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A Convolutional Neural Network ensemble model for Pneumonia Detection using chest X-ray images

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ABSTRACT

Pneumonia is a respiratory infection caused by microbes and other environmental factors. It infects the lungs causing a buildup of fluid and difficulty in breathing and is the leading cause for death in children under the age of 5 years. Timely detection proves essential in preventing adverse consequences including death. However, most areas in underdeveloped and developing nations do not have access to conventional diagnostic measures, preventive measures and adequate expert treatment. Computer-aided systems based on machine learning techniques can aid this task. However, most smart diagnostic systems may have the drawback of requiring extensive hardware and heavy computation power. The objective of this experiment is to develop a lightweight, deployable and accurate model to aid in the detection of Pneumonia. A Convolutional Neural Network architecture utilizing three different models of varying kernel sizes was developed. The outputs of these models were combined using a novel weighted ensemble approach which proposes an adjustable threshold value to change the model's diagnostic capabilities as required. The flexible threshold value provides a means to adjust the weightage given to each model's output and hence change the classification result depending on the actual case on hand. The model was evaluated on metrics including accuracy, recall, precision and f1-score and was able to achieve a high recall value of 99.23% with an f1-score of 88.56% which are critically high values for the given domain resulting in almost no chances of a Pneumonia positive case being misclassified. The absence of transfer learning or deep neural networks makes the model lightweight and hence, a plausibly deployable diagnostic-aid solution. Further studies were carried out to find methods such as – larger dataset, better preprocessing and more – to improve the model performance.

1. Introduction

Pneumonia is an infection of the lungs in which the air sacs inside the lungs get filled with pus and fluids, inhibiting the oxygen intake and making breathing painful. It can be caused by viruses, bacteria, immunological disorders, chemicals and in some cases fungi. Based on different infections, Pneumonia can be classified into CAP (Community Acquired Pneumonia), HAP (Hospital Acquired Pneumonia) and VAP (Ventilator Acquired Pneumonia). CAP accounts for the largest proportion of Pneumonia cases.

Pneumonia is a widespread disease, especially among children in socio-economically backward areas who do not have access to medicines, diagnostic procedures and other preventive measures. It is the single largest infectious cause of death in children worldwide, killing 740,180 children under the age of 5 in 2019, hence accounting for 14% of all deaths of children below five years of age [1]. The greatest incidence can be noted in South Asia and West and Central Africa [2]. The prevalence of Pneumonia also increases with age [3], posing a risk to people above the age of 65.

Due to the heavy mortality rates in children, researchers and scientists all over the globe are pursuing more accurate and effective methods to detect Pneumonia.

In 1990, India recorded 690,912 deaths due to Pneumonia and related complications. Out of this number, 522,086 deaths were in children under 5 years of age. However, by 2015 the number of deaths in children under 5 had drastically fallen to 191,418 which is almost one-third of the figure in 1990 [4]. This decrease can largely be attributed to better health technologies such as vaccines but mostly due to improved detection techniques.

Over time, the figure for deaths in elderly due to Pneumonia has steadily risen. Though this rise is attributed to the decrease in environmental factors [5], it is still important to note that early detection can highly boost the chances of receiving adequate treatment. Delay in treatments can drastically increase the chances of death.

A child with symptoms of Pneumonia such as difficulty in breathing should be taken for a diagnosis or a medical expert. This lack of

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availability of diagnosis is highly prevalent in Sub-Saharan African countries with figure lying between a meagre 20%–40%.

Increasing availability of diagnostic techniques and treatments across backward regions can result in a drastic decrease in the mortality rates. Hence, the most important step in battling Pneumonia becomes timely and accurate detection.

Generally, a biological tissue sample or image of the infected area is required for diagnostic procedures. For Pneumonia detection, conventional techniques mainly include a lung biopsy by means of a needle (Needle Lung Biopsy) [6]. This is one of the most primitive and conventional techniques for Pneumonia Detection. The main challenges faced in this technique is the analysis time and requirements on the tissue sample. In backward regions, despite drawing samples, unavailability of sufficient technology can cause a delay of several days by which the disease can increase in severity. The other risk with lung biopsies, is the complications after the test which include hemorrhage and other complications in pulmonary nodules [7].

