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MACHINE LEARNING ASSISTED PNEUMONIA DETECTION

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Abstract:-The creation of hardware and software with intelligence that mimics human behaviour is the focus of the branch of computer science known as artificial intelligence (AI). Computers designed with artificial intelligence are capable of recognizing speech, learning, problem-solving, and planning, among other things. One of the most deadly infections, pneumonia can swiftly cause major damage to the lungs. An infection of the lungs, either bacterial or viral, causes it. A effective course of treatment depends on an early diagnosis. In order to diagnose chest X-rays and simplify the pneumonia diagnosis process for both experts and novices, there is a need for an intelligent and autonomous system. There are models for x-ray imaging-based methods of pneumonia diagnosis and identification that are quick and straight forward. The goal of this study is to create a model that will help in classifying chest x-ray images into normal (healthy) and abnormal conditions (sick).Seven state-of-the-art machine learning techniques have been applied to improve accuracy and efficiency, in addition to well-known convolutional neural network models. This article reviews the techniques and approaches for utilizing deep learning to build a model for pneumonia detection. In order to help the chest doctor make decisions quickly, accurately, and conveniently, it is important to find a reliable and effective way to diagnosis pneumonia using X-rays. Annotated datasets were accessible and provided as a testing ground for machine learning techniques. They are performing numerous imaging-related jobs in the medical field. Pneumonia is the leading cause of death in children under five worldwide, accounting for more than 15% of all fatalities. Here, we describe a machine learning-based approach to detecting and localizing pneumonia in chest X-ray images (CXRs). However, you require specialized expertise and experience to appropriately read the X-ray images. As a result, examining X-ray images to look for pneumonia can take some time. The reason is that a variety of different medical diseases, including lung cancer, having too much fluid in your system, etc., can produce visual opacities that are similar. As a result, accurate image reading is highly desirable. It is commonly known

that computers are capable of doing complex computations, therefore developing a model for determining the causes of pneumonia in clinical imaging can increase the precision and understanding of X-ray pictures.
Key words: Chronic kidney disease (CKD), atherosclerosis, hypertriglyceridemia.

Introduction

A branch of artificial intelligence is known as machine learning (AI). The main objective of machine learning is to understand the structure of data and fit that data into models that people can recognize and use.

Machine learning is unique from traditional computational techniques even though it is a subfield of computer science. Algorithms are sets of purposefully crafted instructions that computers use to do calculations or address issues in traditional computing. Instead, computers may train on data inputs and utilise statistical analysis to produce numbers that fall inside a specified range thanks to machine learning techniques. Machine learning enables computers to build models from test data and automate decision-making using inputs from data. The air sacs in one or both lungs become inflamed when someone has pneumonia. The air sacs may swell with fluid or pus (purulent material), causing breathing problems, a fever, chills, and a cough that produces pus or phlegm. Numerous species, such as bacteria, viruses, and fungi, can cause pneumonia. The three primary types of pneumonia are divided into groups based on where the sickness originated, how it spread, and how it spread. Plague caused by bacteria: The most common cause of bacterial pneumonia is streptococcus pneumonia. Legionella pneumophila and Chlamydophila pneumonia can also result in bacterial pneumonia. Pneumonia is usually caused by respiratory viruses, especially in young children and the elderly. Virus-related pneumonia is typically not hazardous.

In order to get beyond the restriction of execution time, Graphical Processing Units (GPU) have become crucial in contemporary medical image processing applications, especially in the context of machine and deep learning approaches. Practically all medical image processing projects employ GPUs as accelerators to deliver better and faster results because they can significantly speed up parallel processing. Machine learning has already proven to be an effective technique in fields like object recognition and segmentation, picture classification, natural language processing, etc.

