An Exploratory Analysis of Soft Computing Algorithms for Classification of Pneumonia

Manasa C[1], Bindu S [2], Ruthu R [3], Sushma P [4]
[1]*Assistant Professor, Department of Information Science and Engineering, Global Academy of Technology, Bangalore*
[2,3,4]*Student, Department of Information Science and Engineering, Global Academy of Technology, Bangalore*

Abstract- **Pneumonia is an acute pulmonary infection that can be caused by bacteria, contagions, or fungi and infects the lungs, causing inflammation of the air sacs and pleural effusion, a condition in which the lung is filled with fluid. They regard for further than 15 of deaths in children under the age of five times. It's most common in underdeveloped and developing countries, where overpopulation, pollution, and hygienic environmental conditions complicate the situation, and medical coffers are skimp. Thus, early opinion and operation can play a vital part in precluding the complaint from getting fatal. Radiological examination of the lungs using reckoned tomography (CT), glamorous resonance imaging (MRI), or radiography (X-rays) is constantly used for opinion. X-ray imaging constitutes an on-invasive and fairly affordable examination of the lungs. The white spots in the pneumonic-ray (indicated with red arrows), called infiltrates, distinguish a pneumonic from a healthy condition. Still, casket-ray examinations for pneumonia discovery are prone to private variability. Therefore, an automated system for the discovery of pneumonia is needed.**

I.INTRODUCTION

Pneumonia is a condition of the inflammation of lungs, it primarily affects the small air sacs known as alveoli. This is generally caused by infection with numerous contagions or bacteria, more or less generally due to other microorganisms. The most delicate part is to identify the responsible pathogen. A person is most frequently diagnosed grounded on symptoms and physical examination similar as Casket-rays, blood tests, and culture of the foam may help confirm the opinion. While we look into the statistics, in the USA annually there are further than 1 million people who are rehabilitated with the grouch of pneumonia and unfortunately,50.000 of these people die from this illness. Pneumonia also has killed over a million children worldwide in 2018 and remains a life- changing complaint, the fortunate thing is that, pneumonia can be a manageable by using medicines like antibiotics and antiviral but this is only if it can be diagnosed beforehand. The treatment of pneumonia is extremely important in order to help any complications that can lead to death of the Cases who have diagnosed with pneumonia shows the casket depression signs of fluids filling the air sacs of lungs as for the radiograph picture appears brighter. Several abnormalities may be seen on lung depressions as brighter color may represent similar as cancer cells, blood vessels swelling, and abnormality of heart. To validate the range and spot of an infected area of the lungs, casket-rays is the utmost system. In utmost of these system, emergence of the complaint can be squishy and misinterpreted with another illness and in order to avoid this, the undertaking is pleasing in the enhancement of the processing in medical situations in insulated areas for pneumonia discovery The stylish way of early discovery is through Casket-ray images and these are the best-known and the most common clinical system for diagnosing of pneumonia. The only challenge is that diagnosing pneumonia from casket-ray images is a relatively delicate task indeed for the expert radiologists. The appearance of pneumonia in-ray images is frequently unclear and can be confused with other conditions and can bear like numerous other benign abnormalities. These inconsistencies beget considerable private opinions and kinds among numerous radiologists for the opinion of pneumonia. Thus, the need for motorized support systems to help all radiologists for diagnosing pneumonia from casket-ray images.

II.LITERATURE REVIEW

Pneumonia is an illness that disturbs the lung air sacs of an infected person. It's started by bacteria, fungi, or a contagion that infects the air sacs of lungs that fill up with discharge fluids that leads to chills, fever, coughing with mucus, and breathing trouble among persons diagnosed with this complaint.

COVID-19, conceded by the World Health Organization (WHO) as an epidemic, has dramatically altered the course of humans 'daily lives, their immediate health, and husbandry throughout the world. A fleetly spreading viral complaint, COVID-19 affects humans and creatures. As per World measures, roughly people have failed due to coronavirus complications so far. In utmost cases, it's pneumonia that makes this complaint largely dangerous and potentially fatal. & Ere fore, detecting and diagnosing pneumonia in COVID-19 cases is critical.

