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Research Article

Automatic Pneumonia Diagnosis Using Capsule Network Working in Alignment with CNN Model

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Abstract
As a result of the COVID-19 pandemic, the populace has seen one of the most drastic periods in human history, and the ailment tends to grow fast across the worldwide. It is believed that the disease primarily causes respiratory issues in humans. Recognising this disease has also tend become a difficult activity due to the fact that both diseases have comparable effects on the lungs. It is believed that pneumonia is an infection raised by bacteria in parts of the alveoli in lungs that, if left untreated, can result in death. Thus, the development of an automated method to diagnose the sickness could be advantageous to the human species. As a result of the ongoing growth of these areas of research, it has been seen that the basics of deep learning and machine learning continue to contribute to the execution and examination of healthcare based images and the performance classification of the same. In this study, we evaluate the CNN model and a CNN based encapsulation featured capsule network for predicting impacted and unaffected chest X-ray images patients.
Keywords: automated, CNN, capsule, pneumonia, deep learning

Introduction

The occurrence of Pneumonia in a human individual is characterized by syptoms that might directly target the respiratory system of the body and therefore block ways for air to pass to the lungs. In addition to blockage of air; a presence of liquid form of sac is also witnessed in such a scenario; wherein it might result a person in short of breath and thereby cause breathing problems. The disease tends to block the entire respiratory system and cause harm to the human body by making him difficult to breath. The disease is further caused by microorganisms and viruses, which result in the release of fluids that infect the alveoli of the lungs. Pneumonia is typically observed in individuals with weakened immune systems, such as the elderly and babies; it has caused huge deaths worldwide since 2017 and continues to be a lethal infection if not properly detected [1]. Among MRI and CT-Scans, radiographs are regarded as one of the most important tools for detecting the existence of pneumonia in an individual [2]. On the other hand, analysing chest radiographs is not a pleasant chore for radiotherapists. Figure 1 on the left depicts the presence of air in lung cavities, which looks blatantly evident in a typical patient's chest cavity. Similarly, picture 1 on the right seems bright because lung sacs typically contain fluids. Numerous irregularities in the lung cavities are characterised by a stronger colour, which may indicate the presence of cancer cells or heart issues. Thus, the task is challenging, and the development of a technology to detect thoracic disorders such as pneumonia will improve its identification in remote places. In this study, we examined the performance of ResNet50v2, a variation of a pre-trained CNN model, which was preceded by picture classification and disease detection. The following are the essential contributions of the study:

- Use the CNN-based ResNet50v2 model as the basis
- Assess the model's performance in terms of pneumonia detection accuracy
- Remove the limitations of the existing systems

Figure 1: Pneumonia-free on the left and positive on the right

Literature Survey

Extensive research has revealed that the bulk of disease classifications have been performed utilising deep learning and machine learning.

Authors in [3] constructed a DCNN-based neural network capable of detecting the presence of tuberculosis in a patient and correctly classifying them as affected or unaffected. Using chest radiography, the working method was conducted using GoogleNet and AlexNet, and the model attained an overall accuracy of 97%. Authors in [4] published lung nodule classification using CAD, where the authors applied deep learning techniques for tumour distinction. Similarly, Authors in [5] employed similar techniques to detect disease infection in heart and lung segmental sections.

Authors in [6] evaluated a larger dataset and implemented it to a higher standard than the radiologists themselves. The effort increased its contribution to detect 14 diseases from a large number of generated datasets. The model's name was changed to ChexNet. Authors in [7] investigated the same dataset of ChexNet and proposed the identification of pneumonia using logistic regression. The authors of [8] implemented their work using ImageNet, which provided pneumonia-positive or pneumonia-negative binary classification. The authors of [9] employed a CNN model on X-Ray images and SVM as the classifier to detect the same.

Authors in [10] conducted a comparison analysis for detecting lung infections from distinct radiographic angles that tend to be obscured from a certain perspective. The authors created a method that could be utilised whenever an X-Ray image was presented to a practitioner. As a result of their efforts, 15% of the lateral view that was often concealed during the diagnosis of pneumonia was uncovered. Using PCA and discrete wavelength approaches, Authors in [11] identified MRI images of 66 patients. Their research was predicated on the notion that DL is utilised in the majority of medical detection applications; hence, the authors proposed the identification of pneumonia in patients as a crucial method for resolving complex issues. Authors in [12] obtained a database including 32,717 photos of thoracic patients and screened them using radiography. The study was complemented by a hospital-obtained dataset containing information on pneumonia pictures. The observed classification accuracy of the approach for infected patients was 98%. Moreover, CAD systems were utilised to facilitate the research.

