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Article

X-Net the AI Radiologist Assistant

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Abstract: The integration of deep learning methodologies into radiology has the potential to revolutionize the diagnosis of chest diseases. However, there is a significant gap between deep learning researchers and medical professionals, which hinders the translation of these advancements into clinical applications. We have created a prototype system that enables medical practitioners to assess the effectiveness of deep learning algorithms in chest X-ray diagnosis. Our system is intuitive and freely accessible, and it can be accessed via web browsers, including mobile devices. The system employs a client-server architecture to deliver code and network weights through a secure URL, while preserving the privacy and confidentiality of patient data. We believe that this prototype system will serve as a catalyst for collaboration and knowledge exchange between deep learning researchers and medical professionals. By providing medical practitioners with a practical tool to evaluate the capabilities of deep learning algorithms, we anticipate enhanced diagnostic accuracy and improved patient outcomes. Moreover, this system is poised to encourage collaborative efforts, enabling the seamless integration of expertise from both domains, ultimately propelling advancements in the field of medical diagnosis of chest diseases using X-ray imaging with AUC score of 76% accuracy.

Keywords: deep learning; chest X-ray; diagnosis; medical imaging; collaboration; densenet; CNN; AUC; JavaScript

1. Introduction

Lung diseases are a prevalent global health concern, affecting a significant number of individuals in the world. These diseases can be attributed to various factors such as genetics, infections, and smoking. Appallingly, Lung diseases contribute to approximately 3 million annual deaths worldwide, ranking as the leading cause of mortality, particularly among young individuals and children. However, by accurately detecting specific types of diseases, the potential exists to substantially reduce this number and provide timely and appropriate treatments, eliminating the possibility of misdiagnosis.

In today's time, Computer-aided diagnosis (CAD) plays a crucial role in medical imaging, with X-ray imaging being widely used for lung disease screening and diagnosis. Despite the cost-effectiveness and accessibility of X-rays, accurately diagnosing diseases from radiographs remains challenging, necessitating the development of CAD systems to improve physician productivity and healthcare accessibility. However, the widespread adoption of deep learning tools in medicine is hindered by challenges such as uncertain business models, limited understanding of AI technology in healthcare, expertise gaps in health data science and AI, hospital inertia, data access issues, and regulatory hurdles. Overcoming these obstacles is essential to leverage the potential of deep learning and foster collaboration between AI researchers and healthcare professionals for enhanced patient care.

To address these challenges and explore the potential of deep learning tools in chest X-ray diagnostics, we have developed an accessible prototype system and you can see the use cases in Figure 1. This system serves as a valuable second opinion, allowing medical professionals to process X-ray images and obtain confirmatory or supportive insights for their diagnoses. The system operates via a web-based interface, facilitating user-friendly interaction, and generates detailed reports on identified diseases and the specific regions of abnormality. Crucially, the system preserves patient privacy by ensuring that all data remains securely on the user's machine. By this we can effectively detect the abnormalities found in the X-ray.

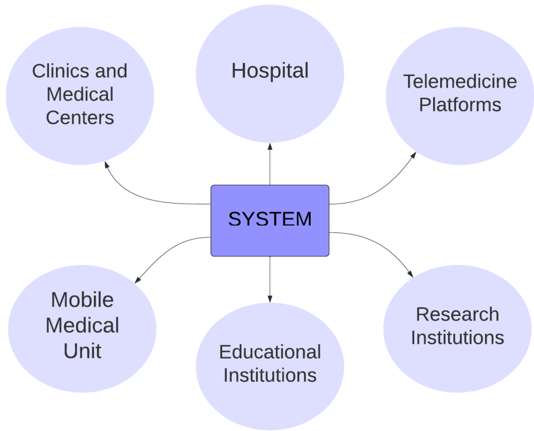

Figure 1. Application Use Scenarios.

