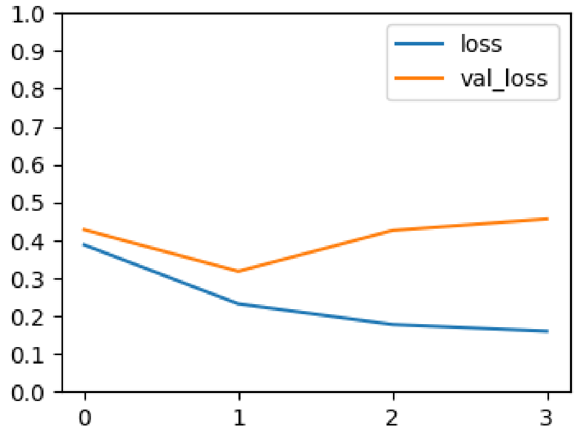
6. PERFORMANCE ANALYSIS

6.1 Convolutional Neural Network (CNN)

The interactive heatmap presents the confusion matrix, offering a graphical summary of predictions. This matrix contrasts actual test images with model predictions generated by CNN after the training process. Rows correspond to predicted classes, while columns represent the actual test values. From the table it is evident that model predictions are almost accurate, But we can also infer that the normal class has more misclassifications. These are indicated by the intensity of the green colour, i.e., the more intense the colour, the more accurate the prediction is. The intensity level can be viewed on the right side.

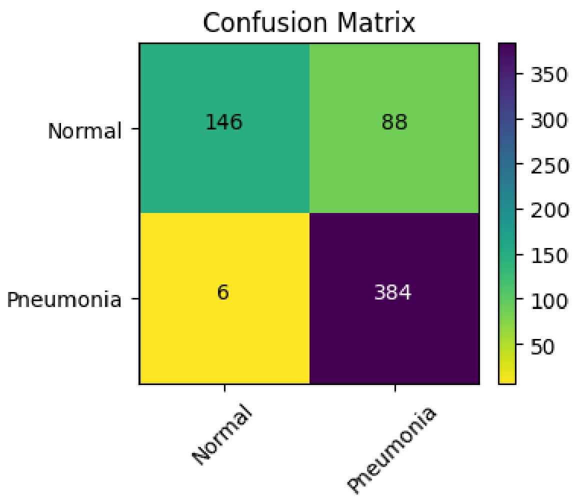


The graph depicts the plot between loss and validation loss of CNN model training. We used 5 epochs and patience as 2. While in the beginning, the loss is very high around 0.4, validation loss is below 0.5, during training, till the first epoch, both loss and validation loss comes down. During the 2nd epoch, there was a substantial increase in validation loss even though the loss was decreasing, the training still continued as we specified patience as 2. After the 3rd epoch the validation loss continues to rise, and the model initiates early stopping.

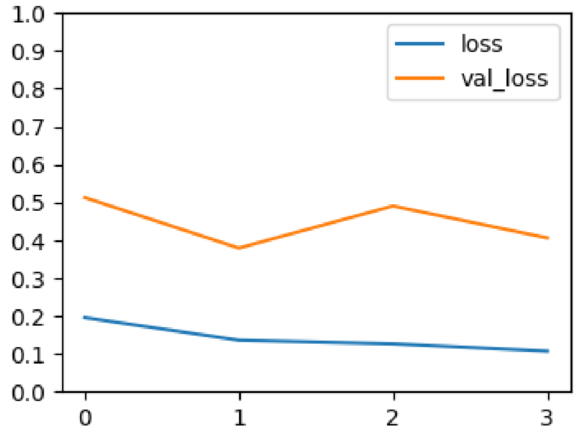


6.2 DenseNet201

The interactive heatmap presents the confusion matrix, offering a graphical summary of predictions. This matrix contrasts actual test images with model predictions generated by CNN after the training process. Rows correspond to predicted classes, while columns represent the actual test values. From the table it is evident that model predictions are almost accurate, But we can also infer that the normal class has some misclassifications. These are indicated by the intensity of the green colour, i.e., the more intense the colour, the more accurate the prediction is. The intensity level can be viewed on the right side.