Authors in [13] did a study using 20,000 photos to detect pneumonia in infected patients. The study project was based on a DL model with an approach to the CNN concept. The method of feature extraction was performed on 224 picture pixels in 20-pixel batches. The strategy assisted medical practitioners in diagnosing the illness in its early stages, when patients exhibited minimal symptoms. In addition, CNN's trained algorithm could categorise infectious patients as normal or pneumonia-positive. In addition to detecting and differentiating viral fevers such as pneumonia and COVID, the complete operating procedure may also detect and identify viral fevers such as pneumonia.

Authors in [14] experimented with lung segmentation with a technique for dimensionality reduction. The BSE-JRT dataset was used to conduct the study, which assisted physicians in identifying lung-related disorders directly on CXR pictures. The presence of outliers in the dataset enabled the elimination of bone shadows and the implementation of lung segmentation diagnostic.

Methodologies Used

This section of the research paper highlights on the methodologies thus used to implement the execution of the proposed research. It primarily involves the concepts of deep learning and deep learning based CNN, followed by capsule networks and ResNet50.

B. Deep Learning

The working concept of deep learning is primarily based and considered to be as the subset of machine learning algorithms; wherein the execution takes place through the occurrence of neurons. The neurons are thus present as a part of hidden layers in a CNN and thereby form as a base to Artificial Intelligence (AI) [15]. The working of deep learning is however considered to mimic the working of a human brain wherein all the respective neurons are connected to each other through neurons. Hence, a deep learning based algorithm tends to imitate the human brain and thereby performs classification and helps to predict the respective system models.

Therefore, this subset of AI forms the architecture in conjunction with respect to the processing models which were thus used in the late 1980's [16]. DL is defined as the addition of a multilayer network for feature extraction to the ML architecture. In DL architecture, each layer uses the output of the layer below as its input, passes it to the layer above, and repeats the process. Transfer learning, on the other hand, refers to a concept in which data collected and utilised on one dataset can be applied to another dataset with a much smaller population to train, provided that both datasets work on a CNN architecture target with a comparable purpose. In a conventional CNN, this technique is implemented by training the starting parameters using massive datasets. A deep learning model is selected based on a CNN's capacity to extract features. This method is called feature extraction [17]. This method's primary objective is to preserve both the neuron weights and architectural structure of a CNN model.

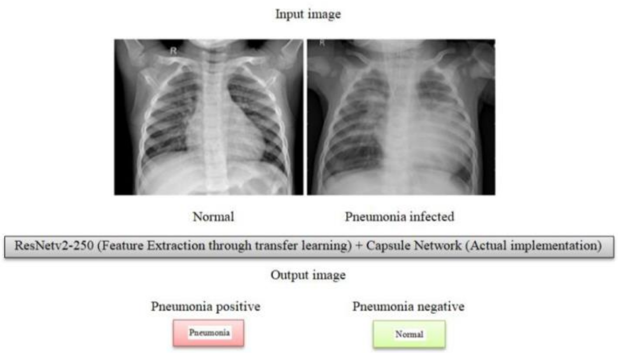

Figure 2: Overall workflow of the research

C. Convolutional Neural Network

A typical convolution layer comprises of multiple neurons within itself that are connected to each other and thereby executed through the working implementation of mimicking a human brain. The entire implementation occurs through the implementation of a feed forward based neural network wherein the implementation is divided in to two phases; with each phase responsible to perform feature extraction technique and thereby classifying the respective features thus obtained. The entire implementation is iterated until the final output from the process of classification is obtained. However, the execution takes place in terms of layers and occurs through the execution of mathematical operations such as convolving multiple layers together to accomplish a certain level of biases which can further be assigned to the respective weights of the neurons. Following are the layers thus involved in a typical convolutional neural network:

