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Convolutional Neural Network and Visual Geometry Group-19 for Automated Chronic Obstructive Pulmonary Disease Detection in Radiograph

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ABSTRACT: Chronic Obstructive Pulmonary Disease (COPD) is a major lung disease and significant cause of death across the globe. Detection of COPD through traditional methods has some drawbacks including costs, the availability of qualified professionals. Although traditional diagnosis has its drawbacks, since the inception of deep learning with Convolutional Neural Networks (CNNs) and the Visual Geometry Group (VGG) there are now more modern methods to make these diagnoses. The researcher's specific area was a dataset of chest X-ray images published by the NIH, and then used the various models provided within Kaggle including CNNs and VGG to assess their predictive values. The VGG-19 model was shown to have greater performance over CNN in terms of accuracy, F1 score, precision, and recalls. The review shows the VGG framework allows for enhanced work processes for specialists and clinicians who finally need to diagnose a patient with lung disease and may or may not be undergoing another medical professionals process of elimination. The review also finding out that supervised machine learning algorithms for can enormously augment COPD predictions.

KEYWORDS: COPD, image processing, CNN, VGG-19, X-ray images.

I. INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD) is progressive lung disease and an important global burden of health. It is characterized by difficulties breathing and airflow limitation, often caused by long-term exposure to irritating gases or particles. Cigarette smoking is the most common exposure that leads to COPD. Timely detection of COPD is crucial because appropriate treatment and management. Medical imaging, especially chest X-rays (CXR), offers a quick and easy way to screen for lung diseases. Advances in artificial intelligence (AI) and deep learning have resulted in increased interests in automating the diagnostic process using imaging data. This study investigates the application of Convolutional Neural Networks (CNN) and the pre-trained deep learning model VGG-19 to automatically detect COPD from chest radiographs. By training both a custom CNN model and the VGG-19 architecture, we seek to evaluate their effectiveness in accurately classifying chest X-ray images as either indicative of COPD or non-COPD. This proposed approach could function as a significant diagnostic resource, particularly in settings with limited resources, facilitating earlier and more effective detection of COPD.

II. LITERATURE SURVEY

Deepali Saini & Sumit Kushwaha [1] This study takes a closer look at machine learning for diagnosing and classifying COPD, pointing out both the strengths and weakness of algorithms used when handling with medical datasets. XiaoLing Zou et al. [2] This paper merges deep learning techniques applied to chest X-rays with clinical parameters to enhance COPD screening and staging. The findings indicate a notable improvement in diagnostic accuracy Compared to methods that rely solely on images. Fathema Kabir et al. [3] This research proposes a fusion approach that merges X-

rays with patient history, utilizing both machine learning and deep learning models. This hybrid system boosts the accuracy of COPD predictions compared to models that use a single source of data. Aditya Ingol et al. [4] This review highlights the latest applications of deep learning in identifying pulmonary diseases through chest X-rays. It covers various techniques, including convolutional neural networks(CNNs),transfer learning and hybrid methods for classifying diseases. Shangming Yang et al. [5] This study introduces a hybrid deep learning method constructed for the automatic categorization of pulmonary diseases from chest X-rays. The method shows improved accuracy over traditional CNNs. Akibul Haque et al [6] presents CNN model to detect pneumonia. This approach results in high level of classification accuracy, provides CNN's effectiveness in reliable and automated diagnosis. Ikechukwu et al [7] This work presents CX-Net, an collective semantic depth neural network aimed at identifying regions of interest in chest X-rays. The model enhances feature extraction and helps localize diseases more effectively. Nishchint Makode et al. [8] develops a CNN-based method to identify lung disorder from X-ray images. The system showcases impressive classification performance suitable for clinical applications. Patrik Szepesi et al.[9] have developed CNN models for the detection of COPD from chest X-rays, achieving an impressive accuracy of approximately 95%. Ryan Wang et al.[10] have employed transfer learning and feature fusion techniques on chest X-rays to facilitate early disease detection, enhancing accuracy compared to traditional methods.

III. METHODOLOGY

The framework is broken down into six distinct steps that are data accumulation, preprocessing, model construction, training & validation, performance evaluation, and performance comparison.