2. Literature Survey

Extensive research has been conducted on multi-label classification problems in domains such as object detection and text categorization [1]. However, in the wake of the global pandemic, scientists and researchers have shifted their focus towards combating the outbreak. Their efforts have primarily been directed towards three key development aspects. Firstly, considerable efforts have been invested in the creation of vaccines [2]. Secondly, there has been a concerted drive to develop fast and reliable detection methods particularly in the field of medical imaging using radiological systems [3]. Lastly, various data analysis techniques have been employed to estimate the spread and scope of the virus. Ref. [4] introduced a neuro-heuristic approach that effectively addresses subtle variations in lung tissue structure associated with pneumonia, sarcoidosis, cancer, and post-treatment consequences. Through testing, the authors demonstrated the promising potential of this novel method. Notably, the proposed approach offers flexibility and imposes a low computational burden, making it a practical and efficient solution for the analysis of lung conditions.

Explored the utilization of machine learning algorithms in the analysis of medical images, particularly emphasizing the importance of convolutional neural networks [5,6]. They discussed the significance of deep learning in the accurate detection of specific medical conditions. Additionally, the authors highlighted the improved efficacy of neural networks in deep learning and emphasized the clinical implications of employing these advanced techniques in medical image analysis. T. Padma et al. [7], Q. Ke [8] present a method for COVID-19 detection from chest X-ray images. The proposed approach achieves an impressive accuracy for a binary classification (COVID-19 and normal). The study showcases the effectiveness of convolutional 2D techniques in COVID-19 diagnosis. However, the research is limited by a small dataset of only 60 images and focuses solely on classifying COVID-19 and normal cases, disregarding other chest conditions. Enes Ayan et al. [9] focused on the application of deep learning techniques for pneumonia diagnosis. The authors compared the performance of two convolutional neural network models, namely Xception and Vgg16, in pneumonia detection P. Rajpurkar [10]. The results revealed that the Vgg16 network achieved a higher accuracy compared to the Xception network. However, the study solely concentrates on diagnosing pneumonia.

3. System Flow

The application begins with a web-based interface as shown in Figure 2 where medical professionals can upload chest X-ray images for analysis and diagnosis. The uploaded images, undergo image processing, including resizing, normalization, and quality enhancement, to enhance disease detection accuracy. These processed images are then fed into a specialized trained deep learning model that utilizes advanced algorithms and convolutional neural networks (CNNs) to identify abnormalities and diseases, such as pneumonia, consolidation, Edema, and other respiratory conditions [11–14]. The system not only identifies diseases but also detects and highlights specific regions of abnormality within the X-ray images, providing targeted insights for diagnosis and treatment planning. Detailed reports are generated for each uploaded image, containing information about the identified diseases, regions of abnormality, and additional observations or recommendations, supporting medical professionals in their diagnostic process [15]. To ensure data security and patient privacy, all data remains securely stored on the user's machine, eliminating concerns about data confidentiality and compliance.

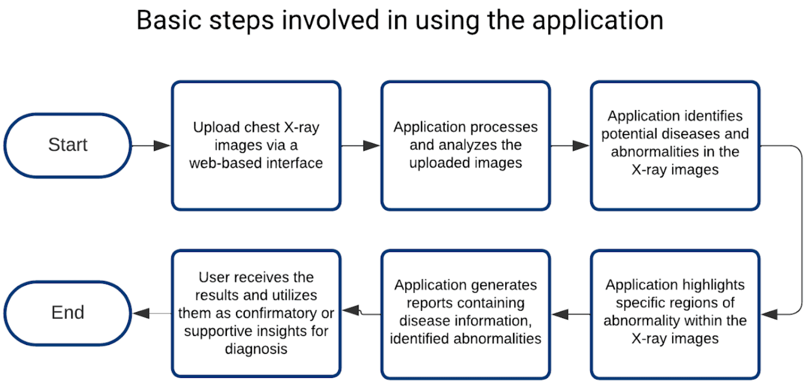

Figure 2. Application Flow.

