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A Novel approach for Chronic Obstructive Pulmonary Disease Diagnosis with TensorFlow-Based Image Analysis

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Abstract: This paper introduces an innovative approach to Chronic Obstructive Pulmonary Disease (COPD) detection through image processing, complemented by a user-friendly web application. Leveraging TensorFlow-based CNNs, the proposed system facilitates comprehensive chest X-ray analysis. The Accuracy, precision Recall and F1 score of the proposed architecture are respectively, 94.29, 93.58, 90.47 and 91.22. The workflow involves dataset loading, preprocessing, and iterative model fine-tuning. Crucially, the web application's interface enables seamless image uploads, result displays, and collaborative discussions among healthcare professionals. By merging advanced image processing techniques with accessibility, this work envisions a future where COPD detection is not only technologically sophisticated but also user-centric, promoting effective collaboration in healthcare settings.

***Keywords**: Chronic Obstructive Pulmonary Disease (COPD), Image processing, TensorFlow-based CNNs, User-friendly interface, Expert systems*

1. Introduction:

Chronic Obstructive Pulmonary Disease (COPD) remains a global health challenge, demanding early detection and effective diagnostic tools to enhance patient outcomes. In recent years, advancements in image processing and deep learning techniques have demonstrated significant potential in revolutionizing the detection of COPD through chest X-ray images. This paper introduces a novel approach, leveraging image processing methodologies and a user-friendly web application, to streamline COPD detection. [1]

As the prevalence of COPD continues to rise, traditional diagnostic methods face challenges, particularly in the wake of global events such as the COVID-19 pandemic. This paper addresses these challenges by proposing a sophisticated image processing pipeline integrated into a web application. The proposed system aims to empower healthcare professionals with an intuitive tool that not only detects COPD through chest X-ray images but also facilitates collaborative discussions through a user interface.

Through a series of systematic steps, we explore the integration of TensorFlow-based CNNs for robust image analysis. The process involves dataset loading, preprocessing, model architecture definition, compilation, and iterative fine-tuning to achieve optimal accuracy. The web application's user interface serves as a pivotal component, allowing seamless image uploads, result displays, and collaborative discussions among healthcare practitioners.

In essence, this paper contributes to the evolving landscape of COPD detection by combining the power of image processing algorithms with the accessibility of a web application. The proposed approach envisions a future where early detection and efficient diagnosis of COPD are not only technologically advanced but also user-friendly, fostering a collaborative healthcare environment.

2. Literature Review

This research by Vasamsetti et al. focuses on addressing significant public health issues related to lung diseases, such as COVID-19, Tuberculosis, and Pneumonia, by leveraging deep learning techniques for early detection. While previous studies achieved high accuracy in binary classifications, the addition of multiple classes has

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increased complexity. The study investigates Chest X-Ray images using pre-trained architectures like VGG16 and EfficientNetB7, employing various normalization techniques for data pre-processing. CNN algorithms are utilized to analyze the dataset and improve the detection process for different classes of lung diseases. The aim is to create a more effective and straightforward model, contributing to enhanced accuracy and efficiency in the diagnosis of lung diseases, ultimately leading to improved patient outcomes. [2]

This study by Khade et al focuses on COPD, a long-lasting provocative lung illness that limits airflow and is often caused by prolonged exposure to irritants, primarily from cigarettes. The research employs CNNs and AI to diagnose COPD based on the classification of breathing patterns and chest X-ray images. To enhance the model's performance, the dataset undergoes preprocessing stages to address issues like imbalance and poor image quality. The proposed hybrid model demonstrates promising accuracy in prediction, outperforming existing systems and offering potential advancements in COPD diagnosis through AI-based image analysis. [3]

The study by Orano et al. addresses the pressing issue of lung diseases, which pose significant health challenges globally. The research emphasizes the importance of timely and accurate diagnosis for effective treatment and improved survival rates. Employing CNN technology, the study focuses on classifying six types of lung diseases—atelectasis, effusion, infiltration, mass, nodule, and pneumothorax—using chest X-ray images. With a dataset comprising 8,125 X- ray , the training NN model demonstrates high accuracy rates of 98.46% in training, 83.99% in validation, and an overall accuracy of 82.53%. The developed application, accessible via computer and mobile platforms, integrates the classification model. This application serves as a valuable extra instrument for radiotherapists and medics, aiding in managerial and enhancing the diagnostic process for lung diseases. [4]

