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CLASSIFICATION OF RESPIRATORY DISORDERS USING SEGMENTATION, FEATURE EXTRACTION AND FEATURE FUSION OF X-RAY IMAGES

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Abstract: Learning about Lung Diseases and their characterization is one of the most interesting research topics in recent years. With the various uses of medical images in hospitals, pathologies, and diagnostic centers, the size of the medical image datasets is also expanding expeditiously to capture the diseases in hospitals. Though a lot of research has been done on this particular topic still this field is confusing and challenging. There are lots of techniques in literature to classify medical images. The main drawback of traditional methods is the semantic gap that exists between the low-level visual information captured by imaging devices and high-level semantic information perceived by a human being. Respiratory disorders have always been the leading infectious disease leading to the death of children under five years old. Timely diagnosis of lung disease is essential. Many image processing and machine learning models have been developed for this purpose. Different forms of existing deep learning techniques including convolutional neural network (CNN), vanilla neural network, visual geometry group based neural network (VGG) are applied for lung disease prediction. The basic CNN has poor performance for rotated, tilted, or other abnormal image orientation. Therefore, we propose a new hybrid deep learning framework by combining segmentation and data augmentation with CNN. X-ray images of the lungs have become the key to the diagnosis of this disease. In this project we are using deep learning technology based on the combination of image segmentation and feature fusion. We used U-NET architecture for the Segmentation model. We try different pretrained models for classification. We also use image augmentation techniques to solve the imbalance in the dataset and increase generalization. In this project we work on classification of respiratory disorders using deep learning techniques. We apply Image segmentation to more accurately divide the lung area, then we extract feature maps from pre-trained CNN models, then we perform feature fusion and finally we classify the data. First, use residuals to achieve image segmentation to more accurately divide the lung area. Feature fusion is a kind of algorithm, which can merge some independent features to a unique feature in order to process them easily.

Keywords— segmentation, feature extraction and feature fusion, classification, UNet .

I. INTRODUCTION

Respiratory diseases, or lung diseases, are pathological conditions affecting the organs and tissues that make gas exchange difficult in air-breathing animals. They include conditions of the respiratory tract including the trachea, bronchi, bronchioles, alveoli, pleurae, pleural cavity, the nerves and muscles of respiration. Respiratory diseases range from mild and self-limiting, such as the common cold, influenza, and pharyngitis to life-threatening diseases such as bacterial pneumonia, pulmonary embolism, tuberculosis, acute asthma, lung cancer, and severe acute respiratory syndromes, such as COVID-19. Respiratory diseases can be classified in many different ways, including by the organ or tissue involved, by the type and pattern of associated signs and symptoms, or by the cause of the disease.

Image segmentation is an extension of image classification where, in addition to classification, we perform localization. Image segmentation thus is a superset of image classification with the model pinpointing where a corresponding object is present by outlining the object's boundary.Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler. Segmentation in easy words is assigning labels to pixels.