4. Methodology

In this project, the model uses 320 × 320 X-rays images by reducing its size [16] and outputs predictions for each of the 14 pathologies as illustrated below on a sample image.

4.1. Dataset

The research project utilizes chest x-ray images sourced from the publicly available ChestX-ray8 dataset. This dataset comprises 108,948 frontal-view X-ray images obtained from 32,717 distinct patients the frequency of each disease images is shown in Figure 3. Each image within the dataset is associated with multiple text-mined labels that identify 14 distinct pathological conditions [17]. These labels can aid physicians in diagnosing 8 different diseases. For our specific project, we have focused on a subset of approximately 1,600 images from the dataset [18].

- 1,600 images to be used for training.
- 300 images to be used for validation.
- 400 images to be used for testing.

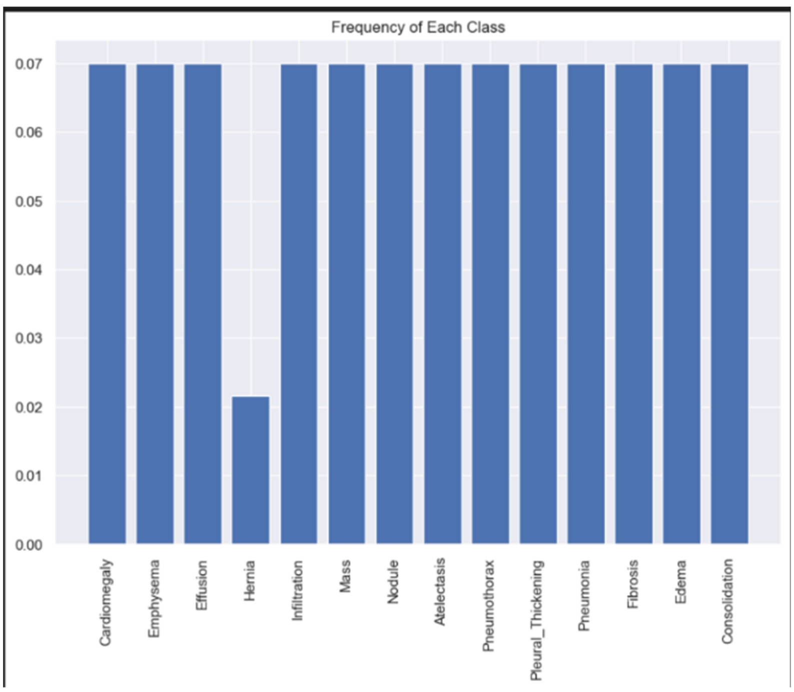

Figure 3. Class Frequency.

It is important to note that there has been no data leakage among the training, validation, and testing sets. The dataset is supplemented by a CSV file containing the ground truth labels for each corresponding X-ray image.

4.2. Data Cleaning and Preprocessing

The data preprocessing steps in this paper aim to prepare image data for deep learning tasks. These steps involve operations such as image extraction, visualization, analysis, and generation of histograms to understand the properties and distributions of the pixel intensities. The code also creates data generators that apply preprocessing techniques like centering and standard normalization to the images for training, validation, and testing. One important aspect addressed by the project is class imbalance. By computing class frequencies and visualizing class distributions, the output provides insights into the severity of class imbalance. It further calculates class weights to adjust the impact of different classes during model training. These class weights help in mitigating the bias caused by imbalanced class distributions, ensuring fair representation and improving the model's ability to accurately predict minority classes [19]. Overall, these data preprocessing steps facilitate the normalization and enhancement of image features, enable a better understanding of class distributions, and improve the performance and fairness of deep learning models trained on imbalanced datasets.

