

Chest Abnormality Detection Using Cnn

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Abstract— As a result of the outbreak, an unusual virus spread event has occurred, threatening human safety worldwide. To prevent infections from spreading quickly, large numbers of people must be screened. Rapid Test and RT-PCR are common testing tools for regular testing that are used to test all COVID-19-affected users. However, the increasing number of false positives has paved the way for the investigation of alternative test methods for coronavirus-affected patients' chest X-rays have shown to be an effective alternate predictor for testing if an individual is affected with the COVID-19 virus. However, consistency is, once again, dependent on radiological experience. A diagnostic decision support device that assists the physician in evaluating the victims' lung scans can alleviate the doctor's medical workload. Machine Learning Techniques, specifically the Convolutional Neural Networks (CNN) VGG16 model is used to train datasets and use trained models to predict, have been developed in this project. Four distinct deep CNN architectures are tested on photographs of chest X-rays for the treatment of COVID-19. The collection of datasets of covid 19 X-ray imageries and non-covid 19 X-ray imageries are used to train the model and test its accuracy. CNN-based architectures were discovered to be capable of diagnosing COVID-19 disease. To enhance the model's generalization capability and mitigate overfitting, data augmentation techniques are applied during training. The trained model's performance is evaluated using various metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) on a separate test dataset. Additionally, visualization methods are employed to interpret the model's decisions and identify regions of interest within the chest X-ray images. Experimental results demonstrate the efficacy of the proposed methodology in accurately detecting COVID-19 and pneumonia from chest X-ray images.

Keywords— Deep Convolutional Networks, Transfer Learning, Chest Abnormality detection, Insufficient labeled training data, ResNet, ImageNet, Convolutional Neural Network.

I. INTRODUCTION

Chest diseases, particularly COVID-19 and pneumonia, continue to pose significant challenges to global healthcare systems, necessitating accurate and timely detection for effective treatment and containment. Chest X-ray imaging serves as a pivotal tool in the diagnosis of these diseases, enabling clinicians to visualize abnormalities in the lungs and surrounding structures. However, manual interpretation of X-ray images is time-consuming, subject to inter-observer variability, and may not always be readily available, especially in resource-constrained settings. In recent years, the

advent of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized medical image analysis, offering automated and scalable solutions for disease detection and classification. CNNs can learn intricate patterns and features directly from raw image data, making them well-suited for complex medical imaging tasks.

This paper proposes a novel approach for automated detection of chest diseases, specifically targeting COVID-19 and pneumonia, utilizing CNNs with the VGG16 architecture. The VGG16 model, renowned for its depth and simplicity, has demonstrated remarkable performance in various image classification tasks and serves as a robust backbone for our framework. The primary objective of this research work is to develop a reliable and efficient system for chest disease detection that can assist healthcare professionals in prompt diagnosis and decision-making. By leveraging deep learning techniques, we aim to enhance diagnostic accuracy, reduce workload, and expedite patient care processes

II. RELATED WORK

Vandecia fernandes et al. developed a sustainable version of the COVID-19 image recognition from X-ray images. There is a finite amount of photos available, first and foremost. There aren't enough datasets gathered and published for experts to use because the pandemic has only been spreading for a few months. Furthermore, given that breast X-ray images can reveal the severity of an issue to the human body, scientific researchers may find it imperative to develop a smart device that would enable quick and thorough identification and understanding of viral infections. It has been concluded that approach transfer is both realistic and practicable for this research issue, after a thorough evaluation of the current technology and the difficult conditions they face. Training deep neural networks is part of this technique. [1]

Deep CNNs indeed acquire higher performance with the use of a huge dataset as compared to a smaller one. Granting there is an enormous range of infected COVID-19 patients globally, however, the variety of publicly had chest X-ray photos online is insignificant and dispersed. For this reason, the authors of this work have defined a reasonably huge dataset of COVID-19-infected chest X-ray images even though normal and

pneumonia photographs are right away on hand publicly and applied in this study. [2]

