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Mediflex Diagnostics
Detection of COVID, Pneumonia Using CNN

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Abstract - At the end of 2019, a new form of Coronavirus, called COVID-19, has widely spread in the world. To quickly screen patients with the aim to detect this new form of pulmonary disease, in this paper we propose a method aimed to automatically detect the COVID-19 disease by analyzing medical images. We exploit supervised machine learning techniques building a model considering a data-set freely available for research purposes of 85 chest X-rays. The experiment shows the effectiveness of the proposed method in the discrimination between the COVID-19 disease and other pulmonary diseases.

Pneumonia remains a threat to human health; the coronavirus disease 2019 (COVID-19) that began at the end of 2019 had a major impact on the world. It is still raging in many countries and has caused great losses to people's lives and property. In this paper, we present a method based on DeepConv-DilatedNet of identifying and localizing pneumonia in chest X-ray (CXR) images. Two-stage detector Faster R-CNN is adopted as the structure of a network. Feature Pyramid Network (FPN) is integrated into the residual neural network of a dilated bottleneck so that the deep features are expanded to preserve the deep feature and position information of the object. In the case of DeepConv-DilatedNet, the deconvolution network is used to restore high-level feature maps into its original size, and the target information is further retained.

I. INTRODUCTION

Covid-19:

The COVID-19 outbreak has risen to the status of one of the most severe public health issues of the last several years. The virus spreads rapidly: the reproduction number of COVID-19 varied from 2.24 to 3.58 during the initial months of the pandemic, indicating that each infected individual on average transmitted the disease to two or more others. Consequently, the number of COVID-19 infections grew up from a few hundred cases (most of them in China) in January 2020 to more than 43 million cases in November 2020 disseminated across the world.

Pneumonia:

According to a study by Liu et al. in 2015, among the 5.9 million deaths of children under 5, over 15.6% were due to pneumonia; timely diagnosis and treatment could greatly reduce this mortality level. However, the contrast in chest X-ray images is low, making manual evaluation inefficient. Computer-aided diagnosis can enhance efficiency and lead to timely treatment.The size, shape, and position of pneumonia can vary a great deal. Its target contour is very vague, which leads to great difficulty with detection, and enhancing the accuracy of detection is a major research problem. At present, detection algorithms include two-stage object detectors such as Faster R-CNN and one-stage detectors such as YOLO and SSD. The latter uses an additional stage to complete the task of multiscale target detection. They are faster than two-stage detectors but less accurate. Medical testing has high requirements for accuracy, and two-stage detectors have an advantage in this respect.

II. LITERATURE SURVEY

Artificial intelligence approaches have repeatedly given accurate and dependable outcomes in applications that use image-based data. Using deep learning techniques, researchers have been investigating and analyzing chest X-ray images to identify COVID-19 in recent years.

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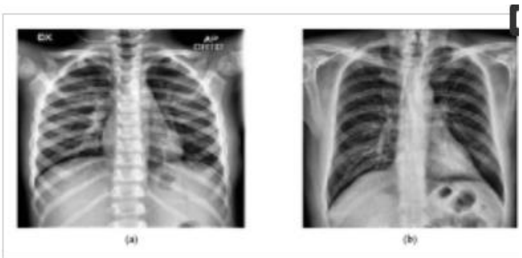
In, the images were normalized to extract enhanced features, which were then fed into image classification algorithms utilizing deep learning techniques. Five cutting-edge CNN systems, VGG19, MobileNetV2, Inception, Xception, and InceptionResNetV2, on a transfer-learning scenario, were tested to detect COVID-19 from control and pneumonia images. Experiments were conducted in two parts: one with 224 COVID-19 pictures, 700 bacterial pneumonia images, and 504 control images, and another with the prior normal and COVID-19 data but 714 instances of bacterial and viral pneumonia. In the two- and three-class classifications, the MobileNetV2 net had the greatest results, with 96.78% and 94.72% accuracy, respectively.

Three CNN architectures (ResNet50, InceptionV3, and InceptionRes-NetV2) were evaluated in relation to COVID-19 identification in, utilizing a database of just 50 controls and 50 COVID-19 cases. ResNet50 achieved the highest accuracy of 98%.

III. PROPOSED METHOD

Covid-19:

A chest X-ray database was used to experiment with this study. This database is currently one of the popular public X-ray databases, containing 3616 COVID-19 cases along with 10,192 healthy, 6012 lung opacity and 1345 viral pneumonia images. However, only COVID-19 (3616) and healthy (10,192) X-ray images were extracted for this study. As a result, the dataset includes studies of COVID-19 and healthy individuals with a matrix resolution of 299 × 299 (two X-ray examples are shown in. EnsNet, a system for scene-text removal, was used to remove annotations from certain images. EnsNet is capable of automatically removing all of the text or annotation from an image without any prior knowledge Thereafter, the images were scaled down to the classifier's standard resolution (for instance AlexNet was 256 × 256 pixels, whereas GoogLeNet was 224 × 224 pixels). After resizing the picture, the machine learning classifier used the enhanced (52,000) images in a ratio of 80% data for training, whereas 20% was used for testing. shows the details of the dataset.