With the advent in technology, superior technologies have been developed for carrying out lung biopsies [8,9]. However, all procedures have certain risks associated with them.

Chest X-rays are the most common procedure to detect Pneumonia. X-rays of the thoracic cavity are captured and evaluated by expert physicians. Infectious areas are spotted by identifying white spots in the lungs. These images can also help identify other complications such as abscesses or pleural effusions. A lot of expertise is required post X-ray procedures as well as determining whether a radiological scan is required [10]. However, this procedure has its own problems. A good-quality chest X-ray is often difficult to perform and to interpret in ≥ 65 years old, and other techniques need to be adapted for this [11].

Computed Tomography (CT) scans shows the finer details of the lungs than may be visible in an X-ray and proves to be a better alternative in certain cases [12,13]. It also details other important parts such as the airways. The low-dose computed tomography, a variation of computed tomography (CT scan) proved to be a more adequate tool for diagnosing pneumonia in the elderly population [11,14].

Both these procedures involve radiation, which can cause cancer despite the risk being small [15,16]. Both of these techniques are ultimately analyzed by humans. This leaves room for error despite the involvement of expertly trained professionals. Computer driven solutions however, do not involve humans and are relatively free from that risk. Such solutions are currently on the rise driven by computer vision and machine learning techniques.

Machine Learning techniques utilize calculative powers of computers optimally to learn patterns from the data provided. This information can then be used to make predictions on other data samples. These techniques employ mathematical algorithms to learn the information and can be applied on a vast range of data such as images, text, audio, real-time video feed [17], etc. Machine Learning and Deep Learning techniques are constantly evolving and have been widely used in the medical domain with beneficial results [18–20].

Pneumonia Detection is a classification problem in which the data provided must be classified into the category of Pneumonia or Normal. Different machine learning algorithms for classification problems can be adopted for this task.

Support Vector Machines (SVM) can be used for regression as well as classification and work on the principle of decision boundaries [21]. A support vector machine can be used on numerical data processed and obtained from images [22,23].

K-Nearest Neighbors (KNN) is a lazy learning algorithm which classifies samples based on distance to other neighboring samples. KNN can be applied in various ways such as on feature extracted numerical data [22], audio data [24] and more.

Other machine learning classification techniques such as naïve bayes classifier, random forests, etc. can also be applied [23,25,26]. However, Convolutional Neural Networks (CNN) prove to be the most efficient at classifying Pneumonia Images from chest X-rays and scans [27] and [28].

The recent COVID-19 pandemic resulting in a rise of Pneumonia cases has once again showcased the problem Pneumonia poses to our society as a whole. The main motivation of the authors behind the experiment and subsequent article is to combat the widespread impact Pneumonia has on the backward elements of society due to the unavailability of accurate and accessible diagnostic technologies and timely cure. The main contributions the authors hope to make with this novel technique is to provide a lightweight deployable solution that does not require extensive hardware and is easily accessible. Furthermore, the flexible classification technique employed should allow medical experts to easily tweak the model to adjust to the actual cases they have on hand. The authors hope that the suggested approach can aid and pave way for solutions for early detection of Pneumonia. This can help experts to improve upon existing diagnostic techniques and enable early detection of the disease even in backward regions. This, in turn, can enable adequate cure and preventive measures ultimately resulting in lower mortality rates and maximum recovery.

2. Related works

Over the years, several researchers and scientists have experiment with various methodologies to perform Pneumonia Detection.

Stokes et al. [29] employed three machine learning techniques – logistic regression, decision trees and SVM – to classify clinical information of patients into bronchitis or pneumonia. The decision tree technique provided the fastest result with the highest recall value of 80%. Other metric values such as AUC had an average value of 93%. The authors discuss that the reliability on symptomatic information can provide results up to only a certain amount of accuracy. Using image information that can physically locate traces of the disease can provide better diagnostic as well as predictive results.