- Convolutional layer
- Pooling layer
- Fully connected layer

For the process of execution of a CNN; the initial two layers of the CNN are responsible to perform the feature extraction and execution process wherein an image is given as input and thereby used to extract features that are relevant to the execution of the system model. The output from this layer is further given as input to the next layer wherein the features thus extracted are used for the purpose of classification in the next stage. It is primarily in this stage that the occurrences of mathematical operations of carrying out respective convolutions are performed. With respect to the weights and biases thus attached to the neurons; all the activation functions are performed and the stage of image processing is thus carried out. At this stage; the kernels are also thus involved in the entire processes which are responsible to establish grid patterns amongst the images obtained from the repository. This process tends to enhance the image processing stage and thereby increases the overall performance of the system model. Figure 3 below depicts the working layers of a traditional CNN:

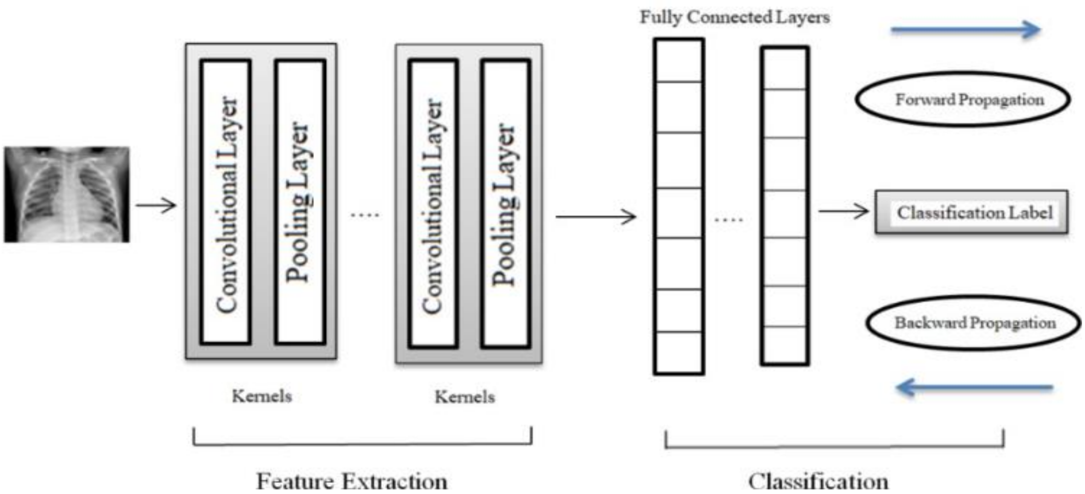

Figure 3: Conventional illustration of CNN

D. Capsule Network

The fundamentals of convolutional neural network tend to exhibit and the requirements thus needed to implement the proposed research. However, the notion of utilizing multiple hidden layers of deep learning based algorithms is fulfilled through the implementation of capsule networks. All the existing limitations of a conventional CNN is overcome through the implementation of capsule networks. One of the most significant layers of the CNN model tends to be the convolution layer and happens to be the first initial layer of the architecture. This layer is further enhanced through the usage of capsules; wherein multiple layers are combined together and encapsulate together to effectively use the available data. This is termed to be as the upper layer of the capsule and thereby meets all the hierarchical needs of deep learning based models. The associated hidden layers also tend to simplify the complexity of the system thus involved by establishing a transalational relationship between the associated layers. Primarily, a capsule network is an extension to the existing layers of CNN; wherein all the limitations of CNN are thereby eliminated through its usage. One such limitation of a CNN is that the rotational transformations of CNN are easily overcome through the implementation of capsules. This however leads to the generation of scalar entities and thereby produces scalar vectors. In the next stage of its implementation, the involvement of pooling layers are also implemented through the execution of max pooling layer and using its respective activation function such as ReLu.

E. ResNet50v2

Throughout the literature survey thus conducted it can be observed that the implementation of deep neural networks based on deep learning involves the working of multiple hidden layers within itself. The layers thus present helps to process an image thus provided to the machine for further classification of pneumonia patients. The hidden layers of the same help into the process of image classification and thereby simplify the process of complexity thus involved in the entire process. This helps to enhance the overall robustness and efficiency of the system model thus developed. The creation of one such deep learning b=network which is based on the concepts of hidden layers is termed and referred to as ResNet50. The hidden layers present in this network helps to reduce the overall complexity of the system model and thereby tends to increase the overall accuracy of the system model. A conventional illustration of a ResNet model is depicted in figure below:

