Solution Review

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Comparison

Investigation through current literature and experimentation helped our project to create a model that uses static images of chest X-rays to identify the pneumonia diagnosis. The model currently achieves 93% accuracy when combined, while our CNN achieves 73% on the small test set when run alone. The team compared our model to other CNN models such as Xception, VGG19, Resnet50, and InceptionV3. While these models average approximately 89 - 92% accuracy, when combined with our model applying ensembling, the model can achieve much higher accuracy at around 93% on the test set. Additionally, the accuracy of our model performance might improve even further - this mission presents the comparison of the current results of our model to others in the literature [Table 1].

Table 1: Accuracy of each model based on the small test set

Model	Accuracy
Inception	91%
Resnet	92%
VGG	90%
Our CNN	73%
Xception	92%
Densenet	93%
Esembled model	93%

While our model performs the worse in a small test set, this is not a reliable indication of how well it performs compared to the others. When the test set is substantially larger, the accuracy of our model improves to 82%, while still worse than the other models; it shows that it performs significantly more beneficial with a large dataset. For the accuracy of all the models on our larger test set of 2268 images, see [Table 2]

Table 2: Comparison of model accuracy on larger test set

Model	Accuracy
Inception	97%
Resnet	94%
VGG	95%
Our CNN	82%
Xception	97%
Densenet	95%
Esembled Mode	96%

The amount of techniques used in pneumonia diagnosis has improved significantly over the last decade. There are many highly developed solutions available nowadays. (*Chhikara P,2020)* One of the solutions offered by Nirma University proposed an approach that uses Image Processing in detecting pneumonia based on the clouds in chest X-ray. The technique that was used in this case was image thresholding. This procedure distinguished the stable part of the lung from the part impacted by pneumonia. *(A. Sharma,2017)*

X-Rays are the most often used imaging examination tool back in 2017 and now. It can be concluded that the use of CT-Scans and X-rays in investigating the images of the lungs is one of the most influential and widely used strategies used by researchers. It must be explicitly highlighted due to the high need rate caused by the latest COVID-19 pandemic, which causes severe pneumonia.

The project focused on 5856 images within the Pneumonia dataset for training, 624 images for testing, and 76 for validation divided into normal and pneumonia cases. Similar to our project, they studied the performance of ResNet50, Inception-v3, DenseNet201, and Xception. These networks have proven to be highly effective for medical imaging applications such as the detection of pneumonia. *(Narayanan, B,2020)*

We have compared our model to other convolution network models such as Xception, VGG19, Resnet50, and InceptionV3. While these models average around 97.9% inaccuracy, we will obtain virtually similar accuracy on the test set at approximately 93 percent when combined with our model using ensembling. The method of the above project is as follows (Figure 7), which demonstrates the thoughtful manner in which precision is obtained.

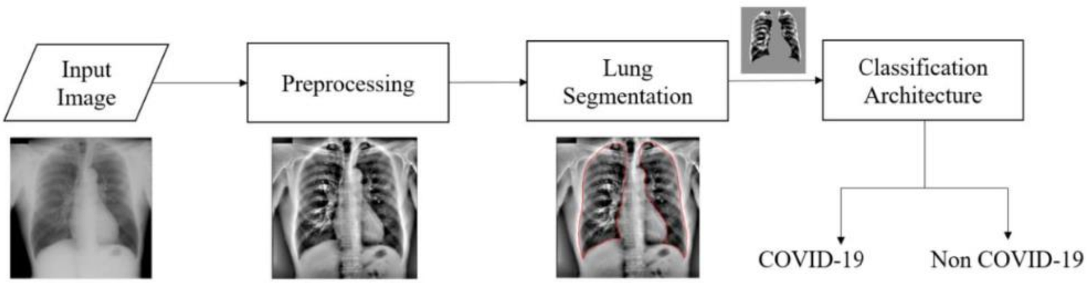

Figure 7. Top-level block diagram of enhanced baseline and recommended Computer-Aided Detection (CAD) systems for COVID-19 in chest radiographs.

In keeping with the theme of the COVID-19 epidemic and pneumonia that has resulted from the events, one of the more recent remedies is worth noting. Wang and Wong developed a deep CNN called COVID-Net to detect COVID-19 cases from 14,000 chest X-ray images, but the achieved accuracy was only 83.5 percent. *(L. Wang,2020)*

Wang and Wong stated that the dataset includes 358 CXR images from 266 COVID-19 patient cases. There are slightly more hospital reports and related CXR images with CXR images of no pneumonia and non-COVID19 pneumonia. There are 8,066 patient cases with no pneumonia (i.e., normal) and 5,538 patient cases of non-COVID19 pneumonia.