Yue et al. [30] utilized CT scan images and used 6 features to detect Pneumonia. The model achieved an AUC of 97% but the evaluation was carried on small datasets and hence cannot be generalized.

Compared to classical machine learning models, Deep Learning models based on CNN architectures tend to deliver superior results.

Stephen et al. [31] formed and trained a custom CNN model from scratch. The model produced a maximum training accuracy of 95.31% and a validation accuracy of 93.73%. Data augmentation techniques were also implemented in the preprocessing.

Transfer learning models are CNN architectures that have been pre-trained on certain classes of images. These models can be used as stand-alone CNN models for training or as feature extractors.

Rajpurkar et al. [32] utilized the DenseNet-121 [33] CNN model on the ChestX-ray14 dataset [34] consisting of 112,150 frontal chest X-ray images. The model achieved an f1-score of only 76.8%.

Only accuracy scores cannot be used to evaluate a model's performance. In medical domain tasks generally, recall values must also be high as the need to prevent false negatives is high.

Varshni et al. [35] used DenseNet as a feature extractor and applied an SVM classifier on the processed inputs. The dataset used was ChestX-ray14. Various transfer learning modules were experimented before fixing DenseNet. The model achieved an AUC value of 80.02%.

Kundu et al. [36] used an ensemble model of three transfer learning architectures — GoogLeNet, ResNet-18 [32] and DenseNet-121. The final proposed model achieved an accuracy of 86.85%. However, incorporating three transfer learning models into an ensemble technique proves to be computationally expensive.

Zhang et al. [37] proposed a confidence-aware module to carry out the task of anomaly detection in chest X-ray images. This model worked only on determining the anomalies and gave an AUC score of 83.61%.

While Transfer Learning models help reduce the effect of data scarcity as they are trained on a larger dataset, employing such architectures and training them results in heavy computational expenses. Simpler CNN models on the other hand are much less computationally

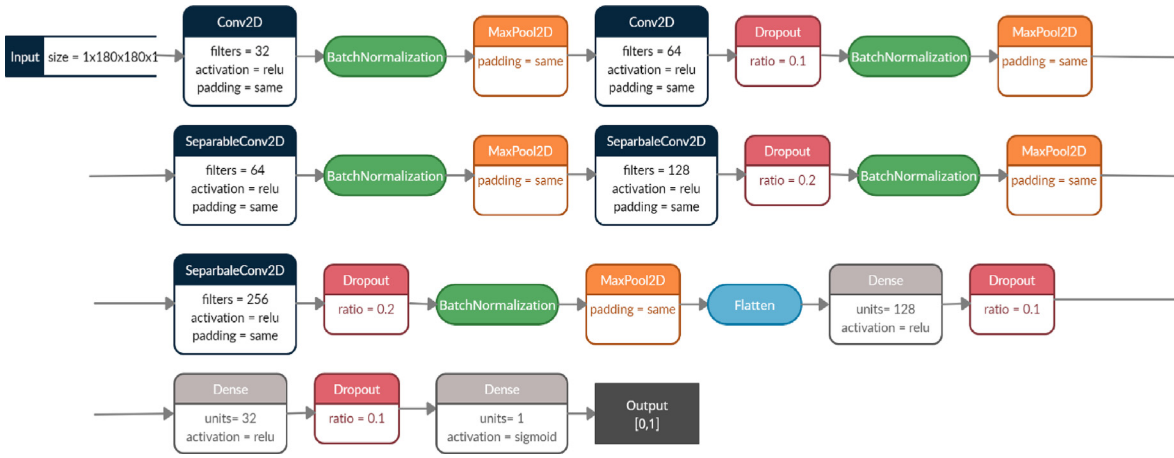

Fig. 1. CNN architecture used for this experiment.

expensive. Combining more than one model, or employing ensemble techniques on simple CNN models has not yet been explored in depth.