Deep literacy models automate the process and insure speedy, artful, and complete results when handed with x-rays of case plays an important part in perfecting the quality of healthcare with reduced costs and speedier response this kind of approach is supervised literacy approach in which the network predicts the result grounded on the quality of the dataset used. Transfer literacy is used to gain advanced training and confirmation delicacy. From this new approach there's a lot of significance where cases can be defended from pneumonia. There's also an Issue where complaint frequently get mixed with the other complaint, radiologist find it grueling to diagnose the particular complaint so deep literacy ways break all these problems by prognosticating the correct delicacy. This fashion uses deep literacy and has proven to be veritably helpful to give a quick and accurate opinion of the complaint that matches the delicacy of a dependable radiologist.

As observed from all the below papers we're suitable to identify the methodology they've used along with pros and cons. Taking a look into papers.

The proposed methodology presents the architectural design that's divided into three stages preprocessing, handover literacy and refinement, and bracket. This fashion is accepted in the enhancement of the processing in medical situations in insulated areas for pneumonia discovery. The experimenters were suitable to train and assessed CNN model's performance and classify casket-rays with normal and infected with complaint using different classifiers The progress in a further intelligent future is now productive through generations. This technological enhancement moment reached new step closer in mortal intelligence. It's veritably effective in amulti-layered structure when carrying and assessing necessary features of graphical images. [1]. This paper presents the detailed trials and evaluation way accepted to test the effectiveness of the proposed model. Their trials were grounded on a casket-ray image dataset proposed in. they stationed Keras open- source deep literacy frame with tensor flow backend to make and train the convolutional neural network model. All trials were run on a standard PC with an Nvidia GeForce GTX TITAN Xp GPU card of 12 GB, cuDNN v7.0 library, and CUDA Toolkit9.0. The data was extemporized using the subfolders containing pneumonia (P) and normal (N) casket-ray images. They reused with doing several data addition styles to instinctively increase the size and quality of the dataset. This process helps in working overfitting problems and enhances the model's conception capability during training. This will go a long way in perfecting the health of at- threat children in energy-poor surroundings. The study was limited by depth of data. With increased access to data and training of the model with radiological data from cases and nonpatients in different corridor of the world, significant advancements can be made. [2] The dataset was downloaded fromKaggle.com. Casket-ray images were employed for feeding our network. It comprises of total casket X shafts in of two orders, one is Pneumonia and the other is Normal. Out of total images, images were stationed for training the model and 634 images were employed for testing purpose and rest of them are used for the confirmation dataset. The process includes-processing, Dealuminations and data tuning. The work represents the three different styles of transfer literacy for diagnosing pneumonia veritably efficiently. Three distinct algorithms were first trained and validated for classifying the two orders. Among the three algorithms it was observed that VGG16 (96.7) and VGG19 (95.6) performs nearly same, VGG16 being slightly better whereas ResNet model has smallest delicacy of88.14. Pneumonia is an infestation in one or both lungs. [3] They extend the algorithm of F-RCNN by adding a branch which induces double mask prognosticating whether the given image pixel contributes to the given part of the object or not. Also, it's easy to train a Mask R-CNN and it adds a small outflow in terms of running time which is negligible. So, they may consider Mask R-CNN as an advanced briskly R-CNN. They trained a Retina Net model which is a classic approach for object discovery. Still, the approach doesn't work well in all scripts especially in the case non perpendicular/ vertical objects. With Mask R-CNN this issue can be resolved. [4] This composition analyzes the target area of the training data of the pneumonia-ray dataset. In the traditional Faster R-CNN algorithm, the size of the anchor box depends on empiricism. Thus, this composition refers to the system of generating the anchor box in YOLOV3 and uses the K-Means algorithm to determine the aspect rate suitable for the dataset. In this study, the K-Means algorithm is used to dissect the target region of the training set, and the pneumonia anchor box with three scales of (72, 73), (102, 120), and (140, 279) were generated. In this exploration paper a result of low complexity residual neural network with a ballooned tailback structure, called as DeepConv-DilatedNet, is invoked as the backbone of a two- stage sensor using Faster R-CNN. Because of the turbidity of the pneumonia target, the image has further been enhanced with the CLAHE algorithm to make the target area more prominent. [5]Four CNNs were trained and estimated using five-fold cross-validation in this study. The performance of different networks for the testing dataset is estimated after the completion of the training phase and was compared using the following six performances criteria delicacy, perceptivity