Image segmentation is essentially segmenting an image into fragments and assigning a label to each of those. This occurs on a pixel level in order to define the precise outline of an object within the frame and its class. Those outlines — otherwise known as the output — are highlighted with either one or more colors, depending on the type of segmentation.
In recent years, segmentation has had great successes in various medical images analysis tasks including detection of atherosclerotic plaques, pelvic cavity assessment , ear image data towards biomechanical research , skin lesions detection, etc. This has led to its expansion to lung disease detection and specifically to lung field extraction. Lung segmentation is an incredibly important component of any clinical-decision support system dedicated to improving the early diagnosis of critical lung diseases such as lung cancer, chronic obstructive pulmonary disease (COPD), etc. . However, it constitutes a very challenging task.
Lung segmentation is difficult to achieve due to the fact that lung pathologies present various appearances different from the normal lung tissue. There exist dozens of lung diseases including the ground-glass opacity, consolidation, cavity, tree-in-bud and micro nodules, nodules, pleural effusion, honeycomb, etc., and each of them possesses different shape, texture, and attenuation information at CT images.
U-Net is an architecture for semantic segmentation. It consists of a contracting path and an expansive path. The contracting path follows the typical architecture of a convolutional network. It consists of the repeated application of two 3x3 convolutions (unpadded convolutions), each followed by a rectified linear unit (ReLU) and a 2x2 max pooling operation with stride 2 for downsampling. At each downsampling step we double the number of feature channels. Every step in the expansive path consists of an upsampling of the feature map followed by a 2x2 convolution ("up-convolution") that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the contracting path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution. At the final layer a 1x1 convolution is used to map each 64-component feature vector to the desired number of classes. In total the network has 23 convolutional layers.
The feature fusion process is defined as gathering all the important information from multiple images, and their inclusion into fewer images, usually a single one. This single image is more informative and accurate than any single source image, and it consists of all the necessary information. The purpose of image fusion is not only to reduce the amount of data but also to construct images that are more appropriate and understandable for human and machine perception.
Features like local features, shape features and spatial features, segmentation region and different positions within the lung are thought to be important for CAD systems. Nevertheless, these techniques used to derive good features are non-trivial. Fortunately, deep neural networks have recently gained considerable interest for feature computation due to its ability to learn mid- and high-level image representation. Rapid advances in deep neural networks have resulted in the development of new variants of convolutional neural networks (CNNs),Deep learning methods have not been thoroughly tested for reducing false positive lung nodules, especially by utilizing non-medical archive learning. Our experiment results show that the deep feature fusion may be sufficient in comparison with the hand-crafted features.
Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.
In machine learning, pattern recognition, and image processing, feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction.
The process of feature extraction is useful when you need to reduce the number of resources needed for processing without losing important or relevant information. Feature extraction can also reduce the amount of redundant data for a given analysis. Also, the reduction of the data and the machine's efforts in building variable combinations (features) facilitate the speed of learning and generalization steps in the machine learning process
We address the problem of medical data scarcity by considering the task of detection of pulmonary diseases from chest X-Ray images using small volume datasets with less than a thousand samples.
We implemented three deep convolutional neural networks (VGG16, ResNet-50, and InceptionV3) pre-trained on the ImageNet dataset and assessed them in lung disease classification tasks using a transfer learning approach. We created a pipeline that segmented chest X-Ray (CXR) images prior to classifying them and we compared the performance of our framework with the existing ones. We demonstrated that pre-trained models and simple classifiers such as shallow neural networks can compete with the complex systems. We also validated our framework on the publicly available lung datasets and compared its performance to the currently available solutions. Our method was able to reach the same level of accuracy as the best performing models trained on the dataset however, the advantage of our approach is in the smaller number of trainable parameters. Furthermore, our InceptionV3 based model almost tied with the best performing solution on the Shenzhen dataset despite being computationally less expensive.
In this project we work on classification of respiratory disorders using deep learning techniques.We apply Image segmentation to more accurately divide the lung area, then we extract feature maps from pre-trained CNN models, then we perform feature fusion and finally we classify the data. First, use residuals to achieve image segmentation to more accurately divide the lung area. Feature fusion is a kind of algorithm, which can merge some independent features to a unique feature in order to process them easily.

NEED OF THE STUDY.

Respiratory diseases are an important cause of morbidity and mortality worldwide, and early and accurate diagnosis is essential for effective treatment and improvement of patient outcomes. X-ray images are a commonly used diagnostic tool for respiratory diseases, but interpreting X-ray images can be difficult and subjective, especially for fire professionals. Less electricity. In this

paper, we propose a new method for automatic classification of respiratory diseases using segmentation, feature extraction and feature fusion of X-ray images. Our plan will include automatic segmentation of the lung and chest region and remove features associated with deep learning algorithms. These features are then combined to determine the presence of various respiratory diseases such as pneumonia, pulmonary edema, and lung cancer.
Experimental results show that our proposed method outperforms other state-of-the-art methods, achieving a high classification rate. Our plan has the potential to improve the accuracy and efficiency of respiratory disease diagnosis and provide timely and effective treatment, thereby reducing the burden people have on the disease and treatment of these diseases.