COVID-Net was initially trained on the ImageNet dataset. Furthermore, the project was compared to deep neural network architectures such as VGG-19 (83% accuracy), ResNet-50 (90.6% accuracy), and the project itself COVID-Net (93.9 percent accuracy). The COVID-Net method obtained the best possible result in the sensitivity test based on infection form, designated as 'Non-COVID-19' and 'COVID-19'; the COVID-Net system achieved the highest possible marks. Regrettably, the COVID-Net test produced the worst effects from the listed architecture in tag 'normal.' The additional results of the project clearly show the importance of the project. Despite this, COVID-Net had the best performance (PPV, Positive predictive value) in detecting pneumonia. In contrast to our initiative, which achieved 93%, the percentage of favorable predictive amounted to 91.3 percent. *(L. Wang,2020)*

Continuing with the Covid-19 case, which seems to be one of the most important cases to date, Chowdhury et al. suggested a method to differentiate a case of pneumonia from a Covid-19 point of view, as the symptoms may be similar, leading to an erroneous diagnosis, resulting in a non-COVID viral Pneumonia being classified as highly suspect of having COVID-19. *(Chowdhury et al.,2020)* Furthermore, the teaching process includes two separate classification systems, one of which was trained to classify COVID-19 and normal X-ray images, and the other was instructed to organize normal, viral pneumonia and COVID-19 pneumonia images. This research uses three separate networks such as MobileNetv2, SqueezeNet, and ResNet18, and five deep networks (Inceptionv3, ResNet101, CheXNet, VGG19, and DenseNet201) to assess the precision and appropriateness of usage. (*Chowdhury et al.,2020)*

Additionally, as mentioned in one of the previous comparisons, the confirmed high accuracy of computer-aided diagnostic tools improves the speed and accuracy of Covid-19 diagnosis. ResNet18 and CheXNet do similarly well when it comes to image classification, although CheXNet and DenseNet201 outperform the others when practicing for augmented images, though the disparity is marginal. (TABLE 2) CheXNet achieves the best accuracy of 99.4 percent without image augmentation and 99.7 percent with image augmentation for two-class classification.

TABLE 2 Weighted Average Performance Metrics for Different Deep Learning Networks for Two-Class Classification Problem With and Without Image Augmentation

Schemes	Models	Accuracy	Precision (PPV)	Sensitivity (Recall)	F1 Scores	Specificity
Without image augmentation	SqueezeNet	99.29	99.3	99.29	99.29	99.29
	MobileNetv2	99.4	99.41	99.4	99.41	99.4
	ResNet18	**99.41**	**99.42**	**99.41**	**99.41**	**99.41**
	InceptionV3	99.41	100	98.81	99.4	100
	ResNet101	99.05	99.08	99.05	99.07	99.05
	CheXNet	**99.41**	**99.42**	**99.41**	**99.41**	**99.41**
	DenseNet201	99.3	99.4	97	97.8	99.75
	VGG19	99.41	99.76	99.05	99.4	99.76
With image augmentation	SqueezeNet	99.40	99.40	99.40	99.40	98.84
	MobileNetv2	99.65	99.65	99.65	99.65	99.26
	ResNet18	99.60	99.60	99.60	99.60	99.31
	InceptionV3	99.40	98.80	98.33	98.56	99.70
	ResNet101	99.60	99.60	99.60	99.60	99.31
	CheXNet	**99.69**	**99.69**	**99.69**	**99.69**	**99.23**
	DenseNet201	**99.70**	**99.70**	**99.70**	**99.70**	**99.55**
	VGG19	99.60	99.20	98.60	98.90	99.80

Nowadays, any initiative highlighting the importance of the pneumonia situation is significant. In the United States alone, over a million people are diagnosed with pneumonia, and over 50,000 die as a result. The dataset contains 77,872 chest X-ray images in this project, and the validation dataset contains 8,652 chest X-ray images. Additionally, three models, ResNet-50, Inception V3, and DensetNet121 were trained separately using deep transfer learning and from scratch. Transfer learning will reach an AUC benefit that is 4.1 percent to 52.5 percent greater than traditional learning. *(Irfan,2020)*

Discussion

Nirma University's project focused on separating suspicious parts of the X-ray images (Fig.2.) from stable elements of the lungs. (Fig.1.) Even though the project did not compare the results of the algorithms we used, it demonstrated the pace of science and Machine Learning only a few years ago. *(A. Sharma,2017)*

Fig. 1.
Normal CXR images

Show All

It went straight to the newest, suitable comparisons, such as many innovative projects in the pneumonia theme, primarily due to the recent outbreak of the COVID-19 pandemic. This project used public datasets, and it was six in total. At the same time, our assignment focuses on one primary dataset. Using one of the pneumonia datasets, the groundbreaking Computer-Aid Detection tool (CAD) achieved an average accuracy of 98.9 percent and 97.9 percent for pneumonia detection and diagnosis, respectively. *(Narayanan, B., 2020)*