4.3. Training of Model

4.3.1. Loss Function

In deep learning, a weighted loss function is employed to tackle imbalanced datasets, where certain classes are underrepresented. By assigning distinct weights to samples or classes, the loss function adapts the penalty for misclassifications. In the context of lung disease classification, a weighted loss function allows for prioritizing accurate predictions for rarer lung disease cases. This approach enhances performance and fairness in the model's outcomes. Careful selection and evaluation of the weighting strategy are pivotal for its successful application.

4.3.2. Training Settings

1. Model Architecture:

The research paper utilizes the DenseNet121 architecture as the base model for feature extraction. DenseNet121 is a deep convolutional neural network (CNN) architecture known for its dense connections between layers, enabling efficient feature reuse and gradient flow [20,21]. The model includes the DenseNet121 base model with pre-trained weights and excludes the top layer (fully connected layers). A GlobalAveragePooling2D layer is added after the base model to reduce spatial dimensions. Additional layers are appended, including a Dense layer with 1,024 units and ReLU activation, followed by Batch Normalization and Dropout layers for regularization. The final layer is a Dense layer with softmax activation, providing the predicted probabilities for each class.

2. Loss Function and Optimizer

The model is compiled using the Adam optimizer, a popular choice for deep learning tasks. The loss function is defined as a weighted loss, which takes into account the class weights calculated based on class frequencies. The weighted loss helps address class imbalance by assigning higher weights to underrepresented classes during training.

3. Model Parameters

The total number of parameters in the model is 8,105,550. Out of the total parameters, 8,019,854 are trainable, indicating the number of parameters that will be updated during the training process. The remaining 85,696 parameters are non-trainable, representing the parameters in the pre-trained DenseNet121 base model.

4. Number of Layers

The model consists of a total of 432 layers, As shown in Figure 4 the model details can be verified.

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, None, None,  0           []
                                 3)]

 zero_padding2d (ZeroPadding2D)  (None, None, None,   0          ['input_1[0][0]']
                                3)

 conv1/conv (Conv2D)            (None, None, None,   9408        ['zero_padding2d[0][0]']
                                64)

 conv1/bn (BatchNormalization)  (None, None, None,   256         ['conv1/conv[0][0]']
                                64)

