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AI-Based Model Design for Prediction of COPD Grade from Chest X-Ray Images: A Model Proposal (COPD-GradeNet)

Serdar ABUT[*1,2] **ORCID** *0000-0002-6617-6688*

[1]*Siirt University, Faculty of Engineering, Department of Computer Engineering, Siirt, Turkiye*
[2]*University of Kansas School of Medicine, Department of Office of Research, Wichita, KS, USA*

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Abstract

Chronic Obstructive Pulmonary Disease (COPD) ranks high among the leading causes of death, particularly in middle- and low-income countries. Early diagnosis of COPD is challenging, with limited diagnostic methods currently available. In this study, a artificial intelligence model named COPD-GradeNet is proposed to predict COPD grades from radiographic images. However, the model has not yet been tested on a dataset. Obtaining a dataset including spirometric test results and chest X-ray images for COPD is a challenging process. Once the proposed model is tested on an appropriate dataset, its ability to predict COPD grades can be evaluated and implemented. This study may guide future research and clinical applications, emphasizing the potential of artificial intelligence-based approaches in the diagnosis of COPD.

Keywords: Artificial intelligence, COPD, Deep learning, Transfer learning, Medical image processing

Akciğer Grafilerinden KOAH Derecesinin Tahmin Edilmesi için Yapay Zeka Temelli Model Tasarımı: Bir Model Önerisi (COPD-GradeNet)

Öz

Kronik Obstrüktif Akciğer Hastalığı (KOAH), özellikle orta ve düşük gelirli ülkelerde ölüm nedenleri arasında üst sıralarda yer alır. KOAH'ın erken teşhisi zordur ve mevcut tanı yöntemleri sınırlıdır. Bu çalışmada, radyografi görüntülerinden KOAH derecelerini tahmin etmek için bir yapay zeka modeli olan COPD-GradeNet önerilmektedir. Ancak, model henüz bir veri seti üzerinde test edilmemiştir. KOAH'ın spirometrik test sonuçları ve akciğer röntgen görüntüleri gibi bir veri setinin elde edilmesi zorlu bir süreçtir. Önerilen modelin uygun bir veri setiyle test edilmesi halinde, KOAH derecelerini tahmin etme yeteneğinin değerlendirilip uygulanabileceği düşünülmektedir. Bu çalışma, gelecekteki araştırmalara ve klinik uygulamalara yol gösterebilir, KOAH teşhisinde yapay zeka tabanlı yaklaşımların potansiyelini vurgulayabilir.

Anahtar Kelimeler: Yapay zeka, KOAH, Derin öğrenme, Transfer öğrenme, Medikal görüntü işleme

[*]Sorumlu yazar (Corresponding Author): Serdar ABUT, *serdarabut@siirt.edu.tr*

1. INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD) is among the top three causes of death worldwide, with 90% of these deaths occurring in low- and middle-income countries. According to a report published in 2021, globally, 3 million people died due to COPD in the year 2012 [1]. It has been assessed that COPD is a prevalent, preventable, and treatable disease. COPD, characterized by chronic airflow limitation, is a combination of bronchitis (airway narrowing disease) and emphysema (destruction of small air sacs). COPD causes different types of damage in the lung parenchyma from person to person due to structural differences in the airways [2].

1.1. The Relationship Between COPD and Chest X-Ray Images

In [3], it was stated that chest X-rays alone cannot be used by clinicians to diagnose COPD and that spirometric tests, the patient's symptoms, and health history must be considered among many criteria for COPD diagnosis. The lack of sensitive diagnostic tests for early stages of COPD results in insufficient diagnosis of this treatable disease in an estimated 60-85% of patients [4]. COPD creates a pattern of damage on lung parenchyma [3], which is reflected in chest X-rays through a technique [5,6] currently being tested on mice [7] and cadavers [4]. The findings obtained with this imaging technique suggest that improvements in early diagnosis of COPD can be achieved using X-ray images [4]. Considering that clinicians use biological vision (human vision) and that the human eye tries to understand images more by using shape information while machine vision tries to interpret images using texture information [8,9], we foresee that the high-accuracy diagnosis of COPD from chest X-rays through machine vision will be possible in the near future.