The study by Jalehi et al addresses the challenge of automating and accelerating the diagnosis of respiratory system diseases through the analysis of chest X-ray images, leveraging CNN technology. The proposed deep CNN model employs transfer learning based on the EfficientNetV2 model, enhancing the efficacy and accuracy of Computer-Assisted Diagnosis (CAD) performance. Through data augmentation methods, fine-tuning, and the application of Grad-CAM for feature highlighting, the model achieves triple classification—COVID-19, normal, and pneumonia. Utilizing publicly accessible datasets, the proposed model attains impressive results on the testing set, with sensitivity at 98.66%, specificity at 99.51%, and an overall accuracy of 99.4%. This performance surpasses the capabilities of the four most recent classification techniques in the literature, emphasizing the model's effectiveness in automated disease diagnosis from chest X-ray images. [5]

This paper by Sharmila et al. explores the application of deep learning for the detection and classification of various lung ailments from chest X-ray images, addressing shortcomings in existing works. The study introduces a pipeline involving the BSHO for chest X-ray images segmentation before classification. The research demonstrates that even simple models like shallow CNNs can rival complex systems, showcasing competitive performance. The proposed CNN-BSHO model, with fewer trainable parameters, outperforms top models on the Montgomery dataset and performs nearly as reliable as the leading solutions for Shenzhen dataset, despite being computationally more efficient. The study employs classifiers such as SVM, NB, RF, and VGG, achieving an accuracy of 98.324% with CNN-BSHO. [6]

The paper by Jahel et al. aims to enhance the accuracy of diagnosing manifold lung ailments from torso X-ray pictures by means of ensemble method. The proposed technique involves stacking three CNN models (MobileNetV3, EfficientNetV2B0, and ResNet50V2) trained on a combined dataset from PA chest radiography, NIH, and TBX11K. The model performs well in categorizing four lung disease cases (pneumonia class, COVID-19 or covid class, the pneumothorax class, atelectasis class, and normal class), with a degree of sensitivity of 97.25%, specificities of 99.15%, and average accuracy of 98.77%. The sensitivity, specificity, and accuracy for five classes are 91.74%, 97.88%, and 96.68%, respectively. The layering or stacking or piled approach, which employs pre-trained measurements, is successful, demonstrating potential as a dependable automatic diagnostic instrument to assist radiologists in making correct and fast decisions. [7]

The paper by Mitra et al. explores the application of deep learning, specifically CNN, in the detection and classification of lung diseases, with a primary focus on pneumonia and breathing problems. Early identification of such diseases is crucial for effective clinical management. Leveraging ML and DL frameworks, particularly CNN, the project aims to predict lung disease from chest X-ray imageries. The utilization of these advanced technologies enhances the potential for early detection, contributing significantly to the medical field by enabling prompt treatment for patients. [8]

The comprehensive review by Zaidi et al. delves into the application of CAD for lung diseases in CXR using ML and DL techniques. Emphasizing the significance of early detection, the review explores various publicly available CXR datasets for different diseases and provides an in-depth analysis of recent DL models, and ensemble learning methods. Additionally, it discusses CXR image preprocessing techniques, such as enhancement, segmentation, bone clampdown, and data augmentation, to enhance image quality and address data imbalance challenges. The review also addresses the need for interpretability and explainability in DL models, highlighting challenges and suggesting directions for future research to improve the hasty and automated discovery of chest ailments. [9]

This study by Sun et al. addresses the challenge of underdiagnosis of chronic obstructive pulmonary disease (COPD) globally, exacerbated by limitations in spirometry due to the COVID-19 pandemic. The research focuses on developing DL models for automated COPD detection and staging using computed tomography (CT) images. A large, diverse dataset from various hospital settings was utilized for model training and evaluation. Grounded on attention MIL model for COPD detection demonstrated high performance with AUC of 0.934 on the testing set and 0.866 on an external validating subset. The model exhibited generalizability across different scanning devices and slice thicknesses. Additionally, a multi-channel 3D ResNet was developed for categorizing GOLD stages among confirmed COPD patients, achieving a correct grading of 76.4% and showing promising results in the valuation of GOLD cataloguing. The study highlights the potential of CT-based DL approaches as lucrative alternatives for COPD detection, especially in the context of restricted spirometry access during the pandemic. [10]