 conv1/relu (Activation)        (None, None, None,   0           ['conv1/bn[0][0]']
                                64)
```

Figure 4. Model Details.

5. Training Process

The model is trained using the `fit` function on the `train_generator` and validated on the `valid_generator`. The `train_generator` and `valid_generator` are data generators that yield batches of preprocessed images and their corresponding labels for training and validation.

The training process includes 100 epochs, with a total of 100 steps per epoch and 25 validation steps. During training, the model learns to minimize the weighted loss by adjusting the model's parameters through backpropagation.

6. Test Prediction

After training, the model is used to predict the class probabilities for the test dataset using the `predict_generator` function on the `test_generator`. The `test_generator` is a data generator that yields batches of preprocessed test images. The predicted values have a shape of (number of test samples x number of classes), indicating the predicted probabilities for each class. Overall, the training settings involve loading the DenseNet121 base model, adding additional layers, compiling the model with a weighted loss and Adam optimizer, and training the model using data generators. The model parameters and layer information are provided, and the trained model is used to make predictions on the test dataset.

4.4. Model Evaluation

In the process of model evaluation, various metrics are utilized to assess the performance of the developed model. These metrics include AUROC (Area Under the Receiver Operating Characteristic) scores, training and testing accuracy, and the confusion matrix [22]. AUROC scores serve as a valuable indicator of the model's ability to distinguish between different disease classes shown in Figure 5, while accuracy measures the correctness of predictions during training and testing phases. The confusion matrix provides a comprehensive overview of the model's classification results. To enhance the credibility of the research, the obtained AUROC scores are compared with those reported in relevant studies, providing a valuable benchmark for evaluating the model's effectiveness and comparative performance.

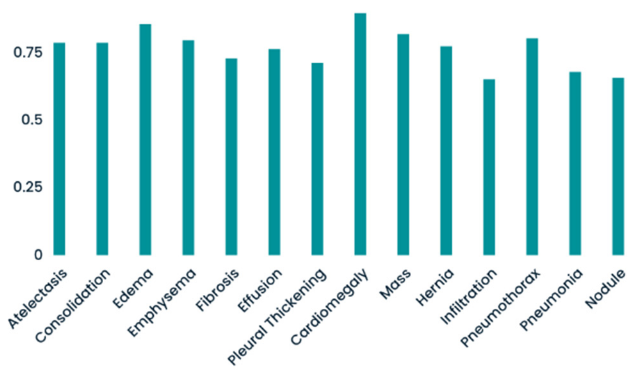

Figure 5. Disease.

DenseNet is a highly effective fully convolutional network widely utilized for various image classification and segmentation tasks in the field of deep learning. It introduced a novel concept called residual connections, where previous features are iteratively concatenated. This approach enhances the information flow and gradient propagation within the network, effectively addressing the problem of gradient vanishing [23]. A DenseNet architecture is composed of multiple densely connected convolutional layers. These layers are interconnected in a dense manner, allowing each layer to receive direct inputs from all preceding layers. This design further promotes information exchange and gradient flow, leading to improved convergence during the training process. The remarkable capability of DenseNet lies in its ability to learn highly expressive representations. It has demonstrated exceptional performance across various computer vision tasks. In this context, the DenseNet-121 model, which is publicly available, is often chosen as a reliable backbone network. The DenseNet-121 model is characterized by four consecutive dense blocks, each consisting of densely connected convolutional layers. These blocks contribute significantly to the model's representational power and enable it to extract intricate features from input images. By leveraging the advantages of DenseNet, researchers and practitioners have achieved remarkable results in image classification and segmentation tasks, making it a popular choice in the field of computer vision.