or recall, particularity, perfection (PPV), the area under wind (AUC), and F1 score In the below equations, while classifying normal and pneumonia cases, true positive (TP), true negative (TN), false positive (FP), and false negative (FN) were used to denote the number of pneumonia images linked as pneumonia, the number of normal images linked as normal, the number normal images inaptly linked as pneumonia images, and the number of pneumonia images inaptly linked as normal, independently. This study presents a deep literacy a deep-CNN grounded transfer literacy approach for the robotization discovery of pneumonia and its class. he brackets delicacy, perfection, and recall of normal and pneumonia images, bacterial, and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98, 97, and 99; 95, 95 and 96; and93.3,93.7 and93.2, independently [6]Casket-ray image preprocessing, data addition, transfer literacy using Alex Net, DenseNet121, InceptionV3, resNet18 and Google Net neural networks, point birth and ensemble bracket. DataPre-Processing and Augmentation All of there-trained models were relatively large to hold this dataset, and each model could be overfitted fluently. To help this, some noise was added to the dataset; it's well known that by adding some noise to inputs of neural network, in some situations, this leads to significant enhancement in generalizing the dataset. AlexNet was trained for 200 duplications at literacy rate of0.001 and also trained at veritably low literacy rate of0.00001; it achieved a test delicacy of92.86 and a train delicacy of93.0. The AUC value was97.83. ResNet18 did better than AlexNet and other models; it achieved an area under the ROC wind as99.36 and test delicacy of94.23. The average computational time for all models on CPU is0.332 s and for GPU it's0.043 s, whereas the ensemble model took0.161 s for calculation. [7] The armature of the proposed model has been divided into three different stages- the preprocessing stage, the point birth stage and the bracket stage. A. There-Processing Stage The primary thing of using Convolutional Neural Network in utmost of the image bracket tasks is to reduce the computational complexity of the model which is likely to increase if the input are images. The original 3- channel images were resized from 1024 × 1024 into 224 × 224 pixels to reduce the heavy calculation and for faster processing. This paper primarily aims to ameliorate the medical artfulness in areas where the vacuity of radiotherapists is still limited. The study facilitates the early opinion of Pneumonia to help adverse consequences (including death) in similar remote areas. So far, not important work has been contributed to specifically to descry Pneumonia from the mentioned dataset. The development of algorithms in this sphere can be largely salutary for furnishing better health- care services. They've observed the performance of colorful pretrained CNN models along with distinct classifiers and also on the base of statistical results named DenseNet-169. [8] In this work, training time data addition system was employed. They used different addition styles similar as shifting, zooming, flipping, rotating at 40- degree angles. Another performance enhancing system in deep models especially in CNNs which is named as transfer literacy. Transfer literacy is the idea of prostrating the insulated literacy paradigm and exercising knowledge acquired for one task to break affiliated bones. In this detail study they compared of the two CNN network's performance on the opinion of pneumonia complaint. While training our model they used from transfer literacy and finetuning. After the training phase, they compared two network test results. The test results showed that Vgg16 network outperforms Xception network by delicacy0.87, particularity0.91, pneumonia perfection0.91 and pneumonia f1 score0.90. Whereas Xception network outperforms Vgg16 network by perceptivity0.85, normal perfection0.86 and pneumonia recall0.94. According to the experimental results and confusion matrices. every network has own discovery capability on the dataset. [9] The distribution of images according to their collected sources are depicted. There are two reasons behind using the images from these sources. First, it's different whereby the images collected from different sources and different countries which is important to design a sophisticated tool to help radiologists to diagnose COVID-19 around the world. Second, the images from these sources are openly available to exploration community and to the general public. Likewise, the images used in this will inclusively be available in a GitHub depository. In this study, a simple yet an effective CNN model together with testing-trained AlexNet for the discovery of COVID-19 complaint from casket-ray and CT images that's available intimately. Likewise, the images (X-ray and CT) used in our disquisition are collected from multiple sources and we inclusively make the radiography images used in this study to descry COVID-19 will be intimately available for the exploration community. [10]The model proposed by et al. is based on a residual learning framework that improves the efficiency of deep network training. DenseNets designs, proposed by Huang et al., provide a rich feature representation while being computationally efficient. ResNet models allow optimizing the entire network easy, which improves model accuracy. To aid medical practitioners, this research developed an automated CAD system that employs deep transfer learning-based classification to divide chest X-ray images into two categories: "Pneumonia" and "Normal." Using an ensemble framework, the decision scores from three CNN models, Google Net, ResNet-18, and DenseNet-121, were integrated to create a weighted average ensemble.The weights assigned to the classifiers were generated using four assessment measures: precision, recall, and f1-score. To help medical practitioners, the hyperbolic tangent function was used to combine an automated CAD system and an AUC. The framework had an accuracy rate of 98.81 percent, a sensitivity rate of 98.80 percent, a precision rate of 98.82 percent, and a f1-score of 98.79 percent on the Kermany dataset, and an accuracy rate of 86.86 percent, a sensitivity rate of 87.02 percent, a precision rate of 86.89 percent, and a f1-score of 86 on the RSNA challenge dataset.