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Pneumonia Detection using Chest X-Ray Images and Machine Learning Techniques

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Abstract— **Chest X-rays have been a crucial diagnostic tool in detecting pneumonia. The disease manifests as inflammation and filling of the air spaces within the lungs, leading to changes in the appearance of the lungs on X-rays. In recent times, advances in computer vision and machine learning have allowed for the development of automated systems for pneumonia detection using chest X-rays. These systems leverage deep learning techniques to analyze X-ray images and identify patterns associated with pneumonia. The use of these systems can aid in early diagnosis and prompt treatment, potentially leading to improved patient outcomes. Despite their promise, there are still challenges to be addressed, including the need for large and diverse datasets for training and the need for further validation of these systems in real-world settings. Nevertheless, the development of automated pneumonia detection systems using chest X-rays has the potential to revolutionize the field of radiology and improve patient care.**
***Index Terms*—Pneumonia; artificial intelligence; machine learning; image processing; convolutional neural network; chest x-rays.**

INTRODUCTION

A serious infection called pneumonia causes inflammation in the sacs of lungs. The fluid that collected in the air sacs may induce a cough that contains pus, phlegm, fever, chills, and breathing difficulties are also present. There are numerous causes of pneumonia, including creatures like viruses, fungi, and bacteria. We can experience pneumonia with varying degrees of severity varying in severity from slight to fatal. It is perceived as the most severe in infants and children, anyone older than 65 years of age and in good health people with issues or compromised immune systems. The patient's symptoms are frequently used to guide the diagnosis together with the doctor's physical examination.
To confirm the diagnosis, doctors can ask patients to undergo procedures like blood tests, x-rays of the chest, and spittle cultures. Pneumonia can be categorized as the hospital- or healthcare-associated pneumonia depending on how it was acquired. bronchitis can be brought on by a wide range of species, from bacteria to fungi to viruses. The most frequent cause of is bacterial pneumonia. Another kind of pneumonia brought on by fungi occurs in those who have weak or ongoing health issues and immune mechanisms. Virus-induced pneumonia has a low severity but has also become quite serious, as in the current COVID-19 situation. People can occasionally develop pneumonia while they are hospitalized for a different illness. This pneumonia case can be serious because the patients are already ill, making the bacteria that causes it resistant to treatment. We are leveraging x-ray pictures to do a predictive detection analysis due to the severity of this disease. The Confusion Matrix, which forecasts the precision of the developed models, has also been discussed.

Diagnostic chest X-rays for lung infections are common and inexpensive. Expert radiologists can distinguish between a normal CXR and one that signals a problem such lung cancer, tuberculosis, or pneumonia. Pneumonia is a common lung disease that can be caused by viruses, bacteria, or fungi. Pneumonia can be fatal for many individuals, but it is most dangerous for young children, the elderly, people who rely on ventilators in hospitals, and those with asthma. Moreover, pneumonia is a deadly disease, especially in third-world countries where millions of people are living in poverty without access to medical care. According to the World Health Organization, air pollution causes the deaths of more than 4 million people every year (WHO). Each year, he is responsible for infecting about 150 million people, most of them are youngsters younger than five with pneumonia. Virus-caused plague is usually mild, but bacterial pneumonia can be highly severe, especially for children. Those who already have a weakened immune system are at greater risk of developing fungal pneumonia. Due to the low cost of CXR compared to other diagnostic modalities such as MRI and CT scans, it is increasingly demanded (CT). Due to the widespread need for CXRs, radiologists do tens of thousands of them annually. Even in the wealthiest countries, there is a severe lack of radiologists despite the widespread need for their services

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RELATED WORKS

In 2021, L Suganthi [1] presented a plan to address the development of an automated lung segmentation and pneumonia (lung inflammation that manifests as a white patch of cloud in the X-ray) detection method in order to improve imaging and treatment of a wide range of pathological lung conditions.

The 200 ill photos and 100 control images are also included in the Kaggle database, which also contains the CXR images. The pre-processing of all the photographs to lower and remove noise while simultaneously boosting aesthetic qualities was the first stage of the recommended approach. The region of interest has been isolated using morphological treatments on the pre-processed pictures. The photos were then segmented using the watershed algorithm and the graph cut technique. A classifier was then used to identify the diseased lung once features had been obtained and pertinent characteristics had been established.