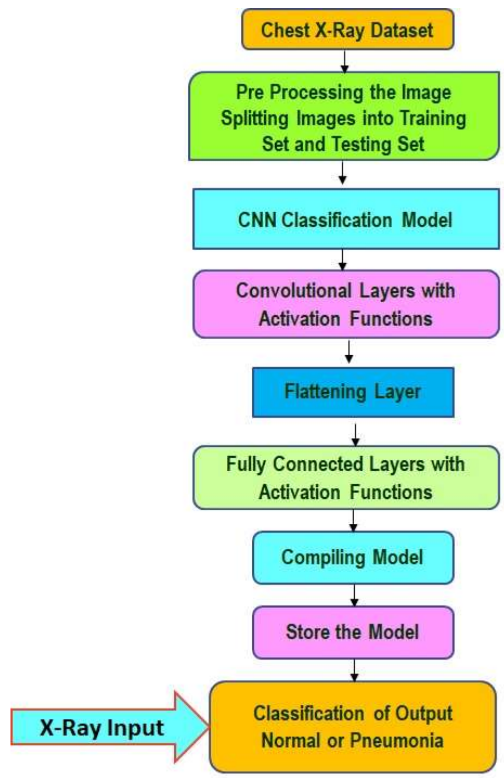

Fig.1 Flow Chart

Methodology

The system is composed of several stages, including feature extraction, classification model building, and description of data collection and processing. These six phases are the data set, data preparation, model development and model evaluation, and training and testing. Details of each stage are covered in the following sections. It was a chest X-ray image, which can either show pneumonia or a normal chest X-ray. For the purpose of subsequently detecting and classifying pneumonia, we have taken representative images from the collection and presented them here. Clean data is needed for machine learning, which depends heavily on data. There are several pre-processing techniques employed, such as dimension reduction, image resizing, and image cropping. The initial data sets showed a number of problems that needed to be fixed before image categorization. It is first necessary to restore the image to its original size. It is possible to crop the image to exclude superfluous background features. The raw pictures come in a variety of sizes. The machine learning model's training data must all be the same size. To differentiate between images of pneumonia and images of healthy people, various machine learning models were employed. The module's objectives are to select the most precise model for prediction and to provide a binary classification of pneumonia's presence or absence in a chest x-ray. We built our systems using traditional machine learning methods, in which the engineer manually selected and retrieved input features based on criteria that he or she thought were appropriate. The methodology that follows was developed to recognize and classify pneumonia in chest X-ray images. Additionally included are image processing and convolutional neural networks. We came up with a model. The process begins by reducing the size of chest X-ray images from their original dimensions. Image pre-processing, feature processing included into the convolution process, network training, and model validation are the primary phases for any image classification system.

Data preparation for the network entails cropping and resizing images, eliminating extraneous pictures, and correcting contrast. Dataset preparation is the practise in question. normalizing and producing winners from raw data. Selection and extraction of component of the convolution layers, only significant features are chosen and extracted before being converted to the appropriate format.