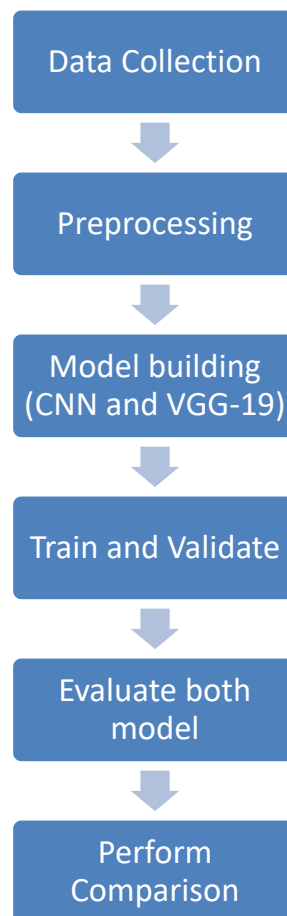


Fig 1: work flow of model

- **Data Collection:** In this study, the dataset needs to be organized in training and testing directories, with subfolders with labels COPD and Non-COPD. The data was obtained from a dataset that was made available to the public via Kaggle.
- **Data Preprocessing:** This step is very important for any dataset, and will help improve the dataset so it can generalize well, along with normalizing the inputs. There are two separate preprocessing pipelines, one for VGG-19 and one for CNN, where pixel values have been normalized to the [0,1] range. To the VGG-19 samples, we applied the preprocess input function to align with the input images it expected.
- **Augmentation:** To boost the model's robustness and reduce overfitting, we implemented real-time augmentation techniques like shear transformations, random zooming and horizontal flipping. We applied both preprocessing and augmentation with the Keras Image Data Generator.
- **Model Building:**
 - **Custom CNN Framework:** CNN was developed using keras Sequential API with few specifications four different convolutional layers with featuring progressively larger filter sizes of 32, 64, 128 & 128 and ReLU activation. Max-pooling layers applied after each convolutional block. A Flatten layer utilized to convert feature maps into a one-dimensional vector.
 - **VGG-19 Transfer Learning Model:** The second model is VGG-19 architecture, which was initially trained on the ImageNet dataset. The original classification layers were eliminated and replaced with a custom classifier A GlobalAveragePooling2D layer for reducing dimensionality. We're looking at fully connected blocks that possesses 512 neurons and uses a ReLU activation function. The VGG-19 model remains unchanged to leverage its pre-trained feature extraction capabilities, with only the customized upper layers being trained.
- **Training and Validation:** The collected datasets was used to train and validate both models. We set 32 as batch size and ran 30 iterations, using Adam optimizer along with a categorical cross-entropy loss function. For training, .fit() function is utilized while validation took place on the test set for each model.
- **Evaluation Metrics:** After training, both models were evaluated on the unseen test data using the following metrics: Accuracy, Precision, Recall and F1-score. Model.Predict() is used to generate forecast and then compare with real labels. For evaluate and estimate evaluation metrics scikit-learn toolkit is used.
- **Model Comparison and Visualization:** A bar chart was employed to display the performances of the two models. The graph displayed these metrics: F1-score; AUC (derived from average performance); Precision; Sensitivity. This illustration emphasizes the relative strengths of the CNN and VGG-19 frameworks. The graph was stored as a high-quality PNG file utilizing Matplotlib.

IV. EXPERIMENTAL RESULTS

The performance of both models (CNN and VGG-19) was evaluated on the test dataset. CNN achieves accuracy of 87% where as VGG-19 achieves 89% accuracy. Along with this, VGG-19 has more F1-score, Precision and Recall compare to CNN, as it is transfer learning and more accurate classifier particularly for image data. Take a look at the visual comparison presented in Fig 2.

Metric	CNN Model	VGG-19 Model
Accuracy	0.87	0.89
F1-Score	0.85	0.88
Precision	0.86	0.87
Recall	0.84	0.85

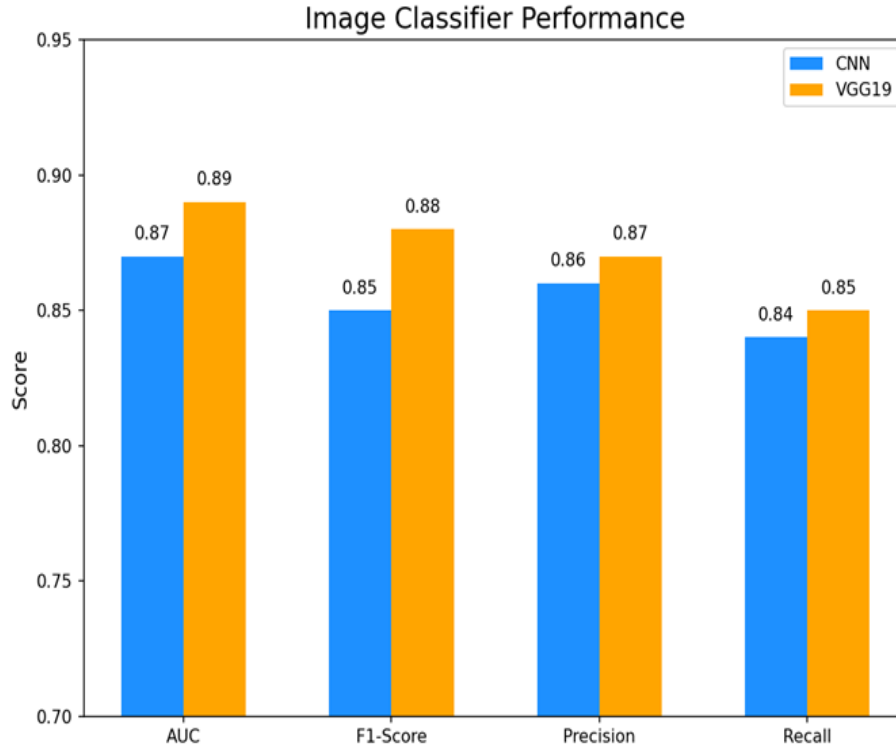


Fig 2: Evaluation of test dataset using bar graph.

V. CONCLUSION

In Conclusion, two deep learning methods—Convolutional Neural Networks (CNN) and the pre-trained VGG-19 model—are quite effective at spotting COPD in X-ray datasets. When we look at metrics such as accuracy, recall, F1-score and precision, the VGG-19 model usually comes out on top compared to the custom CNN, mainly due to its more complex architecture and its knack for utilizing pre-trained features. That said, both models do a solid job of classifying patients with COPD.

This research also emphasizes certain fields where we can improve, such as increasing the distinctness of the dataset, applying data augmentation techniques, and diving into more advanced architectures like ResNet or EfficientNet. Machine learning is incredibly important in medical field, particularly for diagnosing COPD and figuring out most effective treatment choice to the patients dealing with this condition.

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