CNN

As a result of advancements in deep learning, particularly convolution neural network (CNN) applications, the accuracy of classification and object identification has grown substantially. The development of graphics processing units (GPUs) also made a significant contribution to the widespread adoption of CNN in computer vision, overcoming the obstacles of real-time parallel processing of computation-intensive jobs.

Applications of Convolutional Neural Networks for image and video recognition are emphasised. CNN is predominantly employed for image analysis applications such as segmentation, object identification, and image recognition.

There are three distinct types of layers in Convolutional Neural Networks:

1) Convolutional Layer: Typically, the convolutional layer is the first layer in a CNN, in which the image or data is convoluted using filters and kernels. Filters are tiny units that are applied to data via a sliding window of equal depth to the input.
For example, a depth 3 filter might be applied to a colour picture with RGB values that give it a depth of 3.

2) Pooling Layer: Pooling includes a subsample of features so that fewer parameters must be learned during training. The pooling layer typically has two hyper parameters: the spatial extent dimension and the stride (number of features skipped along with width and height).

3) Fully Connected LayerThe output of the convolutional layers displays advanced data characteristics. While this output may be flattened and linked to the output layer, often a fully connected layer is added to discover nonlinear combinations of these characteristics.

The CNN model's fully linked layers are learning a possibly nonlinear function.

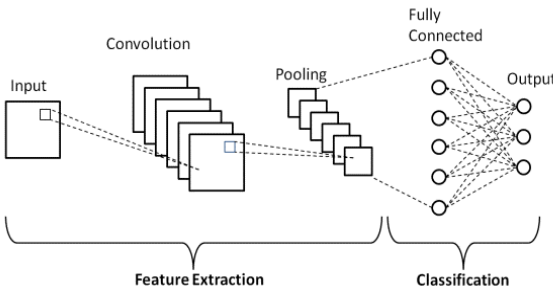

Fig 1: Convolutional Neural Network

In [2], Barrientos proposed program recognition. Pneumonia examination of computerized ultrasound images. The methodology is a rectangular section of a magnified ultrasound image. They collected 15 degrees of pneumonia, which ended up being on 8 out of 23 lung ultrasounds. The comparison vector was separated from the hull and ordered past-like equivalents of positive and negative. So, the required locale was found in the image. in the end, highlights of areas of interest are drawn, when using calculations. This nerve tissue calculation is a sigmoid enactment work with three layers, i.e a work in which the input is hidden and harvested. Finally, preparation and test measures were carried out to achieve pneumonia detection. The method successfully classified vectors with indications of pneumonia with a sensitivity of 91.5% and a specificity of 100%.

Oliveria et al. [3] introduced PneumoCAD, an ML-based network that can discriminate between paediatric CRX pictures with and without pneumonia. The authors collected a subset (20 pneumonia and 20 non-pneumonia) of their 40 photos from an educational knowledge repository [1]. Using an additional 20 randomly chosen test photos from the same database, the system was assessed. Using eight wavelet transform coefficients, texture characteristics were retrieved.

The PneumoCAD prototype is capable of classifying pictures of pneumonia, however its specificity is unpromising. In addition, no preparation is required for this technique. A method for eliminating picture noise. A comparable machine learning-based pneumonia diagnosis system, PneumoCAD, was created. PneumoCAD receives CXR images as input and extracts valuable information using the Haar wavelet transform. A KNN (k-nearest-neighbor) classifier is used to classify photographs of pneumonia. 156 confirmed child chest radiographs were used to train and validate the model (78 with pneumonia and 78 with normal). The average ANN (k=9) accuracy was 91.75 percent. This discovery will aid in the development of future CAD systems, albeit accuracy must be improved. The CNN algorithm is responsible for the CNN calculation, which focuses on the processing of x-ray scanner-captured pictures. CNN uses the image and the gap as recognition examples and more muted highlights.