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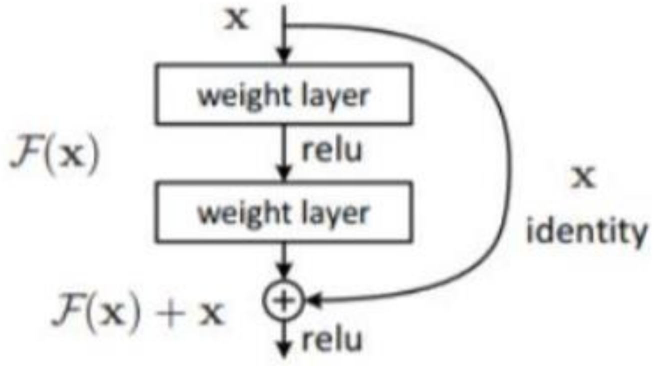

Figure 4: ResNet50v2

The diagram above depicts a linkage that has been established between the respective nodes by assigning the neurons their weights. In addition to this, once the linkage is created, steps of skipping a connection are performed. This step is a significant step in the ResNet architecture and however differs from the output which is so generated. The established skip connection is further called upon its requirement and thereby multiplied by its factor of weights assigned to the respective neurons.

Implementation Details

Researchers have always taken in to consideration to verify a human chest X-RAY in cases were respiratory diseases were in concern. This however occurred in the healthcare area as fascinating. In addition, as datasets are not publicly accessible, addressing this barrier is difficult for them. This research yielded a dataset consisting of 25 photos equally distributed as affected pneumonia patients and not affected pneumonia patients. The images that were initially obtained from the Kaggle repository comprised of two csv files with positive and negative pneumonia patients which were in the JPEG format. The files were further labelled in accordance to the symptom's thus observed from the patients. The initial resolution of the supplied X-Ray images is 1024 pixels, which must be lowered to the appropriate level. In the subsequent step, the image's dimensions are lowered and cropped to obtain uniform measurements across the whole dataset. Images are downsized from 1024 pixels to 224 × 224 pixels as a result. In addition, the dataset is partitioned 80:20 for training and testing purposes. At the subsequent occurrence of the data pre-processing phase, enlarged pneumonia images were converted to binary 0s and 1s. This process was referred to as the process of binarization wherein the obtained image from the Kaggle repository was proposed to be converted into its respective grayscale format so that it could be recognisable by the machine learning algorithm. However, the resolution of the image thus obtained was in the size of 224 x 224 pixels. Figure 5 below briefs on the steps thus carried out to execute the implementation of the research study:

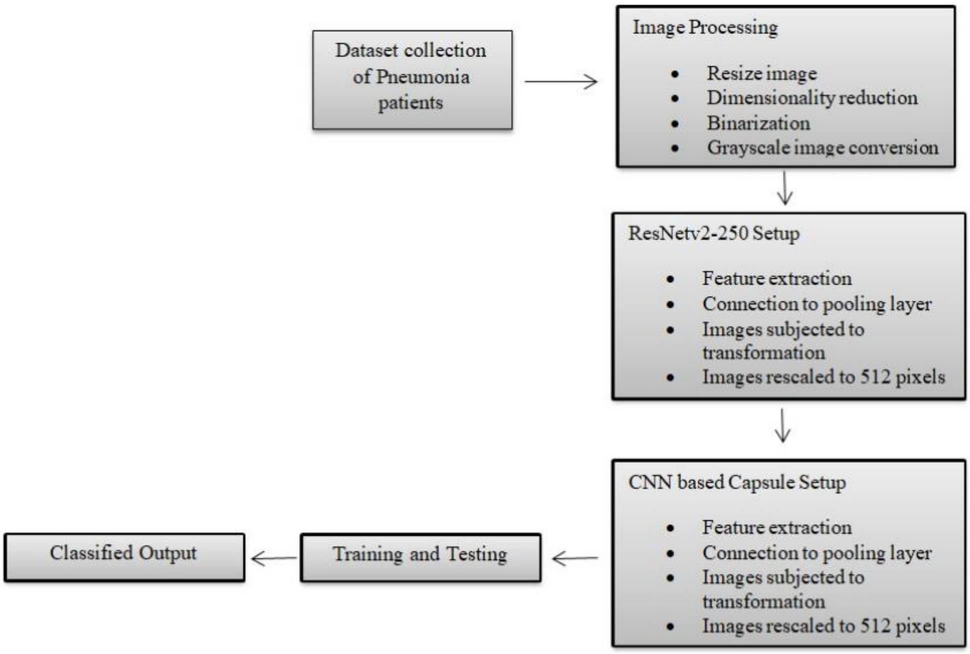

Figure 5: Flow of the study

Results

The accuracy measures thus obtained on the implementation of the research study provided optimised results when combined with the concepts of CNN and capsule networks. With the initialization of 10 cross fold validation; the technique was enhanced in an overall manner and the results were then obtained through classification. Since the dataset included and comprised of images obtained from patients suffering of pneumonia, a binary form of classification was performed so that the dataset could be labelled as either pneumonia positive or negative. However, the radiographic images thus obtained upon the process of image generation using deep learning algorithms; tends to have patients categorised as healthy and diseased. However the overall accuracy and precision thus obtained upon implementation was witnessed to be 0.97 for diseases patients and 0.96 for healthy patients. The loss and accuracy curves are depicted in figure 6 (a) and confusion matrix in 6 (b) wherein the details of accuracy are determined. The table also gives the numerical statistics and figures thus obtained on experimental analysis.

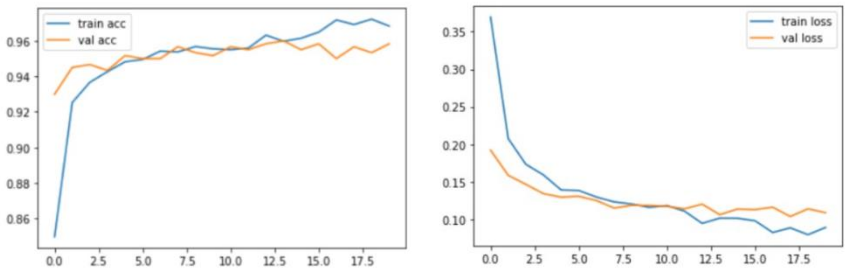

Figure 6 (a): Train and Validation loss of CNN model

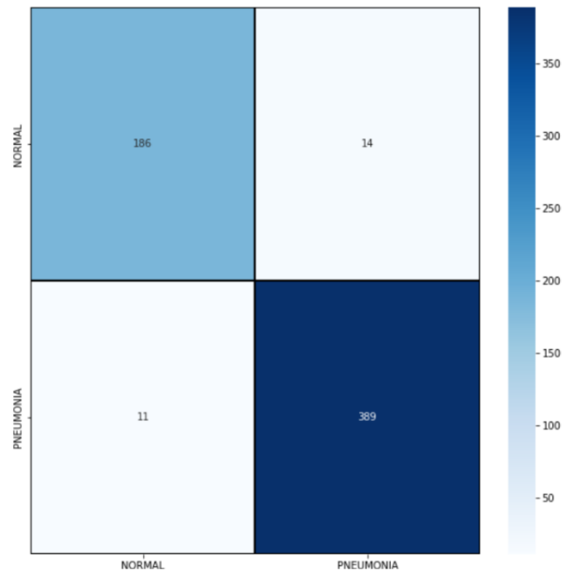

Figure 6 (b): Confusion Matrix of CNN model

The accuracy thus obtained on the conduction of the experiment is witnessed to be 0.97 in an overall manner. If the values of true positives and negatives are also taken into consideration; it can be derived that the total set in the database obtained from repository had 186 healthy patients and 389 diseased patients as identified through the implementation of machine learning algorithms. In addition to the healthy patients who were misclassified has a count of 14 cases.

Table 1: Accuracy obtained through CNN model

Performance Metrics			
Class	**Precision**	**Recall**	**F1-Score**
Normal	0.94	0.93	0.94
Pneumonia	0.96	0.96	0.96
Accuracy	0.97		

Conclusions

Individuals diagnosed and treated promptly for pneumonia have a greater probability of healthy living. A machine based application can automatically detect the presence of pneumonia using pictures of CXR. One of the medical systems that contributes to the education of radiologists and helps to improve the diagnostic validity of pneumonia, it is one of them. To improve healthcare quality while reducing costs and reaction times, it is crucial to build a real time system model for the automated identification of pneumonia. This paper's principal objective is to improve medical competence in regions where radiotherapists are still limited. So, the objective of this research is to identify whether or not an individual carries the virus that causes pneumonia. The authors of the study have suggested making use of capsule networks in conjunction with CNN in order to put their findings into action. Utilizing the pneumonia dataset, a performance study is conducted to determine the model's accuracy. For pneumonia-positive cases, the collected data achieves a precision factor of 97% with a recall factor of 0.96. Further research could include the detection of different thoracic illnesses.

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