[11]The architecture is a combination of two deep learning models. A "ResNet-34 based U-Net" is merged with a "EfficientNet-B4 based U-Net" in the first model. This approach makes use of a range optimizer, BCE (Binary cross-entropy), and Dice Loss with progressive scaling. This model is robust since it may be employed with any dataset that fits the model's image size constraints. They can see that our approach achieved excellent results for the "Efficientnet-B4 based U-Net" model, which has great precision and good recall, but low precision for the "ResNet based U-Net" model. The ensembled model combines the best of both worlds, with the EfficientNet-B4 based U-Net providing high precision and the EfficientNet-B4 based U-Net providing high recall.U-Net based on ResNet-34. When both of these models are combined, outstanding results are obtained. Our first model, the "Efficientnet-B4 based U-Net," however, performed better on its own than our ensembled model. In the real-world setting, the ensembled model generated a fairly good result in terms of precision.[12]This experiment used RSNA pneumonia data from 26684 cases, 6012 pneumonia images (22.03 percent), 8851 normal images (31.19 percent), and 11821 photos (accounting for 44.77 percent). Because the patient's chest pneumonia could occur in one to four locations. To maintain sample balance, we use 6012 photos with annotations, 4/5 of which are chosen as the training set and 1/5 as the test set. In this paper, DeepConv-DilatedNet, a low-complexity residual neural network with a dilated bottleneck topology, is used as the backbone of a two-stage detector based on Faster R-CNN. Due to the turbidity of the pneumonia target, the image has been improved with the CLAHE technique to make the target area more visible. Use to filter the anchor box. Finally, they obtained the results of this method by hastening the algorithm's convergence and improving the forecast accuracy of the target area. By combining the distinct sets of work done in each network, the algorithm's ability to accurately diagnose pneumonia in the RSNA dataset is improved. We compared the model to the classic DetNet59, ResNet50, ResNet101, and VGG16 networks, as well as other high-quality findings, to ensure its validity; our algorithm performed admirably in this endeavor. Networks that do not connect to the dilated bottleneck structure in the deep network lose some feature information, resulting in lower detection accuracy.[13]CNN models were created from the ground up on Kaggle and trained on the Chest X-Ray Images (Pneumonia) dataset. The models were built with the Keras neural network library and a TensorFlow backend. The dataset contains 5216 training photos, 624 testing photos, and 16 validation photos. Data augmentation was used to improve the dataset's results. The training dataset was used to train four models, each with a different number of convolutional layers. CNN classifier model 3 with three convolutional layers has validation accuracy, recall, and F1 score of 92.31 percent, 98 percent, and 94 percent, respectively, which are quite high in comparison to other trained models. CNN has a validation accuracy of 91.67 percent, a recall of 98 percent, and an F1 score of 94 percent. On the same dataset, Liang achieved a recall of 96.7 percent. The models we provided could only reach 92.31 percent accuracy, which is below average, but they did obtain 98 percent recall. High recall values assure a decreased number of false-negative instances, lowering the risk to the patient's life.[14]Deep learning is used to more precisely learn information from X-ray images of patients so that the model can diagnose pneumonia. This study made use of a Kaggle dataset. The VGG16 model was used to develop a pneumonia prediction model. The data was divided into two groups: 80 percent training data and 20% testing data. & The data is loaded into the VGG16 model for training. After training the model with data, the test data were used to make predictions. Using lung X-ray images, this study proposes a two-stage deep residual learning technique for detecting COVID-19-induced pneumonia. The &e model performed well in distinguishing COVID-19 patients from COVID-19-induced pneumonia patients when using the VGG16 model. The &e model predicted pneumonia with an average accuracy of 91.69 percent, sensitivity of 95.92 percent, and specificity of 100 percent. It also increases accuracy and decreases training loss. Parallel testing can be used in the current context to prevent infection among frontline workers and establish primary diagnoses to determine whether a patient is infected with COVID-19. As an alternative diagnostic tool, the proposed method can be used to detect pneumonia cases. The CNN architecture's performance can be improved in the future by adjusting the hyperparameters and transfer learning combinations.[15]