Sousa et al. [4] augmented the author's PneumoCAD [3] by

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evaluating the efficacy of several ML algorithms in identifying paediatric pneumonia using CXR. The PneumoCAD dataset is a self-generated collection of 156 grayscale chest radiographs. According to WHO criteria, an experienced radiologist initially evaluated and commented on these photographs. The author coefficient, energy, contrast, mean energy, correlation, entropy, differential variance, differential moment, mean deviation, differential entropy, variance, reciprocal, cumulative mean, residual mean, cumulative entropy, cumulative variance, standard deviation, and assurance [2]. To identify important characteristics, a sequential forward elimination approach was employed. For instance, the best features for SVM were a correlation, standard deviation, mean deviation, and difference variance. Finally, classification was carried out using three classifiers: SVM, Naïve Bayes and KNN with classification accuracies of 77%, 70%, and 68%, respectively. PneumoCAD has been enhanced by the addition of five machine learning (ML) classifiers, including ANN, naive Bayes, multi-layer perceptron, decision tree, and SVM, as well as three-dimensional reduction techniques (sequential forward selection, principal component analysis (PCA), and kernel PCA). (KPCA)). The authors assessed the effectiveness of the algorithm for detecting pneumonia on CXR for each combination. Using 13 dimensional features produced by KPCA and categorised by Naive Bayes, the greatest accuracy (96%) was attained.

DEEP LEARNING

Deep learning algorithms are widely used for pneumonia detection. The accuracy obtained from deep learning models is quite higher as compared to other models and algorithms.

In [4] proposed by Pooja Rana, Pneumonia Detection Using Deep Learning Algorithms and used different deep learning models like VGG19, VGG16, ResNet50, Inception, CNN, R-CNN, ChexNet, Modified CNN, Transfer Learning (CNN), Mask-RCNN and Dual Net architectures were used. The highest accuracy was obtained by Mask-RCNN which is around 90%. The main problem is computational time, and the cost is very high in this.

Deepak Gupta et al.[5] extended the model Mask RCNN and used Mask RCNN in their model. Although they used regularisation to avoid overfitting, the findings on the testing dataset were less accurate than on the training dataset. By adding more layers, the accuracy may be increased, but many hyper-parameters will need to be changed.

Large Scale Automated Reading of Frontal and Lateral Chest X-Rays Using Dual Convolutional Neural Networks was suggested by Rubin et al. For the lateral and frontal chest x-rays, dual convolutional neural networks were used. Anteroposterior (AP), posteroanterior (PA), and lateral (Lateral) view types are three networks that are trained. They did it with the MIMIC-CXR dataset, which was their biggest dataset. It solely took into account radiograph pixel information while reaching a categorization judgement.

CNN and Transfer Learning were used by Rachna Jain et al. [7] to detect pneumonia in chest X-ray pictures. This paper explains two neural networks with outstanding performance for real-time applications. Both models are extraordinarily accurate and consistent. Model 2 recalls occur up to 90 percent of the time, whereas VGG19 recalls occur 95 percent of the time. The relative f1 scores for the Model 2 and VGG19 networks were 94% and 91%..

Investigation of the Performance of Machine Learning Classifiers for Pneumonia Detection in Chest X-ray Images' was published by Shengfeng Chen et al. ' Using test accuracy, F-score, and the ROC curve, they analysed all seven models and discovered that CNN performed somewhat better than the other models, with a test accuracy score of 98.46%. Surprisingly well, with a test accuracy score of 97.61%, random forest performs. However, there is much time spent waiting and jogging. Additional parameter tuning is required.

Borra Prudhvi et .al[9] introduced techniques like, Vgg16, Vgg19, Inception, Modified CNN, ResNet50, ChexNet, R-CNN, CNN, Mask-RCNN, Transfer Learning (CNN), Dual Net architecture, This models were discussed in this paper. In [9] comparison was done between different models, but the Mask-RCNN model gives the best accuracy.

Singarreddy Harshvardhan et al.[10] Dual Net architecture were discussed in this paper including some transfer learning algorithms. In this analysis also Mask-RCNN performed the best. But in each problem like detection, prediction, classification, and recommendation the computational time and cost are very high.