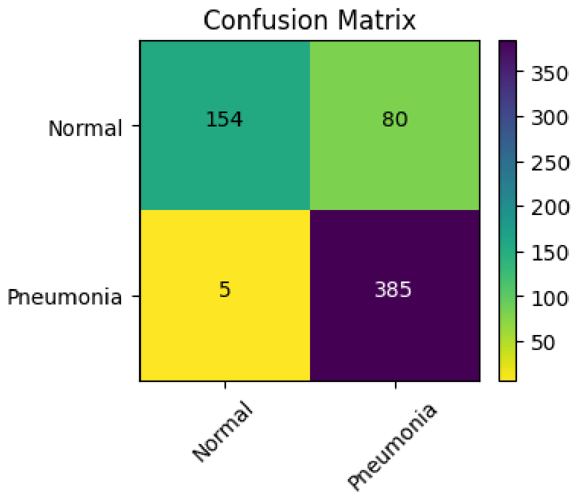


The graph depicts the plot between loss and validation loss of CNN model training. We used 5 epochs and patience as 2. While in the beginning, the loss is very high around 0.2, validation loss is above 0.5, during training, after the first epoch, both loss and validation loss comes down. During the 2nd epoch, there was a slight increase in validation loss but it decreased again in the next epoch, the training still continued as we specified patience as 2. After the 3th epoch the difference between validation loss and loss continues to rise, and the model initiates early stopping.

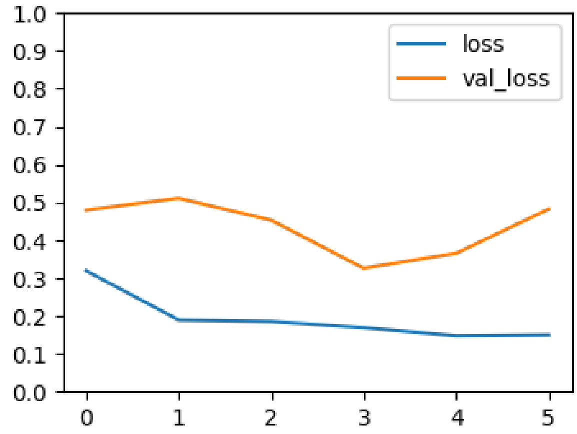


6.1 VGG16

The interactive heatmap presents the confusion matrix, offering a graphical summary of predictions. This matrix contrasts actual test images with model predictions generated by CNN after the training process. Rows correspond to predicted classes, while columns represent the actual test values. From the table it is evident that model predictions are almost accurate, which is indicated by the intensity of the green colour, i.e., the more intense the colour, the more accurate the prediction is. The intensity level can be viewed on the right side.



The graph depicts the plot between loss and validation loss of CNN model training. We used 5 epochs and patience as 2. While in the beginning, the loss is very high around 0.3, validation loss is below 0.5, during training, after the 1st epoch, loss comes down and validation loss increases. After which in subsequent epochs, the loss and validation loss decrease. From the 3rd epoch, there was a slight increase in Validation loss. The training continued as we set the patience as 2. After the 5th epoch the validation loss continues to rise, and the model initiates early stopping.



7. CONCLUSIONS

This research delves into the application of deep learning concepts, specifically convolutional neural networks (CNN) and transfer learning, to investigate their impact on pneumonia detection. Utilising the Chest-Xray-Pneumonia dataset, three CNN models were employed: a basic CNN built from scratch, the pre-trained Densenet201, and VGG16. Results indicate that VGG16 consistently outperforms the basic CNN and pre-trained DensNet201 models in classifying the two pneumonia classes. Image augmentation techniques were employed during network training to enhance classification accuracy in various scenarios.

Our model faces limitations in handling black and white noise in the images for prediction and the absence of a precisely scaled and accurate Chest X-Ray image dataset. We aim to enhance the efficacy of image augmentation in mitigating the challenges posed by complex variations in test images and aspire to create an application enabling users to predict pneumonia at a very cheap rate.

8. ACKNOWLEDGEMENT

I extend my heartfelt gratitude to Saai Vignesh P for his valuable guidance and support in dataset augmentation & model training. His insightful feedback, and support significantly contributed to the refinement of this study.

9. REFERENCES

[1] Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Mohsen Ghafoorian, Jeroen A.W.M. van der Laak, Bram van Ginneken, Clara I. Sánchez, “A survey on deep learning in medical image analysis”, Medical Image Analysis, Volume 42, 2017,

[2] Alapat DJ, Menon MV, Ashok S. A Review on Detection of Pneumonia in Chest X-ray Images Using Neural Networks. J Biomed Phys Eng. 2022 Dec

[3] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019

Vishnuvaradhan Moganarengam, Saai Vignesh P, "Plant Disease Classification using CNN and DenseNet, a Comparative Study", IRJET, Chennai, India, Nov 2021