This paper aims to experiment with an ensemble network of 3 CNN models, to keep the computational expense low while simultaneously maintaining accuracy and other metrics. The outputs of the models are weighted according to their performance and a manual threshold value is used to evaluate the final prediction. The choice of a manual threshold value helps change the final classification and can be used to change recall and precision values as per the requirements in the field (Fig. 1).

3. Dataset and methodology

3.1. Dataset

The dataset used in this research has been provided by Guangzhou Women and Children's Medical Center, Guangzhou and is available as an open dataset on Kaggle. All low quality and unreadable images had been removed before the analysis process. Two expert physicians then graded the diagnoses for the remaining images [38].

The dataset includes 5863 images in JPEG format belonging to two categories — Pneumonia and Normal. It has been divided into three folders, namely — train, test and val. Each folder contains two subfolders of images diagnosed Pneumonia and Normal categories. The train folder contains 5216 images — 3875 of Pneumonia category and 1341 Normal of category. The test folder contains 624 images — 390 of Pneumonia category and 234 of Normal category. The val folder contains only 16 images — 8 of Pneumonia category and 8 of Normal category.

Although the sizes of the images vary, they are all of high quality and have been subsequently resized into the same size before being given to the model for training. Images of the category "Pneumonia" were more than the category of "Normal" images. To solve this problem of imbalance, data augmentation was used. Some examples of images are:

3.2. Pre-processing

Usually, before training a model, the dataset must be pre-processed to allow optimal and error-free running of the model. Original images are in RGB format, but they have been converted to grayscale and resized to 180 × 180 pixels for the purpose of this research. The pixel intensity values were then divided by 255 to normalize them. This changes the range of the pixels from 0–255 to 0–1. This prevents bigger values from influencing the model's learning and should hence, provide a positive outcome.

Data Augmentation helps remove imbalance in the dataset by generating samples of the classes for which data is not available by changing certain aspects of the original images such as rotation, zooming in, flipping the image on vertical or horizontal axis, etc. The Keras API provides functionalities for the same. For this dataset, the techniques used include — rotation, horizontal flipping, width shifting, height shifting.

3.3. Model

A Convolutional Neural Network (CNN) was used for the classification task. A CNN is a multi-layer deep learning architecture consisting of various layers but mainly categorized by convolutional and pooling layers. These layers are used to capture information from image data and extract salient features. CNNs are a breakthrough for tasks operating on image data such as image recognition, classification, etc.

The most important layers in a CNN are the Convolutional layers. These layers are a major improvement over Dense layers as they are able to extract information without disturbing the spatial distribution of images. A neuron in the convolutional layer is connected to only a limited number of neurons in the next convolutional layer [39]. As a result, low level features gain more focus in the first layer and then get aggregated with higher level features in the next layers.

Pooling layers are used to reduce the size of the image without loss of essential information. This is necessary to reduce the computational cost and memory usage. The most common type of pooling and the one that has been used in this experiment is Max Pooling layer.

Two other layers used in this experiment are Dropout and Normalization layers. Dropout layers help prevent overfitting by randomly turning off some neurons for that iteration hence improving the performance of the model. Normalization layers normalize the outputs generated by the computing layers. This helps reduce computation cost.

The ReLU activation function was used in all the layers except the final classifier which uses the Sigmoid activation function. ReLU is faster to compute and does not suffer from saturation problems in deep networks such as the vanishing gradient problem. The Sigmoid function outputs a probabilistic value between 0 and 1 which can be treated as a confidence measure as to which category the input image belongs to. A threshold value can be determined according to which, values above the threshold will be categorized as 1 and those below it as 0.

Three such models were utilized of kernel size 3 × 3, 5 × 5, and 7 × 7 respectively. Such techniques are called ensemble learning techniques [27] and help boost the performance by incorporating the use of more than one similar deep learning models. The final probabilistic

Table 1
Metric values for different models.