III.LITERATURE SUMMARY

The summary of the literature is depicted intable 1

Table 1: Summary of Literature Survey

Sl No	Author Names	Year of Publication	Methodology	Pros	Cons
[1]	Sammy V. Militante, Brandon G. SibbLuca.	2020	Preprocessing, handover learning and refinement, and classification are the three stages of this techniques. Pooling, fine tuning, Transfer learning is are used to extract new features to original parameters.	In this training model it achieved the highest and the lowest accuracy rate through the examined x-ray images.	The technology should be undertaken to improve the processing in medical settings in remote places for the identification of pneumonia.
[2]	O.Stephen, M.sain,U.J. Maduh and D-U Jeong	2019	To develop and train the convolutional neural network model, scientists used Keras, an open-source deep learning framework with a TensorFlow backend. During training, evolutionary-based algorithms and reinforcement learning (RL) have been used to find the best network hyperparameters.	Artificially increase the dataset's size and quality. This procedure aids in the resolution of overfitting issues and improves the model's capacity to generalize during training.	The investigation was hampered by a lack of data depth. Significant improvements can be realized by increasing data access and training the model with radiological data from patients and nonpatients in different parts of the world.
[3]	Maahipatel, ayushSojitra, Zeelpatel, Mohammed Hussain Bohara	2021	We go over the data processing, network architecture, and Soft-effective NMS's enhancement impact in depth for our proposed DeepConvDilatedNet technique. Addition to this preprocessing, augmentation, architrave tuning.	This technique is beneficial since it overcomes the limitation of a small dataset and then fine-tunes the algorithms to make them ready for efficiently detecting pneumonia.	Networks that do not connect to the dilated bottleneck structure lose some feature information in the deep network, resulting in lower detection accuracy.