3. Methodology

Proposed System:

Screening COPD via chest scans using DL techniques CNNs have sparked attention in recent years. There are already techniques that use DL CNNs to identify COPD using chest CT scans, such as the one suggested by Sun et al. Their technique employed an CNN-based algorithm to categorize chest X-rays as having COPD the or not. COPD-negative However, their technology lacked an intuitive interface for showing findings and encouraging conversation. A user interface may considerably increase the system's usability by permitting medical professionals to simply submit photographs, view outcomes, and share their findings with others. A user interface can additionally provide extra details on the forecasts made by the model, for instance the likelihood score connected with them. The present method seeks to expand on the previous system offered by Sun et al. by incorporating a window that allows users to show findings and promote debate. TensorFlow is employed to create the CNN framework and incorporate it into a webapp with an interface for users. The online application allows healthcare providers to input photos of chest X-rays, which are subsequently analyzed by the CNN approach in order to identify whether the individual in question has COPD or not. The findings can be shown on the user interface, together with the likelihood score for the forecast. The system workflow is defined as follows:

I. picture Upload: The procedure begins when users submit a chest X-ray picture using the offered user interface.

II. Pre-processing: The submitted image is pre-processed to assure its quality, which includes deleting any additional data that might compromise the analysis.

III. CNN Prediction: The pre-processed picture is put into a CNN model, that predicts whether or not the image contains evidence of Chronic Obstructive Pulmonary Disease.

IV. Display the results: The prediction findings and related likelihood ratings are displayed to the user via the user interface.

V. Discussion and Collaboration: The user interface provides tools that allow users to debate and participate on the displayed findings with peers.

Advantages:

Introducing an end-user interface to current systems that utilize deep-learning CNNs to diagnose COPD using chest X-rays can significantly increase usability and simplify discussions among healthcare providers. Merging the CNN model with a webapp with a user interface, as well as building a more comprehensive approach, can assist healthcare providers in detecting COPD early on and improving patient outcomes.

DL TensorFlow:

TensorFlow approaches DL is a type of ML that retrains artificial NNs using massive quantities of data to do challenging tasks like speech recognition, picture identification, and NLP. CNNs are an example of a DNN that excels in image recognition. Google's open-sourced TensorFlow DL platform offers an advanced user interface for building and training neural networks. It consists of a set of tools and frameworks that allow developers to create and launch models at scale. TensorFlow's Keras API offers an easy-to-use interface for creating CNNs along with other DL models, rendering them accessible to developers of all skill ranges. To create a CNN in TensorFlow, you generally begin by specifying the network architecture via the Keras API. This includes defining the network's number and kind of layers, in addition to relevant activation functions, normalization approaches, and additional hyperparameters. Once the network is formed, you may compile it by specifying a loss functionality, an optimization function, and any metrics that you want to monitor during training. Finally, we can simulate the neural network on the information utilizing the fit () technique, which iteratively modifies the network weights in order to reduce the loss function. TensorFlow also includes tools for evaluating and displaying the training procedure, such as Tensorflow Board, which allows you to evaluate learnt data representations and monitor metrics including precision and loss over time. After training the model, you can use the predict() method to create predictions on new data. Overall, TensorFlow offers a strong and adaptable framework for creating and teaching DL models, such as CNNs for image identification. However, constructing effective models demands a basic grasp of DL ideas, as well as proper planning and management procedures.

Procedure:

The steps are given below for a step by step procedure

- Import Lib: Essential libraries such as TensorFlow, matplotlib, and sklearn (numpy, pandas) are imported.
- Data Loading: A dataset of lung pictures from individuals who have and those with no COPD is loaded.
- Data Preprocessing: The data is separated into sets for testing and training, with pixel values scaled from 0 to 1.
- The CNN model's architecture is set up utilizing TensorFlow. This includes defining layers, filter measure, kernel size, functions for activation, and pooling layers.
- Model Compilation: To compile the model, define the loss operation, optimizing function, and assessment metric.
- Model Training: A model is tailored to the initial train dataset utilizing its fit() method, which specifies the training data, the amount of epochs, and the size of the batch.
- Model Evaluation: The model gets assessed on testing data using the evaluate() function, which provides an estimate of its correctness.
- Prediction: The model that has been trained is used to determine if a particular lung picture has COPD by passing it through the model and assessing the anticipated label.
- Visualization of Performance: The model's performance is represented by measures like as AUC, PE, SEN, and FS. This stage helps comprehend the design's strengths and limitations.
- Fine-tuning the method involves altering hyperparameters. Model is trained through visualization are iterated until the desired results are achieved.
- User Interface Output: The results, including forecasts and performance metrics, are shown on the user interface.
- Model Storage: The learnt model is saved for later usage, allowing the trained algorithm to be reused without the need for retraining.