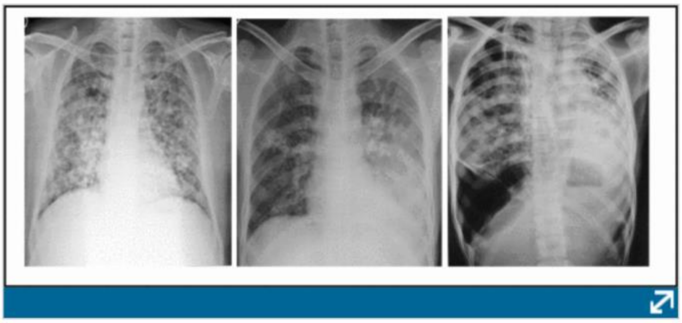

Fig. 2.
Pneumonia affected CXR image

The basic procedure for performing Covid-19 and pneumonia is a radiography examination, a chest radiography image (X-ray or Computer Tomography) conducted and analyzed by a radiologist. However, the methods found in the last few months demonstrate the state of modern technology and medicine, allowing experts to classify pathogens more quickly and precisely. The project COVID-Net is a deep convolutional neural network design for the detection, which presented outstanding results in detecting pneumonia and Covid-19 cases. *(L. Wang, 2020)*

The project owners reported that they plan to boost the sensitivity and PPV factor in the coming years, demonstrating the system's progress with 91.1 percent accuracy.

It is essential to concentrate on the Covid-19 pneumonia case because most of the patients suffered mild to severe respiratory disease, while unfortunately, some developed fatal pneumonia. Flattering of this theme shows that wrong diagnosis in the separation of pneumonia and Covid-19 case can cause care to be delayed, incurring more costs, time and putting the patient at risk of exposure to COVID-19 infection. *(Chowdhury et al.,2020)*

As stated in one of a previous comparison, the reported high precision of Computer-Aided Diagnostic tools improves the speed and accuracy of Covid-19 diagnosis. The project of Chowdhury et al. from 2020 showed that just four viral pneumonia photos out of 1485 were misclassified to COVID-19, while 33 were misclassified to standard. It should be worth noticing that the network is more confused between viral pneumonia and normal images than between COVID-19 and the other two image types. (*Chowdhury et al.,2020)*

Moreover, another interesting project is a chestX-ray14 dataset. This dataset was compiled, while containing, as much as 112,120 chest X-ray images from almost 40,000 patients. The presence or absence of 14 thoracic pathology marks, including pneumonia, was noted in the dataset that follows.

The training dataset contains almost 80,000 chest X-ray images, while the validation dataset contains 8,652 chest X-ray images. *(Irfan,2020)*

To summarize the literature review listed in this comparison, there are several different examples, with varying degrees of precision, from which our project will benefit the most. The effectiveness of the models ranges from 73 percent to nearly 98 percent in classifying common and pneumonia patients, as well as bacterial and viral pneumonia, using X-ray images and deep learning algorithms.

Recommendations

COVID-19 detection algorithms focused on chest radiographs may be an essential new tool in the fight against this disease. Those algorithms are one example of a technology that can provide timely and valuable information about a patient's condition. There was a modern, groundbreaking, novel solution for COVID-19 CAD in chest radiographs in the project sample that is immune to a class imbalance in training results. *(Narayanan, B,2020)*

The next project discovered in this comparison is COVID-Net, which is vital to note when detecting pneumonia or other lung inflammation. COVID-Net is the first neural network architecture developed for COVID-19 detection to use a lightweight projection-expansion-projection-extension (PEPX) framework, which allows for increased representational capability while significantly reducing computational requirements. *(L. Wang,2020)*

According to Irfan, the findings affirm the efficacy of transfer learning by offering a low-cost implementation option for deep learning-based systems for quicker and more reliable clinical rollout. *(Irfan,2020)*

To sum up, our team, on the other hand, built the model with the fewest layers for this project. Adding additional layers to our model would be enormously advantageous compared to the Densenet, VGG, Inception, or Resnet, or other high layered models. Indicating that it could dramatically improve its stability and theoretically produce comparable results to these high accuracy models. Furthermore, as a next step, it could be useful to apply additional Data Augmentation to help minimize overfitting when training and increase the number of images in the testing phase.

Additionally, in the launch of the project, and based on the knowledge from the literature review and current solution it might be worth noting the resource costs. Our model is the least resource intensive out of all the model, and fastest to train and make a prediction. Additionally, in the launch of the project, and based on the knowledge from the literature review and current solution, it might be worth considering the resource costs. While our model isn't as accurate as of the other models, it is regarded as the fastest and least computationally expensive, allowing it to be trained on smaller hardware.

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