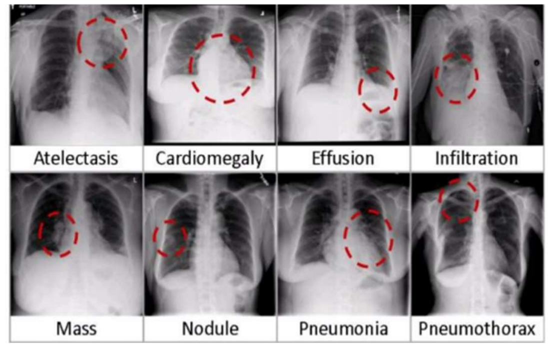

Fig.2 Examples lung-disease images extracted from the chest X-Ray datset

Testing: The training data is the biggest (in - size) subset of the original dataset, which is used to train or fit the machine learning model. Firstly, the training data is fed to the ML algorithms, which lets them learn how to make predictions for the given task we use a test set, a brand-new dataset for the model, during this phase. To properly test the model, the test set's ground truth must be comparable to the training set's while being uncorrelated. This improves the test's reliability and validity. The problem is that lung opacities on chest X-rays are binary divided into three different groups: opacity, no opacity, and not normal. The fundamental issue is that different X-rays exhibit varying brightness, resolution, and zone of interest characteristics. We create a system that can recognize the visual sign of pneumonia in medical chest radiographs and, if positive, also generates projected bounding boxes around lung opacities in order to simulate this task. Our algorithmic approach for identifying potential pneumonia causes was created using Faster-RCNN. According to our tests, Mask-RCNN was more accurate in its predictions than other object identification techniques like You Look Only Once (YOLO3) and U-Net image detection architectures. We created the basis network of Mask-RCNN pre-trained on COCO weights2 by using traditional residual convolutional neural networks (i.e., ResNet50 and ResNet101) for extracting features from actual human lungs, ROI Align as a classifier, and bounding box as a regressor. In order to facilitate scaling during inference and losses, we developed pixel-level lung opacity segmentation using ROI classifiers. This was accomplished using stochastic gradient descent (SGD) with a batch size and picture size of 16 and 512 512, respectively, and a training time of 11.2 hours for 20 epochs. Only positive photos were used to train our model at first, and subsequently all images having a foreground IoU threshold of 0.3 were used to fine-tune it. As part of the training, augmentation3 was also done.

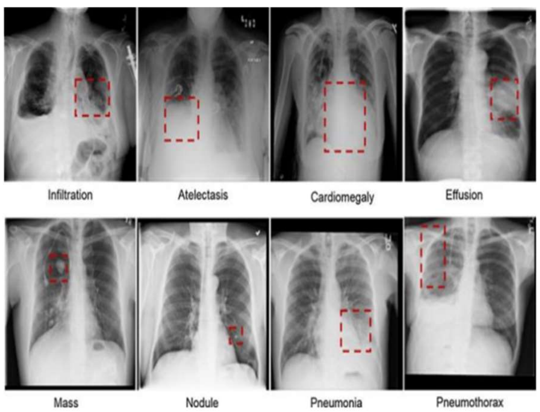

Fig.3 Samples images taken from dataset

Training: After post-processing, we use the entire training set to generate our final prediction set using an ensemble of two trained models. Since our main interest is on bounding boxes that are "hits," we made separate forecasts for each model. Dataset: A substantial chest radiograph dataset from RSNA7 that annotated 30,000 exams from the initial 112,000 chest X-ray dataset was used as the training set. We used a dataset from STR8 that essentially produced con- senses annotations for six chest X-rays as our test data. The annotated collection, which emerges after training our system for evaluation, contains the participants' ground truth. The actual 30,000 sample sets are made up of 15,000 samples with labels like "Pneumonia," "Consolidation," and "Infiltration," while the remaining 3,000 samples are chosen at random to have labels like "No Findings," which do not mention pneumonia. They created a unique identification for each of the six samples. Samples were annotated and rendered inaccessible to other people's annotations using unique web-based annotation system. Each radiologists practitioner who took part in the training first performed on the same set of 50 exemplary chest X-rays in a hidden manner, and then were visibly annotated to the other practitioners for the same 50 chest X-rays. The questions were, "Does an X-ray with healed rib fractures enumerate and no enumeration as "Nor- mal"?" and for preliminary calibration. We discuss adjudication as we collect data for such a challenging project. If a bounding box in a multi-read case does not match the bounding boxes of the other two readers, it is deemed isolated, indicating that neither of the other two readers identified that particular region of the image as having pneumonia. Whenever the adjudicator determines that it is valid, the isolated bounding box will continue to hold a favourable minority belief; otherwise they initially assigned a confidence rating to the bounding boxes. A low confidence bounding box was also removed, and an acceptable pneumonia group was created by combining high and moderate boxes. They toss a low probability bounding box and look at the labelling to determine whether or not there is lung opacity. One of the two thoracic radiology practitioners made the decision on the opposing bounding boxes in multi-read situations where consent wasn't obtained. The practitioners also found that the combined percentage of the three readers' notes in the final decision was higher than 15%. They used intersection for the remaining bounding boxes when at least 50% of one of the bounding boxes coincided. For numerous readers, this procedure successfully eliminates specific pixel data, including affirmative pixels. 1500 read instances were selected from the 4500 triple cases in the training set in order to average out the few potential discrepancies between single and multi-read cases. Additional triple read examples totaling 3000 were added to the test set. Majority voting distinguishes weak labels. The radiologists collected data while adhering to the following rules:

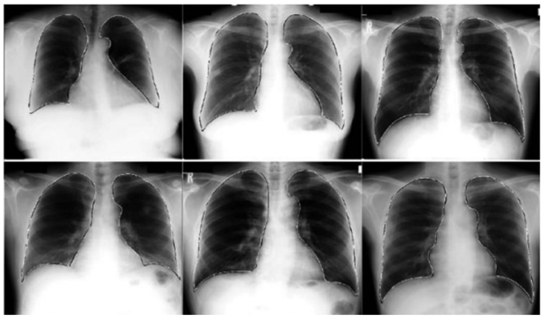

Fig.4 Samples images from dataset

Bounding box (Lung Opacity): A patient's chest radiograph reveals a fever and a cough that are likely signs of pneumonia. They came up with relatively few conjectures while lateral radiography, serial examination, and clinical data were put on hold. Based on Fleischner's findings, they took into account every location that was more opaque than the surrounding area. Additionally ignored were nodules, apparent masses, linear atelectasis, and lobar collapse given that the collection is very uneven, the current status of the patient class and labels obtained from the X-ray images. The imbalance of the training and test dataset, with too many negatives and too few positives, causes a serious problem because we want for high recall yet the model may predict all negatives to obtain high accuracy. Whether the current imbalance is appropriate in this circumstance is a matter of debate. We check to see if there would be any benefits from changing the class distribution in this case. We trained our model using two training data sets, one balanced and the other not. More photos are subsequently added to the negative (0) class to create the balanced dataset. We've already talked about the augmentation techniques, such as flipping, rotating, scaling, cropping, translating, and noise addition . The inclusion of the images in the current negative class could lead to the development of a brand-new feature that is not present in the other classes. For instance, the negative class will have a collection of images with the right and left halves of the bodies inverted whereas the other class will not if we choose to flip every image in the negative class. This is undesirable because the network could gather irrelevant (and incorrect) information. For instance, the network might learn that an image with the left side of the body positioned in a specific way is more likely to indicate something other than pneumonia. The average of the intersection over union (IoU) of the coupling prediction and ground truth bounding boxes is what we employ. As an evaluation metric for the task of identifying pneumonia, the IoU can be calculated from the paired threshold, which is the region of the predicted bounding boxes and ground-truth bounding boxes. It uses the following IoU formula:

In this part, we give the outcomes of our predictions, followed by those of the ensemble model.

We carry out ensembling due to the labelled dataset in Stage 2, which contrasts with the incredibly unbalanced dataset in Stage 1. The difference in the dataset is due to radiologists not having enough time during their shifts to read a lot of pictures. This topic was discussed before in the article. We overlay the likelihood of the labels from the ground truth to assess if it is flipped or not. This illustrates the possibility of disparities between anticipated bounding boxes and ground truth bounding boxes in precise forecasts. NVIDIA Tesla P100 GPU and Tesla K80 were used in Stages 1 and 2 to create the suggested model, which further shows the need for efficient computational resources when modelling such tasks on totally imbalanced datasets .The prediction outcome of our model at the specified threshold, with Stage 2's best prediction set of bounding boxes and ground-truth boxes being the outcome.

Classifiers using machine learning

Neural Network: The theory is based on how the human brain works; it makes use of the same notion of how neurons in the brain communicate. In order to activate additional neurons and learn the proper weight for prediction, different layers of neurons communicate with one another.

Random Forest: This method eliminates over-fitting and improves accuracy by averaging the results of several decision trees.

Support Vector Machine: This method finds a hyperplane between the datasets by using a vector. In order to separate the various classes, the hyperplane acts as a barrier. In addition, outcomes are shown here after categorising the newly acquired data (in which group it belongs since they are all divided by a hyperplane).