II. LITERATURE REVIEW

First Lingzhi Kong, Zhiyuan Ren, Yan Zhou, Wei Ding, and Jinyong Cheng [1] proposed a medical image classification method that achieves 98% accuracy. They used image segmentation to extract only the required areas of the image and Xception network for feature extraction. The LSTM model was used for classification. The study also utilized feature fusion to improve the accuracy of the model.Risheng Wang, Tao Lei, Ruixia Cui, Bingtao Zhang, Hongying Meng, and Asoke K. Nand [2] conducted a survey on medical image segmentation using deep learning. Their findings showed that supervised learning models performed well on large sets of labeled data, while weakly supervised models achieved good performance using small sets of labeled data.Feng-Ping and Jun-e Liu [3] proposed a medical image segmentation algorithm that uses optimized convolutional neural networks and adaptive dropout. The study showed that cross-layer connections and dropout increased the generalizability of the model, and the proposed method's segmentation effect improved compared to traditional machine learning and other deep learning methods.Weibin Wang and Dong[4] Liang used deep convolutional neural networks for image classification in their study on focal liver lesion classification. The study showed that fine-tuning significantly improved the accuracy of classification, especially for small training samples.[5]The study by IJERT proposed a brain tumor detection and features extraction method that utilized morphological processing, segmentation by watershed algorithm, feature extraction through co-occurrence matrix, and train and test SVM, KNN, and ANN. The study showed that ANN achieved an accuracy of 92%.Vairaprakash Gurusamy and Subbu Kannan[6] conducted a review of image segmentation techniques that focused on the various methods widely used to segment the image. The study showed that segmentation algorithms were based on similarity and discontinuity properties.Santiago Vitale, Jose Ignacio Orlando [7], and their colleagues proposed a novel hybrid deep learning algorithm framework for automatic lung disease classification from chest X-ray images. The proposed 2D CNN model ensured robust feature learning, and the extracted 1D features were optimized using min-max scaling. The CNN features were classified using different machine learning classifiers such as AdaBoost, SVM, RF, BNN, and DNN, resulting in an overall accuracy improvement of 3.1% and a computational complexity reduction of 16.91% compared to state-of-the-art methods.

III. RESEARCH METHODOLOGY

The process described below involves using augmentation techniques to create variations of X-ray images and corresponding alpha masks, with the aim of increasing the amount and diversity of data available for training. The U-net model, a type of convolutional neural network commonly used for image segmentation tasks, is then trained on this augmented data.

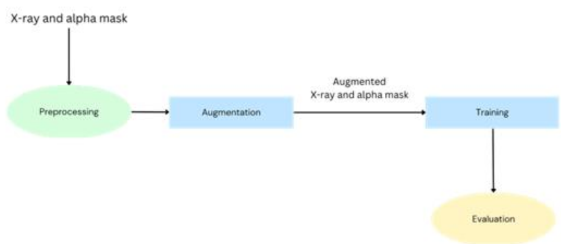

figure 1 : segmentation model training

This involves feeding the network pairs of X-ray images and their corresponding masks, with the aim of enabling the model to learn to accurately segment the images into different classes. Finally, the trained model is evaluated to assess its performance on a separate set of test images, with metrics such as accuracy, precision, and recall used to quantify its effectiveness. Overall, this process forms a key part of the pipeline for developing and refining image segmentation models for medical diagnosis and other applications.

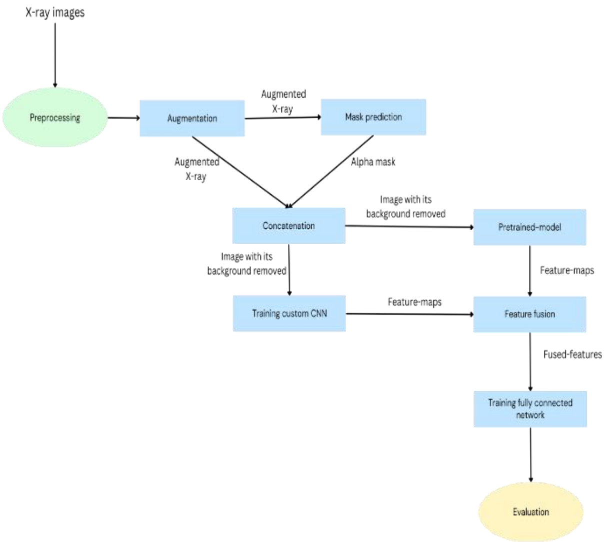

figure 2 : classification model training

The above figure shows the training process of the classification model. During training of the classification model the techniques like feature fusion and feature extraction are used. The noise or background of the input x-ray image is removed by using a segmentation model that we have trained previously.
The noisy image(contains background) is sent to the segmentation model. Segmentation model generates alpha masks for the image; the alpha mask contains the transparency values for each pixel. This is similar to png image format. The input image is concatenated with an alpha mask in the concatenation module. This results in change of image dimension from 3 channels to 4 channels. The concatenation module produces an image which does not have any background. The output(without background) of the concatenation module is sent to the classification models.
The concatenation module can be implemented using different techniques, depending on the specific application. For example, it can be done using simple operations such as pixel-wise merging or more advanced techniques such as guided filtering or deep learning-based methods.
The alpha mask generated by the segmentation model is a crucial component in the concatenation module. It acts as a binary mask that separates the foreground from the background and allows for the extraction of the object of interest.The concatenation module is an important step in many computer vision applications that require the isolation of foreground objects. It can be used in a variety of contexts, such as object detection, tracking, and segmentation.
In addition to improving the accuracy of the classification model, the concatenation module can also help reduce computational costs by removing unnecessary background information from the image.The alpha mask generated by the segmentation model can be used in other image processing tasks as well, such as image editing and compositing. For example, it can be used to create a seamless composite of the foreground object onto a different background.