In recent years, artificial intelligence methods, especially deep convolutional neural networks (DCNNs), have been widely used to enable clinicians to automate tasks such as the classification of COVID-19 from CT [10] and chest X-ray images [11-13], determination of the severity of COVID-19 [14], diagnosis of proximal femur fracture from MR images [15], early detection of pathological changes in bone microstructures [16], disease diagnosis using laboratory test results [17], determination of the effectiveness of Shapley value in identifying low-quality and valuable data for pneumonia detection [18], and localization of common chest diseases on chest X-rays [19], and improving the performance of radiologists in breast cancer screening [20]. With the proliferation of deep learning models, the field of medical image processing has garnered widespread interest, particularly in radiology [21-23]. The results of these studies aimed at solving complex problems suggest that the idea of predicting COPD stages using artificial intelligence methods through chest X-rays will be successful. Therefore, COPD-GradeNet will fill an important gap in the literature.

1.2. Advancements Offered by Deep Learning Tools

In the diagnosis of lung diseases, lung X-rays are frequently used. Artificial intelligence-based studies have been carried out to assist in the diagnosis of emphysema [24], which can be seen in individuals who smoke but do not meet the criteria for COPD, despite being commonly seen in COPD patients [25-28]. In these studies [29-31], Computerized Tomography (CT) used for classifying emphysema or airway-dominant for the classification of COPD disease was used as a model input. Considering that the severity of emphysema may not correlate with the severity of COPD and that lung tissue characteristics of COPD patients in the same stage may show significant changes [31], and given that X-ray images that are more economical and cause less radiation exposure will be used in our project compared to CT, the COPD-GradeNet model with the theoretical infrastructure presented in this study differs from other studies on COPD staging.

Wang et. al. [11] developed a machine learning model using lung X-ray images to identify pneumonia caused by COVID-19. With this deep learning-based model, the diagnosis and severity of pneumonia caused by COVID-19 were determined, whether pneumonia was caused by COVID-19 was

identified, and the lesion areas of pneumonia were color-coded to provide information to radiologists. The results of this deep learning-based artificial intelligence model were reported to have a 98% match with the diagnoses of radiologists [11]. In our study, we aim to determine the disease level of individuals classified into 4 different stages of COPD and 1 control group without COPD, using only lung X-rays, through deep learning models according to the guidelines proposed in [3].

In a study proposing a machine learning-based model to aid expert radiologists in distinguishing COVID-19-induced pneumonia from other types of pneumonia using lung X-ray images, 420 X-ray images were analyzed [13]. Different feature extraction methods were used to represent X-ray images in lower dimensions. Based on these features, a test set consisting of 25 COVID-19, 31 normal, and 28 non-COVID pneumonia X-ray images was classified with an accuracy of 94% (AUC) [13]. Most feature extraction methods used in literature are similarly applied in different applications [32]. For example, the local binary pattern method is used in fingerprint applications [33] as well as iris recognition applications [34]. However, deep learning methods learn problem-specific features and perform data-driven dimensionality reduction. Therefore, deep learning can solve much more complex problems [35]. A study on MR images compared feature extraction methods and reported that deep learning methods were successful compared to classical feature extraction methods [36]. However, deep learning models require a large number of samples [35]. The lack of a large and shared dataset consisting of labeled lung X-ray images for COPD stages is thought to be the reason why this topic has not been studied in the literature. In this study, we plan to perform feature extraction with deep learning methods as we believe COPD staging is a complex problem. We expect that such a COPD-GradeNet model will provide effective results with labeled lung X-ray images of at least 500 individuals from the control group and from each of the four stages of COPD, totaling 2500 individuals.