Using a chest X-ray image, the observations apply flexible and powerful deep-learning methodologies, including the employment of six CNN models to predict and identify whether the patient is untouched or impacted by the condition. To monitor the accuracy of each version getting learned, GoogLeNet, LeNet, VGG-16, AlexNet, StridedNet, and ResNet-50 models using a dataset of 28,000 images and a 224x224 decision with 32 and sixty-four batch sizes are used. The study also uses Adam as an optimizer, giving all of the models an adjusted 1e-four learning rate and a 500-epoch. During the development of models, both GoogLeNet and LeNet received a 98% accuracy rate, VGGNet-16 received a 97% accuracy rate, AlexNet and StridedNet models received a 96% average accuracy, and the ResNet-50 model received an 80% accuracy rate. For total performance training, GoogleNet and LeNet fashions have the highest average accuracy. The six models identified were possible to perceive and predict a pneumonia illness, which included a normal chest X-ray. [3]

In this paper authors classify the three varieties of X-rays, The image writer used the ensemble method at some stage in prediction, each picture is surpassed through the type layer where they checked whether an image is COVID-19, pneumonia, or ordinary. [4]

III. PROBLEM DESCRIPTION

The problem statement for chest disease detection using deep learning involves addressing the significant challenges in healthcare, including the early and accurate identification of chest diseases through medical imaging, such as X-rays and CT scans. Inefficiencies in traditional diagnostic methods, human error, and delays in diagnosis can lead to suboptimal patient outcomes and increased healthcare costs. Leveraging deep learning models and algorithms, the aim is to develop a robust and reliable system that can autonomously and swiftly analyze these images, enhancing early disease detection, reducing misdiagnoses, and ultimately improving patient care and healthcare resource allocation in an increasingly burdened healthcare system.

This paper focuses on developing an advanced chest disease detection system using deep learning techniques, with a primary goal of improving early diagnosis and treatment of conditions such as lung cancer, pneumonia, and tuberculosis. The system will leverage convolutional neural networks (CNNs) and other deep learning methodologies to analyze medical imaging data, primarily X-rays and CT scans. The following are the key features and components of this research work.

Features of this work:

- **Image Analysis:** The system will be capable of processing and analyzing chest X-rays and CT scans to identify abnormalities, lesions, or patterns indicative of chest diseases.
- **Multi-Class Classification:** It will classify the detected abnormalities into various chest disease categories, including lung cancer, pneumonia, tuberculosis, and more.

- **Deep Learning Model:** The project will employ state-of-the-art deep learning models like CNNs, trained on large and diverse datasets to ensure accuracy and generalization.

- **Efficiency:** Emphasis will be placed on optimizing the model for speed and efficiency to provide timely results, particularly in emergency situations.

- **User Interface:** The system will feature a user-friendly interface for healthcare professionals, allowing them to upload images, receive prompt analysis, and access detailed diagnostic reports.

- **Real-Time Support:** The project will investigate the possibility of providing real-time or near-real-time diagnostic support, which could be crucial in emergency room settings.

- **Validation and Testing:** Rigorous validation and testing will be conducted to assess the model's performance, accuracy, and reliability, comparing its results with expert radiologists and other diagnostic methods.

- **Data Privacy and Security:** The project will prioritize data security and privacy by implementing robust measures to protect patient information and ensure compliance with healthcare regulations

- **Scalability:** The system will be designed to scale with increasing data and user demands, making it suitable for deployment in various healthcare settings

- **Research Collaboration:** Collaboration with medical professionals and institutions will be encouraged to continually improve the system and ensure its alignment with clinical practices.

- **Continuous Learning:** The system will be updated periodically with new data and research findings to enhance its diagnostic capabilities and accuracy.

This paper aims to revolutionize chest disease detection by providing healthcare professionals with a powerful tool that complements their expertise and assists in achieving earlier, more accurate diagnoses, ultimately leading to improved patient outcomes and more efficient healthcare resource allocation.

IV. SYSTEM DESIGN:

Data Collection: The first component of the system design is to collect a large and diverse dataset of chest x-ray images. The images should be high-quality, and high-resolution, and should capture various types of chest diseases. The dataset can be collected from various sources such as hospitals, clinics, and online repositories.