Adaboost's ensemble-based technique: which uses the output of one tree as the input of the following one after some modifications. Accuracy and over-fitting are enhanced by doing this.

Logistic Regression: This classification technique identifies relationships between dependent (label) and independent (features) variables by taking probability into account.

Decision Tree is a machine learning classifier that is built on graphs.

False positive statistics show that patients are rarely misdiagnosed as having pneumonia when they are actually healthy. Although several models have accuracy that is comparable to one another, we can more easily evaluate the models when we take additional metrics into account. TP rate is a significant factor to consider while comparing the models. The suggested DCNN model's robustness is investigated using the K fold cross validation method. To assess the results, additional metrics can be analysed, including training accuracy and loss, validation accuracy and loss, and of course model correctness. Although the model's accuracy is rather high—nearly 90%—the magnitude of the dataset raises the danger of overfitting. Additionally, the prediction model could possibly be used as a decision support tool due to its 90% accuracy, although there is still much work to be done. Medical experts must still be involved and present for the appropriate diagnosis of any condition. It is crucial to collect as much data as possible in order to create an accurate and trustworthy illness categorization model.

Experiments with other CNN and pre-processing settings, data augmentation methods, and the use of additional X-ray datasets with extra data labels showing other illnesses are also part of future research steps.

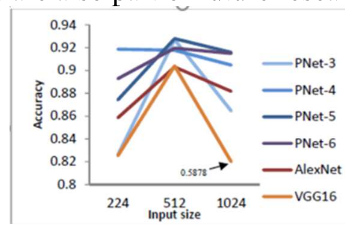

Fig.5 Accuracy

Although the images are of very high quality and are of various sizes, they were later downsized for the model's training. Due to data augmentation, more X-ray images classified as "Pneumonia" were added to the training dataset in order to increase the number of training instances of "Normal" images. a few samples of X-ray images together with their associated labels.

Implementation

Step 1: download the dataset using this link. The dataset has folders labelled Test, Train, and Validation. For training our model, we'll need test and training datasets. The validation dataset will next be used to validate our model.

Step 2: Import all of the required Keras modules, such as Image Data Generator, Model, Dense, Flatten, and others. We're going to write generic code, which means all we have to do to make it work with VGG16, VGG19, and resnet50 is modify the name of the library.

Step 3: This is followed by providing our image size, which is 224 by 224 for the VGG16 architecture. The number 3 indicates that we are working with RGB-style photos. Next, we'll offer our data pipeline for training and testing.

Step 4: At this point, we'll import the VGG16 model. When importing, we'll use image Net's weights and include We only dropped the first and last layers because our difficulty is with the two categories Pneumonia and Normal, not with the 1000 different categories that are included in imageNet. Instead, we will create our own layers and add them to VGG16.

Step 5: After importing the VGG16 model, we must make this crucial adjustment. by utilising the for loop to go over each layer while changing the trainable flag to False, preventing the training of any additional layers.

Step 6: To determine how many output labels we should have, we will attempt to count the number of classes in our train dataset.

Step 7: Since the first and last columns were erased in the preceding step, we will simply create a flattened layer and then add our final layer using a softmax activation function. Len (classes) represents the number of categories in our output layer.

Step 8: By combining the VGG output with prediction, we can now build a model. When we look at the model summary, we can see that there are just two categories in the last layer.

Step 9: At this point, we will compile our model using the Adam optimizer and an accuracy-based optimization metric.

Step 10: Using Image Data Generator in Keras, we must import our dataset into Keras after the model has been built. We employ metrics like rescale, shear range, and zoom range to create additional features; they will be useful throughout the training and testing phases.

Step 11: Utilizing the flow from directory () function, we will now insert the images. Please ensure that we pass the same image size that we did earlier. Batch size 4 denotes that 4 photographs will be sent for training all at once. Class mode is categorical, meaning that it only accepts two options: pneumonia or not.