Aseel Ghazi et al.[11] compared two CNN models: VGG16 and Xception for diagnosing pneumonia. While the Xception model outperforms the VGG16 model in terms of sensitivity metrics, the VGG16 model outperforms the Xception model in terms of accuracy, specificity, precision, and f-score. Al Mamlook et al. presented seven models—random forest, decision tree, K-nearest neighbour, adaptive boosting, gradient boost, XGBboost, and CNN—for identifying and categorising pneumonia from chest X-ray data. Particularly, the f-score and accuracy score were used to compare all of these models. The accuracy score attained by the CNN model was 95.46%, somewhat better than the other machine learning models.
All CNN are followed by ReLU to gain higher performance. Precision, recall, F1-score, and accuracy statistics for the CNN model are the best, coming in at 98%, 98%, 97%, and 99.82%, respectively.

Techniques utilizing artificial intelligence can be utilized to identify a number of illnesses, including pneumonia. For diagnosing medical conditions, research has been conducted utilizing a variety of machine learning approaches. They have demonstrated the work in the area of medical image detection in this part. They evaluated the funding in light of its advantages and disadvantages. A powerful model for medical picture identification has been developed using a variety of datasets.

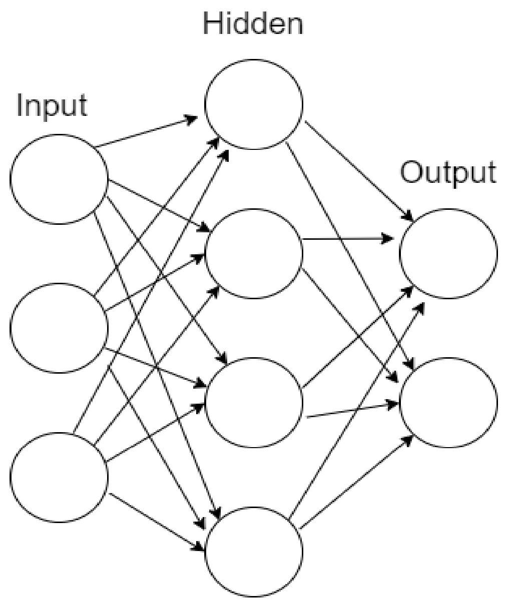

Fig 2: Neural Network

Detecting medical images is a challenging process, hence an efficient strategy is required. One of the methods that may be used to train medical picture collections is deep learning. The deep learning RestNet-101 and RestNet50 models were utilized in the study to identify pneumonia Khatri et .al[12]. Based on certain qualities, various outcomes have been obtained when taking these strategies into consideration. An efficient deep learner approach was thus developed that combines both strategies in order to make up for this disparity. A dataset of 14,863 X-ray pictures was employed in this investigation, and a precision of 96% was attained. Although the model produces acceptable precision, it has limits since merging the RestNet models is difficult and can reduce precision with the bigger datasets.

Jiang Xingfang et. al[13] proposed transfer learning techniques VGG19 and Deep Convolutional Neural Network (DCNN) for better results. A deep learning network DenseNet-121 which is a 121 layer Convolutional Neural Network model was used for pneumonia diagnosis. This method obtained a higher F1 score than specialized doctors. And also proposed a CNN model which extracted the features of images.

The dataset was firstly divided into three parts for training, testing, and validation for pneumonia or normal. In this research paper, CNN and ANN models were used. VGG19 was also used alongside the deep learning models. The highest accuracy was obtained from the VGG16 model i.e. 94.27% and it outperformed the other deep learning models. All the models had good performance after using the activation function ReLU. The training and validation accuracy was 97% for the VGG19 model, so it has the potential to achieve good results.

Fawad et .al[14] proposed a deep CNN based framework, in which they developed feature extraction of chest x-rays which was based on novel framework with AlexNet and classified the features extracted using a SVM classifier, and compared our results with D-CNN based models. Additionally compared by using several classifiers. With the KNN classifier, features that are retrieved using AlexNet descriptors have a maximum accuracy of 80%. Additionally, the HOG descriptor has poor accuracy. While SVM employing a Gaussian Kernel has an accuracy of 70%. The outcomes showed that the suggested approach had a 99.4% accuracy rate. AlexNet with SVM has 100% specificity and 98.3% sensitivity, respectively. F1 has a score of 0.99.

In[15],authors used backpropagation algorithm of ANN for pneumonia detection using RCNN and supervised learning from dataset containing chest x-rays image Backpropagation has supervised learning training and always uses adjustment pattern of weights to obtain the lowest possible error values between the outputs (actual and predicted).