5. Observations and Results

5.1. Web-App for Radiologist's Assistance

The application is made only for laboratory use to assist the radiologists. This will be a helping hand for their assistance where in our application the model makes predictions. The web-app is shown as below in Figure 6:

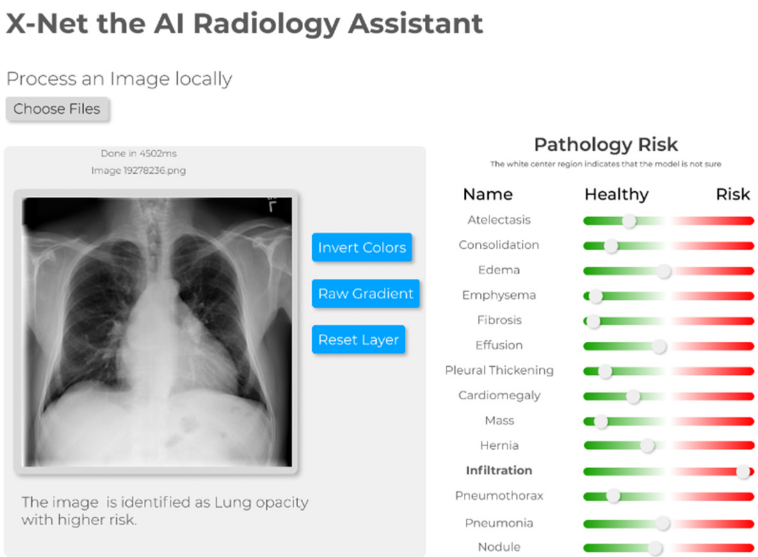

Figure 6. Application Interface.

5.2. Using Microsoft Azure for Hosting the Website

By using microsoft azure platform the code of the frontend can be hosted so it can be accessible easily and a docker image was created to run the backend code i.e., the model to make the prediction. Image is stored in cloud storage.

5.3. AUC Score Comparisons for Different Models

From the table displayed below, we can observe the result clearly mentioning the AUC score of the different models telling which one is the best for different diseases. Average AUC of 0.7601 was achieved as shown in Figure 7 it's the Area under Curve Score for all the 14 diseases trained on our model.

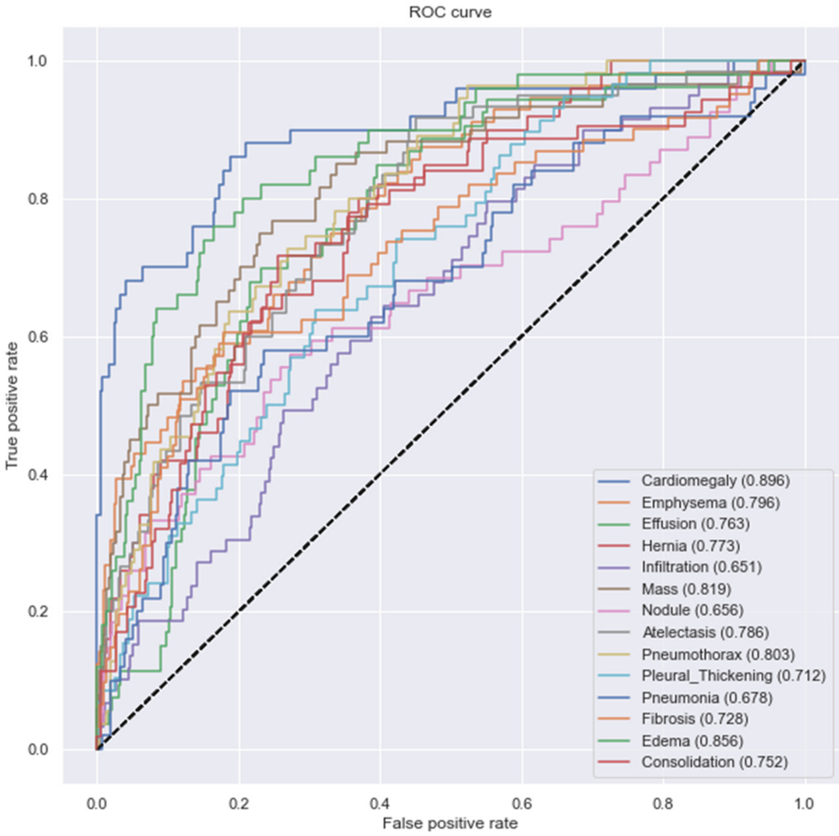

Figure 7. AUC Score.

6. Conclusions

This research paper has highlighted the challenges associated with the development of an automated system aimed at assisting radiologists in making quicker and more accurate decisions. We have discussed both the solutions and obstacles encountered during the system's development, as well as the practical implementation required to bridge the gap between the medical community and deep learning researchers. Presently, the system demonstrates the capability to predict diseases from uploaded chest X-rays and identify infected areas within the images. Future enhancements include incorporating a report generation feature and expanding its scope to encompass other disease detections, such as tumor identification. To enhance the localization of lung diseases in chest X-ray images [24], it is crucial to continue refining algorithms for generating activation maps and training deep learning models on larger and more diverse datasets. This will contribute to the overall effectiveness and reliability of the automated system, thereby benefiting both radiologists and patients alike. By addressing these challenges and pursuing further advancements, we can significantly improve medical diagnoses and foster collaboration between the medical and deep learning communities.

Author Contributions

Conceptualization, Methodology, Software, Model Tuning and Final draft—K.M., Validation, Formal analysis, Resources—E.K., Data Curation, Visualization, Data Collection—H.G. and H.Z. Supervision and Project Administration—S.A. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

Author declares no conflict of interest.

Data Availability Statement

The dataset of Chest-Xray can be found here https://nihcc.app.box.com/v/ChestXray-NIHCC/folder/36938765345 at NIH website. Other than this the model training data, algorithms and model tuning is our findings so they can't be found on internet, but can be done by modifying the densenet model.

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