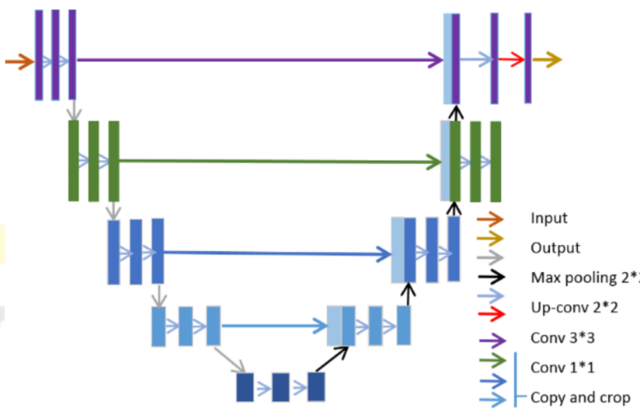

figure 3 : U-NET architecture

We are using the U-Net architecture for mask prediction in the segmentation step of our workflow. The U-Net is a convolutional neural network architecture that was originally designed for biomedical image segmentation tasks, and has since been widely used for various image segmentation tasks.
The U-Net architecture consists of a contracting path and an expansive path. The contracting path consists of several convolutional and max pooling layers, which progressively reduce the spatial resolution of the input image while increasing the number of feature channels. This path is designed to capture high-level, global features of the image.
The expansive path consists of several convolutional and upsampling layers, which progressively increase the spatial resolution of the input image while decreasing the number of feature channels. This path is designed to capture local, detailed features of the image.

In the U-Net architecture, the contracting path and the expansive path are connected by a series of skip connections, which allow the network to combine both local and global features to produce accurate segmentation masks. These skip connections also help to prevent information loss during the downsampling and upsampling operations.
By using the U-Net architecture for mask prediction, we can accurately segment the lung area from the background in x-ray images, which helps to improve the accuracy of the subsequent feature extraction and classification steps. The U-Net architecture is well-suited for this task due to its ability to capture both local and global features of the input image, and its effectiveness in handling complex biomedical image segmentation tasks.