[4]	E. Ayan and H.M. Unver	2019	In the Mask-RCNN model, the researchers used ResNet101 as a backbone detector and compared it to ResNet50.	In medical chest radiographs, an algorithm can detect the visual signal for pneumonia and output either pneumonia positive or negative, as well as anticipated bounding boxes around lung opacities if positive.	When dealing with huge images, the computing cost increases dramatically. Overfitting was avoided, although the training set yielded lower outcomes when compared to the test set.
[5]	Li,X,chen,F,hao, H&Li,M.	2020	Method used is Faster R-CNN algorithm and compared with the Resnet50 and k-means++algorithm is used to analyze the training set	The algorithm's capacity to diagnose pneumonia accurately in the RSNA dataset has been improved, and the findings have been compared to other high-quality network results. This task is well-served by the algorithm.	In terms of improved accuracy, processing time, and error rate, it falls short.
[6]	B. G. Prasad, Daksh Gandhi, Akshat Jain	2019	Four CNNs were trained and evaluated using five-fold cross-validation. The performance of different networks for the testing dataset is evaluated after the completion of the training phase and was compared using the following six performances metrics: accuracy, sensitivity or recall, specificity, precision (PPV), the area under curve (AUC), and F1 score	Computer-aided diagnostic tool can significantly help the radiologist to take more clinically useful images and to identify pneumonia with its type immediately after acquisition.	The network should be trained using a larger database and operating on an ensemble of pre-trained CNN algorithms to improve detection accuracy, which can be done as a future study. X-ray images of pneumonia are not particularly clear and are commonly misclassified to other diseases or other benign abnormalities.
[7]	Sanjay Kumar Singh, Deepak Gupta, Vikash Chouhan	2020	Chest X-ray image preprocessing, data augmentation, transfer learning using Alex Net, DenseNet121, InceptionV3, resNet18 and Google Net neural networks, feature extraction and ensemble classification	The results suggest that deep learning methods can be used to improve diagnosis relative to traditional methods, which may improve the quality of treatment.	The findings imply that deep learning approaches can be utilized to improve diagnosis when compared to standard methods, perhaps improving treatment quality. noticed that by expanding dataset size, employing a data augmentation strategy, and using hand-crafted features, performance may be enhanced even more.

[8]	V. Sirishi Kaushik, Anand Nayyar, Rachana Jain	2020	The proposed pneumonia detection system using the 'Densely Connected Convolutional Neural Network' (DenseNet-169) is described. The architecture of the proposed model has been divided into three different stages - the preprocessing stage, the feature extraction stage and the classification stage.	Study facilitates the early diagnosis of Pneumonia to prevent adverse consequences (including death) in such remote areas	So far, not much work has been contributed to specifically to detect Pneumonia from the mentioned dataset.
[9]	Enes Ayan, Hail Murat Unver	2020	Training time data augmentation method was utilized. used different augmentation methods such as shifting, zooming, flipping, rotating at 40-degree angles	Xception network is more successful for detecting pneumonia cases than Vgg16 network. At the same time Vgg16 network is more successful at detecting normal cases.	This model lacked the ability to combine the strengths of two networks in order to successfully diagnose pneumonia from chest X-ray images.
[10]	Halgurd S. Mahid, Aras T. Asaad	2020	To test the proposed approach, we collected images from 5 different sources to form a dataset of 170 X-ray images and 361 CT images of COVID-19 disease.	A simple yet an effective CNN model together with testing pre-trained AlexNet for the detection of COVID-19 disease from chest X-ray and CT images that is available publicly	Although they achieved rather high COVID-19 detection accuracy, sensitivity and specificity but this does not mean a production ready solution especially with the limited number of images currently available about COVID-19 cases.
[11]	Liu Mao, Tan Yu Meng, Chen Lina	2020	Retina net and mask r-CNN. They designed an ensemble framework of three classifiers Google Net, ResNet-18, and DenseNet-121, using a weighted average ensemble scheme wherein the weights allocated to the classifiers are generated using a novel scheme	In each layer of the DenseNets model, the feature maps in the current layer are connected with those from the preceding layer diminishing the number of trainable parameters and thus the model is computationally efficient	In some instances, the ensemble framework failed to produce correct predictions, hence a investigation techniques such as contract enhancement of images or other pre-processing steps to improve the image quality is required

[12]	Aayush panth, Akshath Jain	2020	The architecture that is proposed is an ensemble of two deep learning models. The first model is a “ResNet-34 based U-Net” which is ensembled with the second model which is an “EfficientNet-B4 based U-Net”	This model is robust as it can work on any of the datasets that conform to the size of the image that is required for this model. A observation has given astounding results for the "Efficientnet-B4 based U-Net" model that has high precision and decent recall.	The other model, "ResNet based U-Net" had given high recall but low precision. The ensembled model uses the best of both worlds, in that the high Precision quality is drawn from EfficientNet-B4 based U-Net, and the high Recall quality is taken from the ResNet-34 based U-Net. But we can also see that our first model "Efficientnet-B4 based U-Net" individually performed better than our ensembled model in terms of the accuracy metric.
[13]	Shangjie Yao, Yaowu Chen, Xiang Tian, and Rongxin Jiang	2021	faster r-cnn along with it the CLAHE algorithm is used to equalize the gray histogram to enhance contrast and brightness	DeepConv-DilatedNet, is invoked as the backbone of a two-stage detector using Faster R-CNN. Because of the turbidity of the pneumonia target, the image has further been enhanced with the CLAHE algorithm to make the target area more prominent.	To verify the validity of the model, they also compared it in detail with the traditional DetNet59, ResNet50, ResNet101, and VGG16 networks and compared them with other high-quality results; the algorithm does a good job in this task but the Networks that do not join the dilated bottleneck structure lose some feature information in the deep network, so the detection accuracy is not that good.