1.3. The Potential of Deep Learning Tools to Adress COPD Issues

With the COPD-GradeNet model, the following issues can be addressed by determining the stage of COPD solely from lung X-rays without the need for challenging spirometric tests. The difficulties of relying on spirometric tests for a COPD diagnosis can be overcome by taking a lung X-ray and analyzing it with an artificial intelligence model. Respiratory tests can be challenging, especially for elderly patients, and depending on the operator and the patient's condition, these tests may not guarantee consistent results. Respiratory function tests cannot be applied to patients with conditions such as hemoptysis (coughing up blood), tuberculosis, pneumothorax, recent heart attack or stroke, Alzheimer's disease, and dementia who are unable to follow commands. In addition, correct measurements cannot be obtained from respiratory function tests due to noncompliance with commands due to factors such as the patient's sociocultural level and mental illnesses [37].

The COPD-GradeNet we propose can provide an alternative method to respiratory tests by being a model based solely on using a lung X-ray for COPD staging. Additionally, an COPD-GradeNet can be created that will help with the diagnosis using a radiography device, which is available in almost every health center, instead of a respiratory function test device that is not available in every center. CT scans are taken to monitor the course of emphysema caused by COPD. The radiation dose that the human body is exposed to during a CT scan is between 10-20mSv [38], and with multiple CT scans performed at different times during a patient's follow-up, the amount of radiation exposure can reach very high levels that can exceed the carcinogenic effect threshold. Therefore, clinicians around the world tend to take fewer CT scans to protect the patient. By creating a diagnostic model using X-ray technology that exposes the body to radiation at a lower level - between 0.02-0.15mSv [38]- with the COPD-GradeNet model, more observations can be made at earlier stages with less harmful approaches. See [39] for a more detailed comparison of CT and X-ray. Considering that CT devices are not available in every center due to costs and needs, but

radiography devices are widely used, the proposed COPD-GradeNet has the potential to reduce issues associated with CT scans.

1.4. The Feature of the COPD-GradeNet Model to Direct the Studies on this Subject

In the COPD-GradeNet, using a deep learning model that performs feature extraction and classification well, regions related to COPD on lung X-rays will be colored. This process is called localization. After localization, radiological images can be analyzed and reported without human intervention, opening the door to applications that can be reported automatically. In addition, coloring areas related to COPD on the image can speed up clinicians' diagnosis and improve the diagnostic abilities of inexperienced physicians for educational purposes. Indeed, it has been noted that such artificial intelligence models increase the success rates and speed of correct diagnoses by medical doctors [11]. While CT images are reported by specialist radiologists in most countries of the world, lung X-rays are not reported by radiologists and are evaluated by clinicians. The proposed model will shed light on the development of systems that will also serve as artificial intelligence-based reporting for major pathologies in the lungs.

1.5. The Aim and Objectives of COPD-GradeNet

The goal of the COPD-GradeNet is to create an artificial intelligence-based model that can predict the stage of Chronic Obstructive Pulmonary Disease (COPD) from lung X-ray images. Receiver Operating Characteristic (ROC) analysis will be used to evaluate the performance of the AI-based model in classifying the four stages of COPD. The accuracy with which each stage of COPD can be distinguished by the model will be determined by the Area Under Curve (AUC) analysis. The model is expected to produce promising results when the mean AUC value of all groups in classifying the stages of COPD reaches at least 0.80.

The dataset required for training the model includes lung X-rays taken simultaneously with spirometry from a total of 2,500 individuals, with at least 500 images from each of the four different stages of COPD and a control group, which have been diagnosed by expert clinicians. This dataset is assumed to have labels indicating the spirometric stage of COPD and accompanying lung pathologies diagnosed by CT, obtained by examining the spirometry test results conducted simultaneously with lung X-rays. Spirometric measurements should be evaluated as the gold standard for COPD staging, while CT images should be used as the gold standard for lung diseases such as emphysema and bronchiectasis.

Preprocessing: The differences caused by uncontrollable factors in X-ray images (brightness, contrast, etc.) must be eliminated and the images must be standardized in the dataset. This new standardized dataset should be divided into subsets of training (train), validation (validation), and testing in an 8:1:1 ratio, respectively.