Step12: Similarly, we will do the same for the test dataset what we did for the train dataset.

Step 13: In the final step, we fit the model using the fit generator () function, supplying as arguments all the information required for both the training and testing datasets. The execution of this will take some time.

Step14: Create a model file and store this model. So that we don't need to train the model every time we gave input.

Step15: Load the model that we created. Now read an image and preprocess the image finally we check what output our model is giving using model. predict () function.

4. Results

Model accuracy in machine learning refers to the evaluations done to determine whether or not a particular model is the best to explain the relationship between the many problem variables. To train a model for fresh, unused data, we frequently employ training data (sample data). Training set and validation set both accuracy is checked

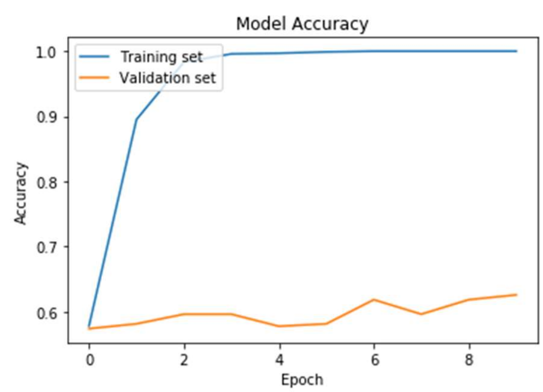

Fig.6 Model Accuracy

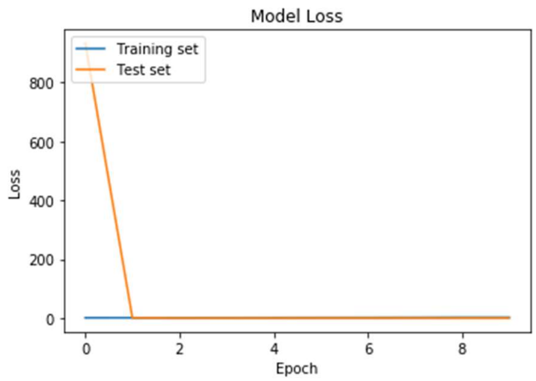

Fig.7 Model Loss

A machine learning loss function measures how well your ML model can forecast the expected result, or the ground truth. The output value of our model and the predicted value based on the ground truth will serve as the inputs for the loss function.

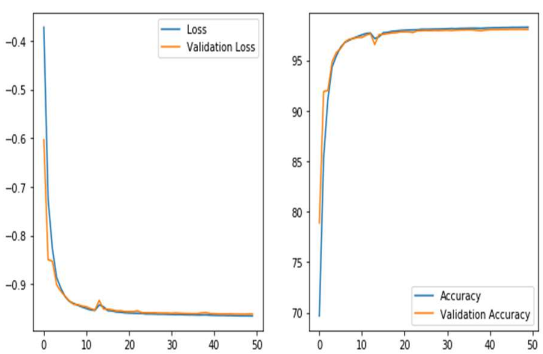

Fig.8 Validation loss and accuracy

A machine learning loss function measures how well your ML model can forecast the expected result, or the ground truth. The output value of our model and the predicted value based on the ground truth will serve as the inputs for the validation loss. Accuracy and validation accuracy is checked in this graph

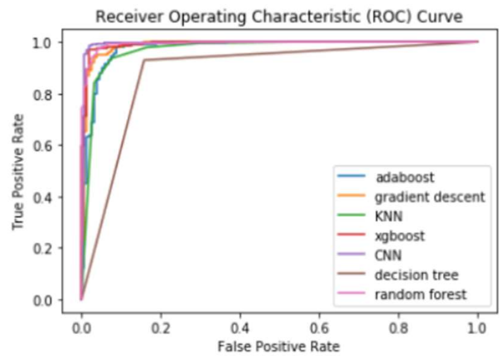

Fig.9. ROC curve

We have samples amongst which we have 90% accuracy if we look carefully, we will see that the dataset is skewed that is, the number of positive samples is far more than the negative samples. So it is not advisable to decide the best model just based on accuracy because it does not represent the data completely. So you might get high accuracy, but your model will probably not perform that well when it comes to real-world samples. Therefore, we need a more reliable evaluation metric and hence, ROC comes into the picture.