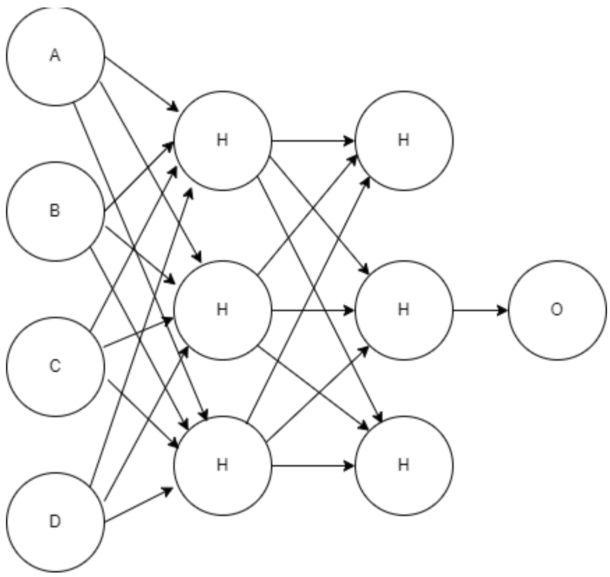

Fig 3. Backpropagation architecture

MLP (Multi Layer Perceptron) networks are also included in backpropagation because they have numerous layer screens for adjusting the weights in their hidden layer. Even if the testing is quick, the training process is slow. This algorithm performs two computing phases, forward propagation (feed forward) and backward propagation, as suggested by its name. The weight and bias settings on each iteration of the network's neurons will be changed.

Breast cancer, tuberculosis, and pneumonia infection are just a few of the chest diseases that an artificial neural network (ANN) can accurately detect and diagnose [16]. To get rid of any unnecessary data, various preprocessing methods were applied. Equalization of the histogram and image filtering were used as techniques to improve the imaging process. These methods are essential for lowering noise and sharpening pictures, which facilitates the quick identification of pneumonia. An important area of research for the diagnosis of pneumonia infection is lung segmentation. To assist identify the existence of pneumonia, a variety of diagnostic criteria, including perimeter, areas, irregularity index, equal diameter, and statistical approaches like standard deviation and entropy, were retrieved and applied to categorize the pictures.

A highly effective ML model is crucial for the intricate pattern recognition required for classifying medical images. Making it a reality requires deep learning, and CNN is one of the best methods for pattern identification because of its multilayer architecture. The extremely thick CNN structure is composed of a number of layers that have various heights, widths, and depths. Weight sharing is also made possible by depth [17]. The input is used to train CNN, and a variety of parameters are found to decide the output. The CNN approach seeks to reduce network discrepancies between anticipated and actual outcomes. The architecture of the CNN model is seen in the picture below.

Saurabh Sharma et .al[18] proposed deep learning techniques for pneumonia detection are surveyed. A convolutional neural network is explained in this paper. VGG16 and VGG19 are used in this paper and compared. ResNet used 50 layers and VGG16 used 16 layers for the computation. Deep CNN with pre-trained classifier model was used with an accuracy of 99.34% whereas the CNN based framework has the AUC score of 0.8 and deep network-based pneumonia detection with accuracy of 91.2%. The problems in these methods mainly were high computational time and inefficient results on challenging frames. Its performance can be further enhanced by using hybridization approach to detect the disease and improve the performance.

Small, localized regions are affected by a particular illness called thorax. As a result of the network's poor performance, the CXR was poorly aligned. According to the study, a three-branch AG-CNN architecture is essential for reducing noise and enhancing alignment from different diseased areas. Additionally, it incorporates international branches to lessen the impact of regional branches in the absence of discriminating indicators. They were able to comprehend different areas of CNN because of the utilization of chestXray-14 datasets. As a result of using this dataset, this approach generated an AUC of 0.87. With regard to parameter modifications, this approach is constrained. It is impervious to any parameter changes that would make it impossible for the model to anticipate a range of data. In order to diagnose and identify the presence of pneumonia infection, an experiment using the CheXNet algorithm with 121 layers of CNN and chest X-ray pictures was conducted by Bhandary et .al[19].