Model	Threshold value	Accuracy	Precision	Recall	F1 score
3 × 3 kernel	0.875	85.58	83.33	96.15	89.29
5 × 5 kernel	0.35	83.65	79.88	98.42	88.30
7 × 7 kernel	0.25	75.00	73.12	94.87	82.59
Combined predictions	0.5	84.12	80.04	**99.23**	**88.56**

measures of the three models were then averaged using a weighting scheme as follows:

$$(\mathbf{0.3} \times \mathbf{3} \times \mathbf{3\_model\_output}) + (\mathbf{0.6} \times \mathbf{5} \times \mathbf{5\_model\_output}) + (\mathbf{0.1} \times \mathbf{7} \times \mathbf{7\_model\_output})$$

The 5 × 5 kernel model provided the best results in terms of recall and hence has been given maximum weight followed by the 3 × 3 kernel and finally the 7 × 7 kernel.

3.4. Evaluation metrics

- Accuracy: It is calculated as the number of correct predictions over total number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- Precision: It is calculated as the actual number of positive predictions over total number of positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

- Recall: It is calculated as the number of positive predictions by the model over actual total number of positive.

$$Recall = \frac{TP}{TP + FN}$$

- F1 Score: It is a metric calculated by involving both precision and recall.

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

A threshold value was chosen manually for the sigmoid classifier to classify the input image into Pneumonia or Normal category. Choice of a threshold value helps balance precision and recall as per the requirements. However, recall is prioritized in problems of such domains and has been treated accordingly for this experiment. Hence, the threshold value was chosen so as to maximize the recall value.

4. Results and discussion

The three models provide varying metric values. However, the approach of applying threshold on combined predictions provides the best result. These results are summed up in Table 1.

We can further check the actual values of our classification by plotting a confusion matrix. The confusion matrix for the final ensemble model is given in Fig. 2.

Combining the models improves results as the classification gets done on a majority voting basis. This helps remove inherent bias that each model individually has. As visible from the table above, the ensemble method provides a high recall of 99.23%. This is very essential in the problem domain as it means that 99.23% of Pneumonia cases were correctly identified as the same. Only 5 Pneumonia images have been misclassified as Normal. This result implies that the chances of a positive case not being detected by the model remain very low. However, the precision value is relatively low. We can also see that 96 Normal images have been misclassified as Pneumonia. This shows that many cases that were not Pneumonia positive were falsely classified as such. The threshold value can be adjusted to change these metrics.

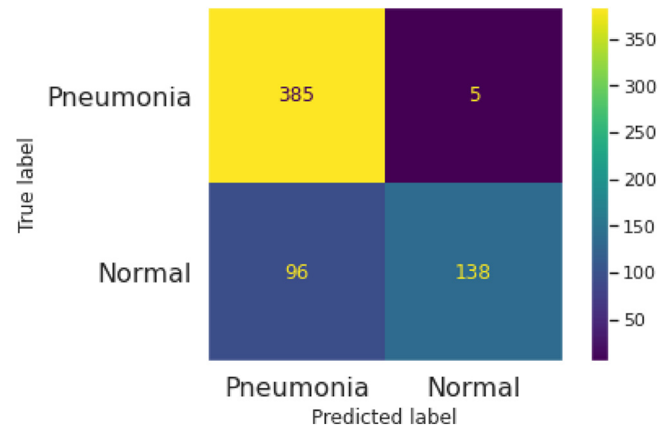

Fig. 2. Confusion matrix for final combined model.

It was observed that a higher threshold value combined with smaller kernel sizes. A mid-range threshold value provided balanced results with medium kernel sizes. This can be attributed to the fact that smaller kernels tend to capture more intricate information whereas larger kernels tend to capture more global information. The smaller details in turn can help minutely classify images hence requiring a higher threshold value.

Ayan et al. [40] implemented a transfer learning ensemble approach on the Kermany dataset, utilizing ResNet-50, Xception and MobileNet. The ensemble network correctly classified a maximum of 381 Pneumonia images out of a total 400 and 217 Normal images out of a total 234. Our proposed approach correctly classifies 385 Pneumonia images and 138 Normal images. Our model has a recall value of 99.23% compared to 97.69% of the transfer learning ensemble network. As the proposed model is to provide a diagnostic aid to experts rather than a stand-alone diagnostic mechanism, the misclassification of Normal cases as Pneumonia can easily be rectified with further clinical testing. The extremely accurate prediction of Pneumonia cases correctly without adding heavy architectures of transfer learning networks is a key advantage of our proposed model.