Authors & Years	**Methodology**	**Modality**	**Classification Type**	**Performance metrics**				
				Accuracy	**Precision**	**Sensitivity**	**F-measure**	**ROC**
Singh, D. *et al. 2020 [18]*	Convolutional neural networks	CT images	Binary	77%	72%	✓	✓	✓
Yan, Qingsen, et al. *2020 [19]*	Deep CNN model	CT images	Binary	97%	93%	✓	×	×
Shan, Fei, et al. *2020 [20]*	Deep Learning	CT images	Binary	63%	60%	×	×	×

Conclusion

This study describes the use of deep learning to classify digital chest X-ray images according to the presence or absence of changes consistent with pneumonia. The implementation was built using Python programming and scientific methods using the CNN model. More research is necessary even if early trials have produced positive results.

Despite the model's excellent accuracy—nearly 90%—the size of the dataset increases the risk of overfitting. Although there is still much work to be done, the prediction model's 90% accuracy makes it potentially useful as a decision support tool. Any problem must still be properly diagnosed by medical professionals who must be involved and present. It is essential to gather as much information as you can in order to produce.

Future research steps will also include experimenting with different CNN and preprocessing settings, data augmentation techniques, and the inclusion of additional X-ray datasets with extra data labels showing other disorders. In this study, we have explained our strategy for diagnosing pneumonia and how the performance of the model depends on the size of the lung picture. We found that the difference between pneumonia present and absent in pictures is rather minor and that a larger image can offer more specific information. However, the cost of calculation also increases significantly when working with large photos. Similar to Mask-RCNN, our proposed architecture offered more context for generating accurate results. We also employed background thresholds when configuring our network for this activity. In order to avoid overfitting while using picture augmentation, dropout and L2 regularisation were applied, although the training set results were weaker than the test set results. Our model can be improved by include additional layers, but doing so would introduce new hyper parameters that would need to be adjusted. We wish to extend our model architecture into further medical imaging disciplines using deep learning and computer vision. In this paper, we introduced a model for identifying and classifying pneumonia from chest X-ray images using machine learning methods based on convolutional neural networks (CNN). When the test accuracy score, F-score, and ROC curve of all seven models are evaluated, CNN looks to outperform the competition with a score of 98.46%. Surprisingly, Random Forest performs well, achieving a score of 97.61% on the test of test accuracy. Because of how long it ran and how long it required to wait, the CNN model was only tested with 100 epochs. We think that with careful parameter tuning and a little more time, the CNN model could yield an even better result. Our model's results show that it outperforms rival techniques that don't need additional training data on chest radiography, showing that image training may be enough for general medical image identification. Additionally, detecting pneumonia with the use of a machine learning-based medical system would enhance the results and benefit both doctors and their patients.

Future Scope

Pneumonia in people who are not properly diagnosed has the potential to be lethal. According to a Globe Health Organization estimate, almost two thirds of the population of the world does not have access to radiological diagnostics in India. In this study, reports of chest X-ray imaging scans are used to construct a deep machine learning-based prediction model that accurately predicts pneumonia in patients. Machine learning increases the efficiency of this task because it is effective at processing visual data.

Python is used to create a powerful model that will assist medical practitioners in the early identification of this devastating condition. Modern machine learning methods are compared to the proposed framework, and it is found to be more effective at prediction with an average accuracy of 84%, which is better than all other classifiers. In subsequent study, the results will be optimised to improve prediction precision. Additionally, more picture data will be obtained, and Hadoop will be used as the foundation for data processing. In the future, we will use big data to collect X-ray images from hospitals in order to train and test the algorithm and forecast results more precisely. This study may be used in related investigations that help develop detection technologies like COVID-19.

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