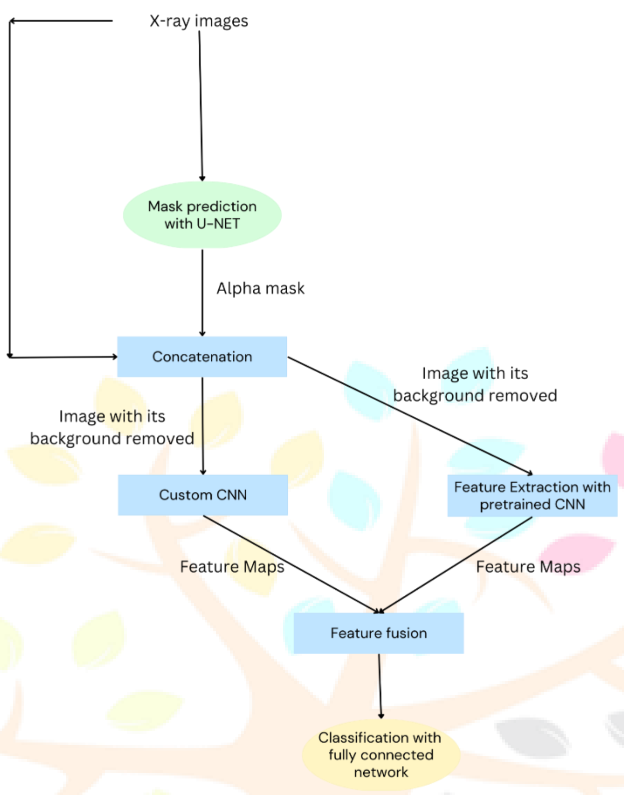

figure 4 : final workflow

Our project aims to develop a deep learning-based system for accurately classifying respiratory disorders using x-ray images. The workflow of our system involves several key steps, which include image segmentation, feature extraction, feature fusion, and classification.
In the first step of the workflow, we take a noisy x-ray image and pass it through a segmentation model. The segmentation model generates alpha masks for the image, which are used to separate the lung area from the background. This process improves the accuracy of the subsequent feature extraction and classification steps, as it eliminates the impact of the background on the final prediction.
Next, we extract feature maps from the segmented image using a pre-trained CNN model. These features capture different aspects of the image, such as edges, textures, and patterns, which are important for accurately identifying respiratory disorders.
In the third step of the workflow, we perform feature fusion to combine the extracted features into a single, more informative representation. This step helps to improve the accuracy of the classification model by reducing the impact of noise and other sources of variability in the input image.
Finally, we pass the fused features through a classification model to predict the respiratory disorder present in the x-ray image. The classification model is trained on a large dataset of x-ray images, and is designed to identify a wide range of respiratory disorders, including pneumonia, tuberculosis, and lung cancer.
Overall, our workflow is designed to take advantage of the latest advances in deep learning to accurately classify respiratory disorders using x-ray images. By combining image segmentation, feature extraction, feature fusion, and classification, we believe our system has the potential to significantly improve the accuracy of respiratory disorder diagnosis.

IV. RESULTS AND DISCUSSION

Below image depicts the original x-ray, segmented image and the predicted mask generated by the segmentation model. The accuracy of our segmentation model is 94.03%.

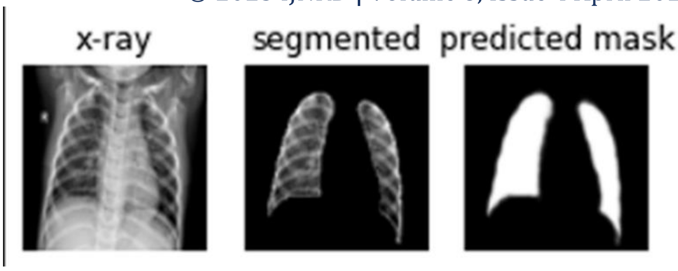

fig 5. predicted mask

The below image shows the TP,TN,FP,FN values of the classification model. The classification model has very few FN predictions which is very suitable for medical applications.

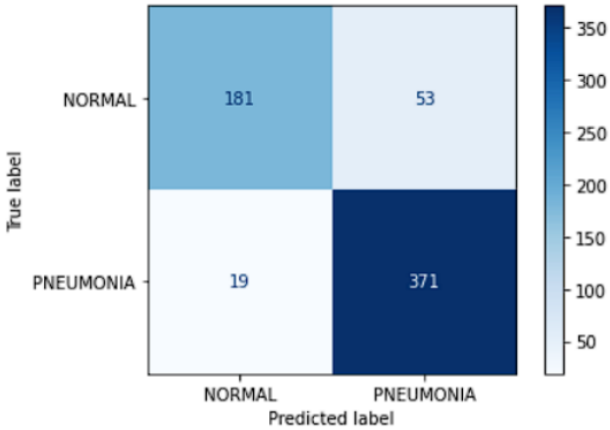

Fig 6. confusion matrix

The below figure shows the training history over 20 epochs The blue line represents the loss and the orange line represents the accuracy.

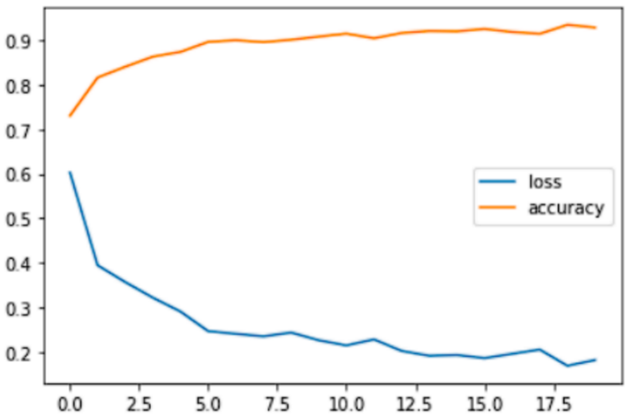

fig 7. model result analysis

Our deep learning model can classify respiratory disorders with 96% accuracy. Our Project has few drawbacks. The first dataset is small. The second drawback is we are classifying only one disease as of now, so we will expand our domain in the coming days.

V. FUTURE WORK

Recently, multiple studies on deep learning have performed well for image classification; however, these studies require large quantities of training data. For the task of lung disease image classification, it is not feasible to obtain large amounts of valid data. Therefore, we proposed a fine-tuning method and achieved high-accuracy lung disease classification solving problems arising from lack of sufficient training data. In addition, we demonstrated that fine-tuning can significantly improve the classification accuracy for lung disease images and that our model with fine-tuning outperforms state-of-the-art methods. In the future, we intend to develop a novel network to achieve more accurate classifications results.

VI. ACKNOWLEDGEMENT

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