Pre-processing: The next step is to pre-process the x-ray images to remove any noise, artifacts, or distortions. The pre-processing step involves several techniques such as image enhancement, image normalization, and image segmentation.

Feature Extraction: The third component of the system design is to extract relevant features from the pre-processed x-ray images. These features can be extracted using several methods such as deep learning, machine learning, or computer vision techniques.

Classification: The fourth component of the system design is to classify chest x-ray images into different types of chest diseases. This classification can be done using several algorithms such as support vector machines, random forests, or deep neural networks.

Figure 1 shows the pictorial representation of the system design.

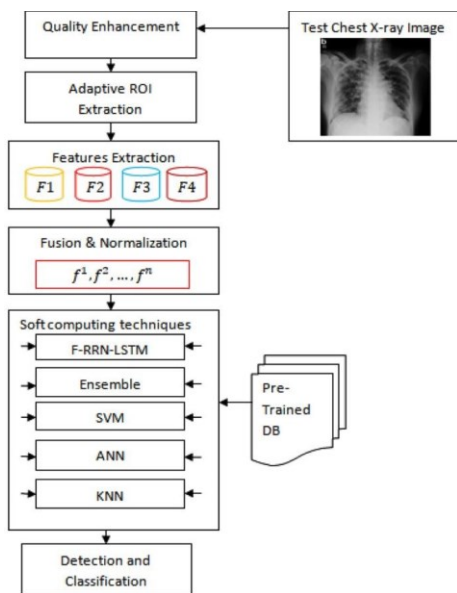


Fig.1 System Diagram

V. ARCHITECTURE DIAGRAM:

Data Collection and Preprocessing:

Gather a diverse dataset of chest X-ray images, including cases with confirmed COVID-19, pneumonia, and normal findings, from publicly available repositories and healthcare institutions.

Ensure proper annotation and labeling of images to facilitate supervised learning, including identification of regions of interest and disease classification.

Preprocess the images to standardize pixel intensities, resize them to a uniform resolution, and apply techniques such as normalization and histogram equalization to enhance image quality and consistency.

Model Selection and Architecture:

Choose the VGG16 architecture as the base CNN model for its depth and simplicity, which has shown effectiveness in various image classification tasks.

Utilize transfer learning by initializing the VGG16 model with pre-trained weights on a large-scale dataset (e.g., ImageNet) to leverage learned features.

Adapt the VGG16 model's architecture to the specific task of chest disease detection by modifying the output layer to accommodate the number of disease classes.

Data Augmentation and Training:

Augment the training dataset using techniques such as rotation, translation, flipping, and scaling to increase the diversity and robustness of the training data.

Split the dataset into training, validation, and test sets to evaluate model performance and prevent overfitting.

Train the modified VGG16 model using the augmented dataset and standard optimization techniques such as stochastic gradient descent (SGD) or Adam optimizer, with a suitable learning rate schedule.

Model Evaluation:

Evaluate the trained model's performance on the validation set using metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

Fine-tune hyperparameters such as learning rate, batch size, and regularization strength based on validation performance to optimize model performance.

Perform cross-validation or bootstrapping to assess the robustness and generalization capability of the model across different subsets of the data.

Interpretability and Visualization:

Employ interpretability techniques such as gradient-weighted class activation mapping (Grad-CAM), guided backpropagation, and attention mechanisms to visualize and explain the model's predictions.

Generate saliency maps or heatmaps highlighting regions of interest in the chest X-ray images indicative of disease presence, aiding clinicians in understanding and validating the model's decisions.

Validation and Clinical Testing:

Conduct thorough validation studies in collaboration with healthcare professionals to assess the clinical utility and reliability of the automated system.

Evaluate the system's performance on an independent test set or in a real-world clinical setting, comparing its diagnostic accuracy against expert radiologists or existing diagnostic methods.

Gather feedback from clinicians to identify areas for improvement and refinement of the automated system, ensuring alignment with clinical needs and standards.