Model Design Data Collection:

The initial phase is to gather a large number of lung X-ray scans, including both not COPD and COPD-true images. The photos should be annotated with the correct COPD status. The dataset contains the following elements: • five hundred train images: three hundred COPD images and two hundred normal images. • more than three hundred test photos, 167 of which are COPD and the other 183 are normal. Image Preprocessing: In order to boost the level and diversity of the X-ray pictures, pre- processing is essential. This can be accomplished using methods such as augmentation, which generates new images by revolving, flipping it, and adjusting the existing ones, or normalization, which involves adjusting the values of the pixels to a certain range. The original picture is converted to monochrome and binary pictures.

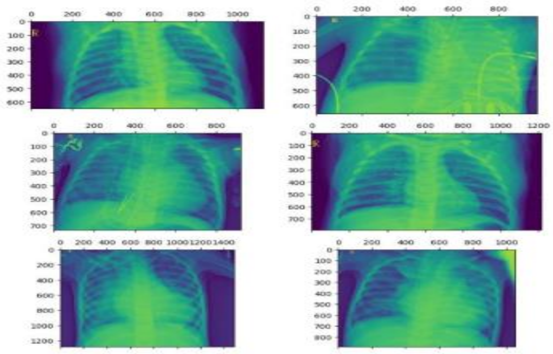

Figure 1:sample training images

Gaussian Filter: To boost the reliability of COPD identification, X-ray pictures will be pre-processed using a Gaussian filter. The Gaussian algorithm is a form of filtering that lowers noise and accentuates edges in the picture. It may also be used to eliminate artifacts, shadows, and other undesired features from an image. Overall, the use of DL with TensorFlow, as well as the pre-processing approach of Gaussian filtering, can help in the accurate and early diagnosis of COPD, leading to improved patient outcomes.

Model Training: TensorFlow is used for conditioning the model with the training data. We train the model for 50 epochs, using a batch size of 17. A binary loss of cross-en is the slope descent objective operation, whereas Adam is the slope descent the optimization algorithm. To broaden the training dataset and prevent overfitting, we also use data augmentation techniques like as rotate, zoom, and vertical flip.

Developing the Training Data Generators: A train dataset producer will be built with TensorFlow. A data generator is a function that produces chunks of data that are fed to the DL model during development. It is critical to develop a training dataset generator capable of efficiently loading the dataset and perform augmentation.

MODEL ARCHITECTURE:

- A COPD detection model created with CNNs typically includes the following layers:
- The input layer accepts input data, such as chest X-ray images.
- Convolutional layers extract characteristics from photos using filters. Each filter extracts and produces a feature map based on a single characteristic in the picture, such as borders or textures. Many layers of convolution can be combined to learn more complex properties.
- Max-pooling layers downsample feature maps by choosing the highest value within a fixed-size window. This reduces the data's complexity while rendering the algorithm more resilient to variations in the input pictures.
- The flatten layer transforms 2D characteristic maps into 1D vectors that may be passed to fully connected layers.
- Fully linked layers use a set of weights to classify input feature vectors using complex activation function. The last fully linked layer's output represents the anticipated class probabilities.
- The output layer consists of just one tensor that has a sigmoid activated function, producing an output in binary format indicating if the input picture contains COPD or not.

The no. of convolutions and Dense layers, in addition to the filters size, may be modified based on the complexity of the problem and the dimensions of the input images. Batch norm, dropping out, and additional regularization procedures can help enhance model performance and decrease overfitting.

Performance Evaluation: After training the model, its efficacy and proficiency are tested on a test set. These may include metrics like F1 score (FS), recall(SEN), accuracy(AUC), and precision(PE).

1. Accuracy (AUC) Definition: AUC quantifies the comprehensive exactness of the model by computing the ratio of appropriately projected cases to the total no. of cases.

• Formula:

$$AUC = \frac{TotalNumberofPredictions}{NumberofCorrectPredictions}$$

• Interpretation: AUC is a overall degree of correctness but may not be fit for imbalanced datasets, wherever the groups have significantly different sizes.