[14]	V. Sirish Kaushik, Anand Nayyar, Gaurav Kataria, Rachna Jain	2020	CNN models have been created from scratch and trained on Chest X-Ray Images (Pneumonia) dataset on Kaggle. Keras neural network library with TensorFlow backend has been used to implement the models. Data augmentation has been applied to achieve better results from the dataset. The four models have been trained on the training dataset, each with different number of convolutional layers. Each model was trained for 20 epochs, with training and testing batch sizes of 32 and 1, respectively.	The models presented by them at best could achieve 92.31% accuracy which is lower, but 98% recall has been achieved. High recall values will ensure that the number of false-negative instances is lower, hence lowers the risk to the patient's life. CNN classifier model 3 and model 4 can, therefore, be effectively used by medical officers for diagnostic purposes for early detection of pneumonia in children as well as adults. A large number of X-ray images can be processed very quickly to provide highly precise diagnostic results, thus helping healthcare systems provide efficient patient care services and reduce mortality rates.	It is hoped that transfer learning models would be trained on this dataset that would outperform these CNN models. It is intended that larger datasets will also be trained using the models presented in the paper. It is also expected that neural network models based on GAN [32], generative adversarial networks, would also be trained and compared with the existing models
[15]	M. D. Kamrul Hasan, SakilAhme, Z. M. Ekram Abdullah, Mohammad Monirujjaman Khan, Divya Anand, Aman Singh, Mohammad AlZain, and Mehedi Masud2	2021	A deep learning algorithm is used to learn features from patients' X-ray images more accurately so that the model can detect pneumonia more accurately.	This research suggests a two-stage deep residual learning technique using lung X-ray images to identify COVID-19-induced pneumonia. & Model showed good performance in differentiating COVID-19 patients and patients with COVID-19-induced pneumonia using the VGG16 model. &model predicted pneumonia with an average accuracy of 91.69%, sensitivity of 95.92%, and specificity of 100%. It also reduces training loss and increases accuracy	To improve the CNN architecture performance by adjusting the hyperparameters and transfer learning combinations. Another feasible way to determine the best model for pneumonia and COVID-19 could be an improved, complex network structure.

IV.METHODOLOGY

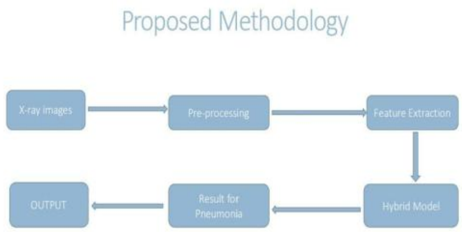

Figure 1: Methodology

The main goal to build a model to detect pneumonia using the x-ray images which will lead to faster than traditional methods with the better performance and accuracy. Classification of the x-ray images into their classes based on their severity. From the past 2 years since covid19 hit us we have seen many suffer from pneumonia and this has caused a lot of deaths. The age group that has been noticed to have been mainly affected is from 18-50, Our main goal is to focus on this particular age group and to show how this affects everyone based on their age as well also on the severity at which they are affected. Hence our main goal from this project is to focus on the different group of people and going into to detail about the specifications rather than just grouping the people who have been affected into a general group.

V.CONCLUSION

The main goal is to propose a deep learning-based approach to classify pneumonia from chest X-ray images using transfer learning. It was observed that performance could be improved further, by increasing dataset size, using a data augmentation approach, and by using hand-crafted features, in future. The findings support the notion that deep learning methods can be used to simplify the diagnostic process and improve disease management.

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