Deployment and Integration:

Integrate the validated automated system into existing clinical workflows and healthcare infrastructure, ensuring compatibility with electronic health record (EHR) systems and regulatory compliance.

Provide user-friendly interfaces and tools for clinicians to interact with the system, facilitating seamless adoption and usability in clinical practice.

Establish protocols for monitoring and updating the system's performance over time, incorporating new data and insights to continuously improve diagnostic accuracy and reliability.

VI. RESULTS

The following figures show the step by step implementation of the research work

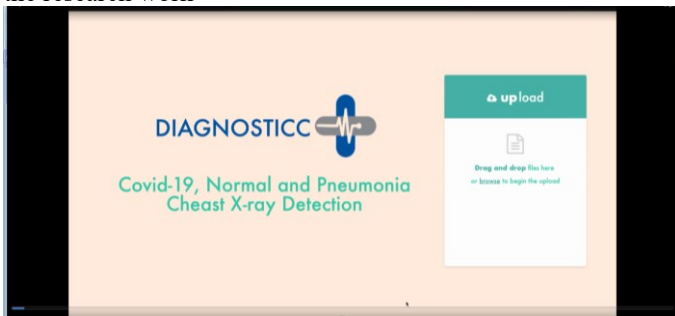


Fig. 2- HOME PAGE OF COVID-19,NORMAL AND PNEUMONIA CHEST X-RAY DETECTION

Figure 2 shows the home page of the Covid-19, Normal and Pneumonia Chest X-Ray Detection. This page fetches the input from the user to predict whether the chest x-ray is healthy or infected.

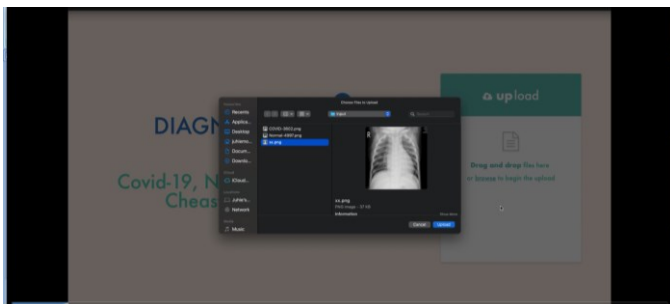


Fig 3 - UPLOADED IMAGE FROM DATASET

Figure 3 shows the uploaded image from Dataset. This image describes the process of uploading the x-ray image by the user. Image can be browsed from our system or can be uploaded from cloud for prediction.

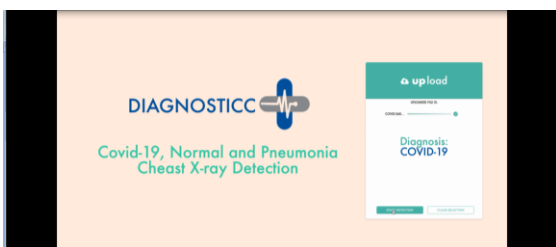


Fig 4 - PREDICTION OF COVID-19 DISEASE

Figure 4 shows the prediction of Covid-19 Disease. This image shows the predicted results from the input image provided by the user. This image depicts the results of the image on whether it is a healthy or an infected lung based on the algorithms used for training the dataset.

VII. CONCLUSION:

In conclusion, the development and evaluation of an automated system for chest disease detection using Convolutional Neural Networks (CNNs) with the VGG16 architecture represents a significant advancement in medical imaging technology with potential implications for clinical practice and public health. Through the systematic application of deep learning techniques and interdisciplinary collaboration, this study has contributed to addressing critical challenges in chest disease diagnosis and management. The results of this study demonstrate the effectiveness and promise of the automated system in accurately detecting chest diseases, including COVID-19 and pneumonia, from chest X-ray images. The trained model exhibits competitive performance compared to existing diagnostic methods, showcasing its potential to enhance diagnostic accuracy, efficiency, and scalability in clinical settings.

VIII. FUTURE WORK:

Deployment of the work as a web application that produces a much faster and more accurate results with real-time data as it's input for the welfare of the general public.

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