2. PE: Definition: PE, also famed as ”positive predictive value”, quantifies the AC of ”positive predictions”. It is the ratio of correctly predicted positive instances to the total no. of predicted positives.

• Formula:

$$PE = \frac{TruePositives}{TruePositives + FalsePositives}$$

• Interpretation: PE is becomes increasingly significant when the cost or no. of false positives is high, and there is a need to minimize false positive predictions.

3. SEN (Sensitivity or True Positive Rate):

- Definition: SEN quantifies the adeptness of the model to capture all the positive instances. It is the fraction of correctly predicted positive instances to the total actual positives.
- Formula:

$$SEN = \frac{TruePositives}{TruePositives + FalseNegatives}$$

• Interpretation: SEN is becomes increasingly significant when the cost or no. of false negatives is high, and there is a need to minimize instances of the positive class being missed.

4. F-score (FS):

• Definition: The FS is the HM of PE and SEN, providing a uniform measure of both. It is especially useful when there is an uneven class distribution.

• Formula:

$$FS = 2 \times \frac{PE \times SEN}{PE + SEN}$$

• Interpretation: The FS glues PE and SEN into a single metric, with higher values indicating a better balance between the two.

BLOCK DIAGRAM:

Interface Design Module:

This section will be given the task of developing the user interface for the system with web development tools such as HTML, JavaScript and CSS for style. The section will allow medical professionals to submit chest X-ray images, assess the results of the forecasts made by the model, and work alongside colleagues on the results.

This module will integrate the CNN model and user interface to identify COPD using chest X-rays. The feature enables healthcare practitioners to easily submit and analyze photos and results.

4. Results and Discussions:

Early identification of COPD can help to prevent further lung damage and improve the person's standard of life. CNNs powered by TensorFlow, in specific, have demonstrated great potential in medical image analysis, including COPD identification with a user interface that displays results and encourages discussion. [11] The system's performance is assessed using evaluation measures like AUC, PE, SPE, and SEN, as previously discussed. In the COPD inputting screen, the user enters an x-ray image and then clicks detect to determine the disease's status. The results of COPD detection. It provides information such as whether the individual has chronic pulmonary disease (and the precision of the model. The findings of this suggested approach (Table 1) properly identify the precise diagnosis of COPD, as illustrated in the graph Figure 1. This shows that the AUC is 94.29%. Lung illness should not be overlooked. Therefore, FN ought to be as minimal as feasible. In that scenario, it is advantageous that SEN (93.58%) is higher than PE (90.47%). Similarly, no patients should be overlooked. As a result, high SEN (93.58%) produces superior results. The output findings reveal that the system performs well, exhibiting a AUC score of 94.29% more than five hundred photos. It may be tried for a higher number of images.

Performance Measure	Percentage
AUC	94.29
SEN	93.58
PE	90.47
FS	91.22

Table 1: Result table

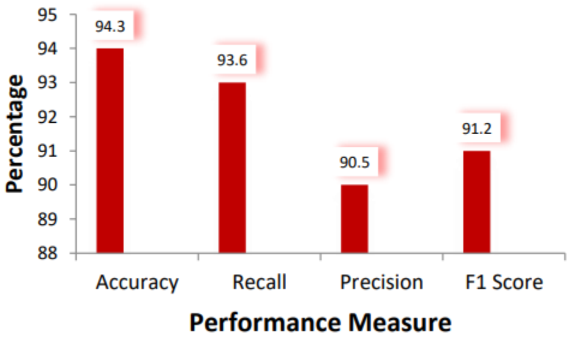

Fig 2: Performance Table (Rounded off)

5. Conclusion:

DL, particularly CNNs, might be utilized to diagnose, categorize, and predict results in COPD patients. Based to research, CNNs can consistently identify among COPD patients and healthy persons, determine the extent of COPD from images, and forecast death in COPD patients using clinical and imaging data. However, the accessibility of big datasets both validation and train remain a difficulty, and CNN models may be difficult to comprehend, limiting their practical use in clinical settings. Further study is required to address these issues and use these findings in clinical settings, where early detection and precise categorization of COPD can significantly improve patient outcomes. In conclusion, CNNs have the potential to profoundly change how we determine, categorize, and predict the development of COPD patients.

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