Kumar Sethy et al. [41] utilized a SVM classifier on deep features of different CNN models on the Kermany dataset. The maximum recall value achieved was 95.33%. Our proposed model provides a better recall value of 99.23% without the requirement of a machine learning classifier on top of a CNN feature extractor.

5. Challenges and future scope

The key to curing Pneumonia is detection or diagnosis from the early traces of the disease in lungs. The main challenges faced by conventional methods of Pneumonia detection such as chest radiographs is that they are subject to inter-class variability and ultimately the diagnosis is dependent on the expertise of the clinician in detecting early traces of pneumonia. Many geographical locations may not have access to such expert clinicians, medical specialists or the required equipment. In such cases, it is very hard to conduct a timely diagnosis and can result in adverse consequences. A faster and more accessible solution is needed.

Deep learning systems have come a long way and can be utilized in multiple ways in the medical domain [42–44]. The technique suggested in this paper can help aid and even ease the diagnosis process to great extents.

The architecture produces a good recall score but has less accuracy and precision. This is likely due to the lack of the data and overfitting. This problem can be solved by collecting more data from people from different geographical locations, ages, ethnicities, etc. Greater variability and volume of data provides better chances for a model to learn the general pattern better and reduce the chances of overfitting.

Furthermore, the architecture comprises of three models to perform ensemble techniques. This greatly increases the computation cost than what would be required for a single CNN model. Hence, adequate hardware must be required to keep the computation time minimum, otherwise the time taken by the model to make a prediction will increase.

The architecture can be expanded to detect multiple categories including types of Pneumonia i.e., viral Pneumonia, bacterial Pneumonia and mycoplasma Pneumonia. Such an architecture could further aid clinicians in accurate diagnosis of the type of Pneumonia the patient is suffering from, which can contribute significantly to the recovery and cure.

Image processing and enhancement techniques can be applied during the pre-processing segment to increase quality of images. Feature extraction techniques can also be employed including a transfer learning network such as in [45–47] to better capture the salient features of the X-ray images. Combining both of these techniques can greatly increase the performance of a deep learning model.

Research should also be carried out in procuring and providing more X-ray images. Frontal views as well as lateral views can be incorporated [48] into a larger model to better identify and diagnose the diseased images. This can also expand the architecture for general thoracic purposes and other lung diseases.

Finally, reducing computational costs can make the model deployable on a browser or mobile application. This can ensure adequate diagnostic measures for people living in remote areas as well, hence reducing the chances of drastic consequences.

6. Conclusion

This article describes how deep learning techniques can be used to categorize digital chest X-ray images according to the presence or absence of Pneumonia. An ensemble framework was utilized which draws its scores from three models of different kernel sizes and then uses a weighted average scheme on the respective predictions to output a final value. A threshold value of choice can then be applied to the final sigmoid output to categorize it accordingly. A high recall value of 99.23% was obtained which is very essential for our problem domain. However, more research is required as the values of precision – 80.04% and accuracy – 84.12%, were lower than what would be necessary in the domain. Pneumonia diagnosis requires the involvement of medical experts and this model can be used as a supportive tool for decision making. While the model is still far from being used as a standalone diagnostic means, the predictions can improve diagnosis time and help guide medical experts by providing fast and accurate results for further testing. The model may be subject to overfitting due to less data. Availability of more data from people of different ages and locations can help the model to capture the salient features better and increase the f1-score, precision and accuracy while maintain a high recall. Further research can be used in data augmentation and pre-processing techniques, CNN model development as well as the availability and quality of X-ray images.

CRediT authorship contribution statement

Harsh Bhatt: Participated in drafting the manuscript, Wrote the main manuscript, Discussed the results and implication on the manuscript at all stages. **Manan Shah:** Participated in drafting the manuscript, Wrote the main manuscript, Discussed the results and implication on the manuscript at all stages.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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