Pneumonia:

In 2018, the Radiological Society of North America (RSNA) [b20] released a dataset on the detection and localization of pneumonia in chest X-rays. The dataset is from the National Institutes of Health (National Institutes of Health) public chest X-ray images, with radiologist annotations. The detailed information of the RSNA pneumonia detection dataset can be found on the Kaggle website The RSNA pneumonia data used in this experiment contains data of 26684 cases, of which only 6012 pneumonia images (accounting for 22.03%), and the remaining 8851 normal images (accounting for 31.19%) and 11821 images (accounting for 44.77%), an image that is abnormal or has no turbidity in the lungs. In most deep learning, images without targets are of no use to the training of the network, so this part of the meaningless data is eliminated in the initial stage. Since the patient's chest pneumonia may have more than one location, there may be one to four locations. Therefore, in order to maintain sample balance, we finally use 6012 images with annotations, of which 4/5 is selected as the training set and 1/5 as the test set. And count the number of lesions in the training set and test set as shown.

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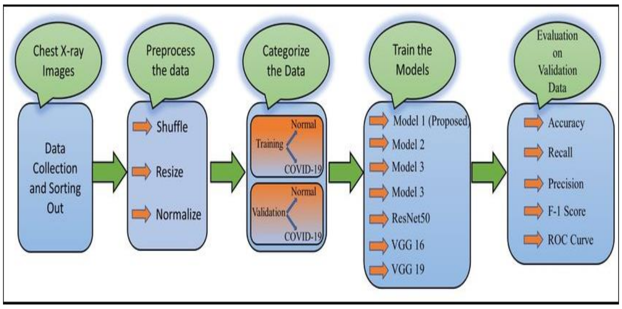
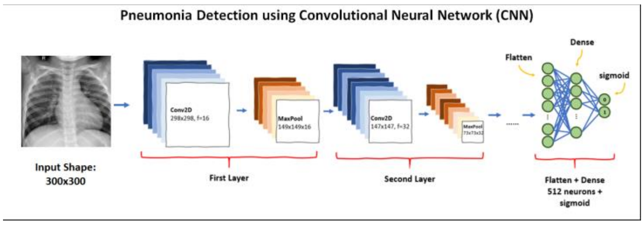
Architecture Diagram:
Covid-19:



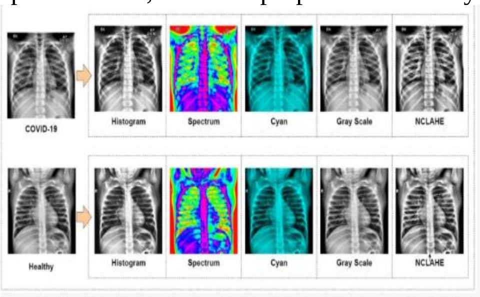
Pneumonia:



IV. RESULTS

Covid-19:

The suggested study used pre-trained CNN models and compared their performance to a new modified MobileNetV2 technique in order to get the highest performance for COVID-19 identification from 52,000 (26,000 COVID-19 and 26,000 healthy) chest X-ray images. Along with the proposed modified MobileNetV2, the VGG16, VGG19, MobileNetV2, ReseNet101, InceptionV3, ResNet50, Google Net, Alex Net, EfficientNetB7, Dense Net and NFNet deep models were assessed in terms of performance and compilation time, since the purpose of the study is to find the most optimal model.



Pneumonia:

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We compare the detection effects of all methods on different quantities of ROI areas, as shown in. No matter single target or multiple targets, the detection effects of our model are preferable to those of other benchmark models. The detection box is closer to the real target, and the number of detection boxes on the target box is closer and more accurate.

V. CONCLUSTION

The chest X-ray images (COVID-19, healthy) were mostly applied to analyse lung problems. The study attempts to understand the specific strengths and weaknesses of common deep learning models in order to identify COVID-19 with acceptable accuracy. This is critical for a doctor's decision-making, since each has benefits and drawbacks. Furthermore, when time, resources, and the patient's condition are restricted, the doctor may be forced to make a choice based on only one modality. In this work, deep learning techniques were used for automatic COVID-19 detection from chest X-ray images. In this paper, a low complexity residual neural network with a dilated bottleneck structure, called 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. In the RPN, we use the Soft-NMS algorithm to filter the anchor box and ensure its quality. To speed up the convergence of the algorithm and improve the prediction accuracy of the target area, we also used the K-Means++ algorithm in YOLOV3 to obtain the initial anchor box size. We implant deconvolutions in FPN to variance in scale and thus facilitate recognition from features computed on a single input scale. Finally, we got the result of this method. Combining the different sets of work done in each network, the ability of the algorithm to detect pneumonia accurately in the RSNA dataset is enhanced.

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