Kartik Thakral et .al[20] introduced combined model which was a merger of CNN based feature extraction model and supervised classifier algorithm which gave an excellent solution for pneumonia detection. DenseNets were used for hyper-parameter values of SVM classifier. Pre-trained CNN models such as VGG16 , Xception, ResNet and DenseNets were used. ResNets outshined the results of all pre-trained CNN’s. The DenseNet-169 feature extractor using the SVM classifier gave 0.79 AUC. The drawback is that there was no history of patients in their evaluation model. And because the model has a lot of convolutional layers, it needs a very high computational power.

The effectiveness of computer-aided methods for spotting pulmonary TB has been investigated [21]. To acquire an X-ray and diagnose pulmonary TB, different factors were examined, such as minimizing patient wait times. The radiologists conducted a visual evaluation on the textural aspects of thoracic X-ray images to perform diagnosis. While evaluating the study's outcomes, they also employed the principal component analysis approach. It was identified, categorized, and distinguished between TB and non-TB items based on numerous experimental arithmetical features. Lower interpretability difficulties are a hurdle when taking PCA into account. Data organization is also crucial for PCA to function well. PCA discovers linear connection between the variables, which is not always the best result.

A Sharma et .al[22] introduced, 'Detection of Pneumonia using ML & DL in Python' the methodology and approach has been explained. All of the X-ray images were trimmed to the ideal sizes for calculating by preprocessing the data. After that, the data was loaded into the RAM. They then created a model checkpoint and a callbacks method. The data was then reorganised, and CNN was utilised to create the model. Finally, they used the confusion matrix to fit the model and determine the accuracy and value loss.

In 2021,Luka Racic et .al[23] proposed the methodology in which ReLU and SeLU were the activation function used in their paper. Leaky ReLU was also used. Another method was used in which some neurons are shut down and not used for iteration. By including the dropout the networks accuracy is increased by 1-2% to boost the performance. Evaluation is done by various parameters such as training and validation accuracy and loss time. The model accuracy was 88.90% even then there is a possibility of overfitting due to size of dataset. In future they will include preprocessing and CNN configurations.

SUPPORT VECTOR MACHINE ALGORITHM

Support Vector Machine or SVM is one of the most popular supervised learning algorithms, used for classification and regression problems. However, it is mainly used for classification problems in machine learning.

In [24], DIAN CANDRA RINI NOVITASARI, RIMULJO HENDRADI, REZZY EKO CARAKA proposed Support Vector Machine (SVM). SVM is a classification method by finding the best hyperplane value and the result obtained from

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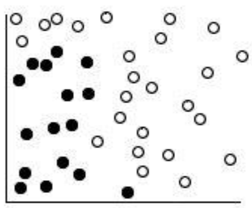
the best classification. Computational Learning Theory. SVM is being developed to address non-linear issues and currently uses linear classification as its main working approach. In order to select the best hyperplane that can most effectively remove the distances (margins) between classes from the data, a basic trick notion has been added to the process. If the greatest distance you can get is the distance between the hyperplanes in each class with the closest data. The hyperplane is the best option in the situation. Vapnik was able to demonstrate the usefulness of SVM for classification issues by categorising the training data into her two classes. SVM uses linear, radial basis function kernels (RBF), sigmoidal, and polynomial.

The SVM machine's fundamental objective is to provide the best decision line it can. That can categorise the many-dimensional space into multiple groups, making it simple to add new data points in the future. The hyperplane is the name of this optimal decision boundary. To generate the hyperplane, SVM chooses the extreme points and vectors. These extreme cases are referred to as support vectors, and the technique is referred to as a support vector machine.

Working –

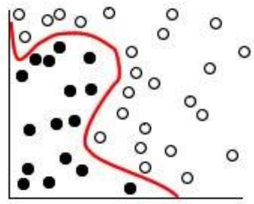
SVM works by mapping data into a multi-dimensional feature space. So the data points are classified, even if the data is linearly non separable. The separator between categories is found, then the data is transformed so that the delimiter can be plotted as a hyperplane. The new data's features can then be utilized to predict the group to which the new record will belong. Consider the graphic below, in which the data points are of two different sorts.

Figure 1.
Dataset



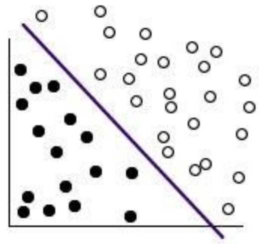
The curve separates the two categories, as shown in figure.

Figure 2. Separator added with data



Hyperplane is defined between the boundaries of two types of data after transformation.

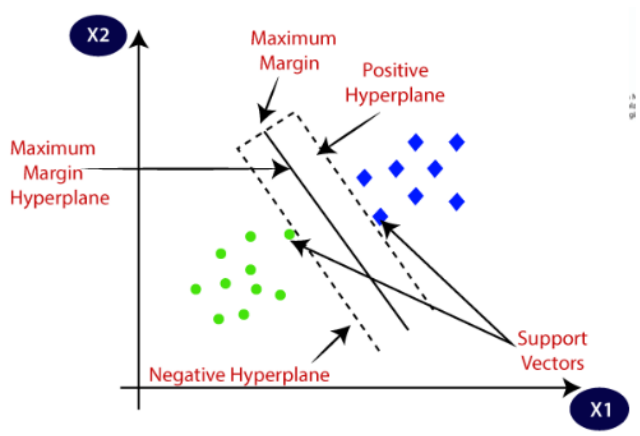
Figure 3. Data Transformed



The function used in the conversion is called the kernel function.

When the breakdown of linear data is straightforward, a linear kernel function is recommended. Other functions must be utilized in other circumstances. Because each function employs various methods and settings, we'll need to test them all to find the optimal model in each scenario.

Figure 4.



CONCLUSION

This study reviewed the current literature on pneumonia detection from chest radiographic data. We have summarized the topic and analyzed the ease of use, the figure of merit, and the computational complexity of the different algorithms which are currently in use. We have also verified that multiple images of chest x-rays are available for the project.

After looking at a number of researchers works that demonstrate how artificial neural networks can be used for pneumonia detection using chest x-rays images including different sizes of image, image segmentation, and other engineering techniques.

Although some pneumonia detection models work with up to 95% accuracy, the sensitivity or specificity of the models is often not what we expect. To assess model performance, all matrices, including sensitivity, specificity, AUC, and F1 measures, should be taken into account. Additionally, the models perform quite well for binary classes but badly for categorization of many classes (viral, bacterial pneumonia, normal, COVID-19). As a result, we should concentrate on creating novel CXR-based techniques for intelligent illness identification utilising simple algorithms that can effectively detect pneumonia infections across a variety of datasets.

REFERENCES

[1] Suganthi, L. & Nirmala, Krishnamoorthi & Deepa, S. & Nagalakshmi, K. & Santhya, M.. (2021). Detection of Pneumonia Clouds From Chest X-ray Images. 10.1007/978-981-15-8530-2_64.

[2] R. Barrientos et al., "Automatic detection of pneumonia analyzing ultrasound digital images," 2016 IEEE 36th Central American and Panama Convention (CONCAPAN XXXVI), San Jose, Costa Rica, 2016, pp. 1-4, doi: 10.1109/CONCAPAN.2016.7942375.

[3] Oliveira, Leandro & Nouer, Simonne & Ribeiro, Luiza & Oliveira, Renato & Coelho, Clarimar & Andrade, Ana Lucia. (2008). Computer-aided diagnosis in chest radiography for detection of childhood pneumonia. International journal of medical informatics. 77. 555-64. 10.1016/j.ijmedinf.2007.10.010.

[4] Sousa, Rafael & Marques, Oge & Soares, Fabrizzio & Sene, Iwens & Oliveira, Leandro & Spoto, Edmundo. (2013). Comparative Performance Analysis of Machine Learning Classifiers in Detection of Childhood Pneumonia Using Chest Radiographs. Procedia Computer Science. 18. 2579-2582. 10.1016/j.procs.2013.05.444.

[5] Jaiswal, A. K., Tiwari, P., Kumar, S., Gupta, D., Khanna, A., and Rodrigues, J. J. P. C., “Identifying pneumonia in chest X-rays: A deep learning approach”, <i>Measurements</i>, vol. 145, pp. 511–518, 2019. doi:10.1016/j.measurement.2019.05.076.

[6] Rubin, Jonathan & Sanghavi, Deepan & Zhao, Claire & Lee, Kathy & Qadir, Ashequl & Xu-Wilson, Minnan. (2018). Large Scale Automated Reading of Frontal and Lateral Chest X-Rays using Dual Convolutional Neural Networks.

[7] Jain, Rachna & Nagrath, Preeti & Kataria, Gaurav & Kaushik, V. & D, Jude. (2020). Pneumonia Detection in chest X-ray images using Convolutional Neural Networks and Transfer Learning. Measurement. 165. 108046. 10.1016/j.measurement.2020.108046.

[8] Al Mamlook, Rabia & Chen, Shengfeng & Bzizi, Hanin. (2020). Investigation of the performance of Machine Learning Classifiers for Pneumonia Detection in Chest X-ray Images. 10.1109/EIT48999.2020.9208232.

[9] D. Saikrishna et al., "Pneumonia Detection Using Deep Learning Algorithms," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2021, pp. 282-287, doi: 10.1109/ICIEM51511.2021.9445310.

[10] D. Saikrishna et al., "Pneumonia Detection Using Deep Learning Algorithms," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2021, pp. 282-287, doi: 10.1109/ICIEM51511.2021.9445310.

[11] Al-Dulaimi, Dalya & Mahmoud, Aseel & Hassan, Nadia & Alkhayyat, Ahmed & Majeed, Sayf. (2022). Development of Pneumonia Disease Detection Model Based on Deep Learning Algorithm. Wireless Communications and Mobile Computing. 2022. 10.1155/2022/2951168.

[12] Khatri A, Jain R, Vashista H, et al. Pneumonia identification in chest X-ray images using EMD. Singapore: Springer; 2020.

[13] Mehboob Qaimkhani, Faiza & Hussain, Md Gulzar & Shiren, Ye & Xingfang, Jiang. (2022). Pneumonia Detection Using Deep Learning Methods. International Journal of Scientific Research. 3. 5. 10.51542/ijscia.v3i3.32.

[14] Jamil, Sonain & Abbas, Muhammad & Khan, Fawad & Rahman, Muhib & Zia, Muhammad. (2021). A Deep Convolutional Neural Network Based Framework for Pneumonia Detection. 10.1109/ICoDT252288.2021.9441539.

[15] Yao, Shangjie & Chen, Yaowu & Tian, Xiang & Jiang, Rongxin. (2021). Pneumonia Detection Using an Improved Algorithm Based on Faster R-CNN. Computational and Mathematical Methods in Medicine. 2021. 1-13. 10.1155/2021/8854892.

[16] Yang Z-Y, Zhao Q (2020) A multiple deep learner approach for X-ray image-based pneumonia detection. In: 2020 international conference on machine learning and cybernetics (ICMLC), pp 70–75.

[17] Sarada N, Rao K. A neural network architecture using separable neural networks for the identification of “pneumonia” in digital chest radiographs. IjeC. 2021;17:89–100.

[18] Artemi M, Liu H (2020) Image optimization using improved grayscale quantization for content-based image retrieval. In: IEEE, pp 1–6

[19] Bhandary A, Prabhu GA, Rajinikanth V, et al. Deep-learning framework to detect lung abnormality—a study with chest X-Ray and lung CT scan images. Pattern Recognit Lett. 2020;129:271–8.

[20] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.

[21] Rohmah RN, Handaga B, Nurokhim N, Soesanti I. A statistical approach on pulmonary tuberculosis detection system based on X-ray image. Telkomnika. 2019;17:1474–82.

[22] Sharma, A & Negi, M & Goyal, A & Jain, R & Nagrath, Preeti. (2021). Detection of Pneumonia using ML & DL in Python. IOP Conference Series: Materials Science and Engineering. 1022. 012066. 10.1088/1757-899X/1022/1/012066.

[23] Račić, Luka & Popovic, Tomo & Cakic, Stevan & Šandi, Stevan. (2021). Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network. 10.1109/IT51528.2021.9390137.

[24] Novitasari, Dian & Hendradi, Rimuljo & Caraka, Rezzy & Rachmawati, Yuanita & Fanani, Nurul & Syarifudin, Mohammad & Toharudin, Toni & Chen, Rung-Ching. (2020). Detection of COVID-19 chest X-ray using support vector machine and convolutional neural network. Communications in Mathematical Biology and Neuroscience. 2020. 1-19. 10.28919/cmbn/4765.