Distinguishing COPD from other lung diseases and coloring the regions related to diseases: To distinguish COPD from other lung diseases that can be diagnosed with CT (Asthma, Congestive Heart Failure, Bronchiectasis, Tuberculosis, Obliterative Bronchiolitis, Diffuse Panbronchiolitis [3]), a multilabel classifier should be used instead of a multiclass classifier. At this stage, the probability of COPD and other lung diseases can be estimated as a percentage. It can be assumed that this goal has been achieved if the AUC value of the model in distinguishing COPD from other lung diseases is at least 0.80. After the trained model achieves classification accuracy, regions that are effective in distinguishing (discriminative) diseases with the highest probability predicted by the model can be colored and weighted on the X-ray image using the object localization technique [40,41]. Thus, the discriminative regions that are effective in distinguishing the disease with the highest probability predicted by the model can be weighted in the X-ray. As a result, an image that will be used as input for the next stage of COPD staging will be obtained. This image will be a weighted image of the regions related to COPD, with other lung diseases filtered out, which will improve the performance of the COPD-GradeNet

2. MATERIAL AND METHOD

2.1. Creation of Dataset

The lung images that will be used as input for the COPD-GradeNet model, as well as information such as respiratory function test results and the stage of COPD, should be obtained. For this, X-ray images of a total of 2,500 people should be obtained, 500 from each group of non-COPD and COPD with 4 stages, who have been diagnosed by expert physicians. It is important to ensure consistent data as the X-ray films are taken simultaneously with respiratory function tests. It should be noted that an equal number of samples (500 each) should be selected from each stage when selecting the X-ray images.

The dataset should be compiled by gathering information about which stage of COPD the patient is in spirometrically and any accompanying lung pathologies determined by CT. Therefore, classification based on spirometrically determined staging from respiratory function tests should be used as the gold standard for COPD staging. For the detection of other lung diseases such as asthma, congestive heart failure, bronchiectasis, tuberculosis, obliterative bronchiolitis, and diffuse panbronchiolitis, diagnoses made by expert physicians from CT images should be used as the gold standard.

Risk of insufficient dataset: There is a risk of not obtaining at least 500 X-ray images from each of the four levels, or even obtaining at least 500 images from each class, but realizing that the problem is more complex than anticipated (i.e., not being able to obtain any model with AUC≥0.80 for each class), which may require more examples. To solve these problems, data augmentation techniques [42,43] such as random flipping in the x and y axes for classes with insufficient X-ray images, random rotation in the range of $[\alpha, \beta]$ degrees, and random scaling in the range of $[x, y]$ can be used to derive new data from existing data, which can improve the performance of the COPD-GradeNet model.

2.2. Preprocessing

The dataset should be created from the information of individuals with COPD stages graded as Grade1, Grade2, Grade3, and Grade4, and a control group with the label G0, who do not have COPD (Figure 1-A). When these images are obtained retrospectively, it should be considered that a patient may have multiple follow-ups and multiple finding labels at the same time. To reflect true learning in COPD-GradeNet model's performance metrics, one image should be taken from each patient. Selecting images from the Anterior-posterior (AP) views of these patients, rather than the posterior-anterior (PA) views, is important as lung patterns are clearer in AP images. A data table should be created indicating which of the 6 diseases were seen with COPD by reading each CT report belonging to these individuals. This data table should consist of columns that include a unique random identification number for each sample, the COPD stage of that individual, and whether the six specified diseases were present or not (Figure 1-A). model.

When considering that the X-ray images to be obtained will be used in the training of an artificial intelligence-based model, it is anticipated that standardization processes should be performed on these images at the preprocessing stage to create a robust model. Examining X-ray images is an important step for medical diagnosis, and problems such as low contrast and low color range in these images make it difficult to see information in bright or dark areas [44].

Low contrast and low brightness problems are commonly observed in X-ray images [45]. Deep convolutional neural networks are developed by taking inspiration from human vision [46-48]. In order to improve the classification performance of these deep networks, it is necessary to eliminate the potential tonal differences that may occur in X-ray images. Therefore, histogram equalization [49] will be performed as a preprocessing step on all X-ray images considered as input to the model.

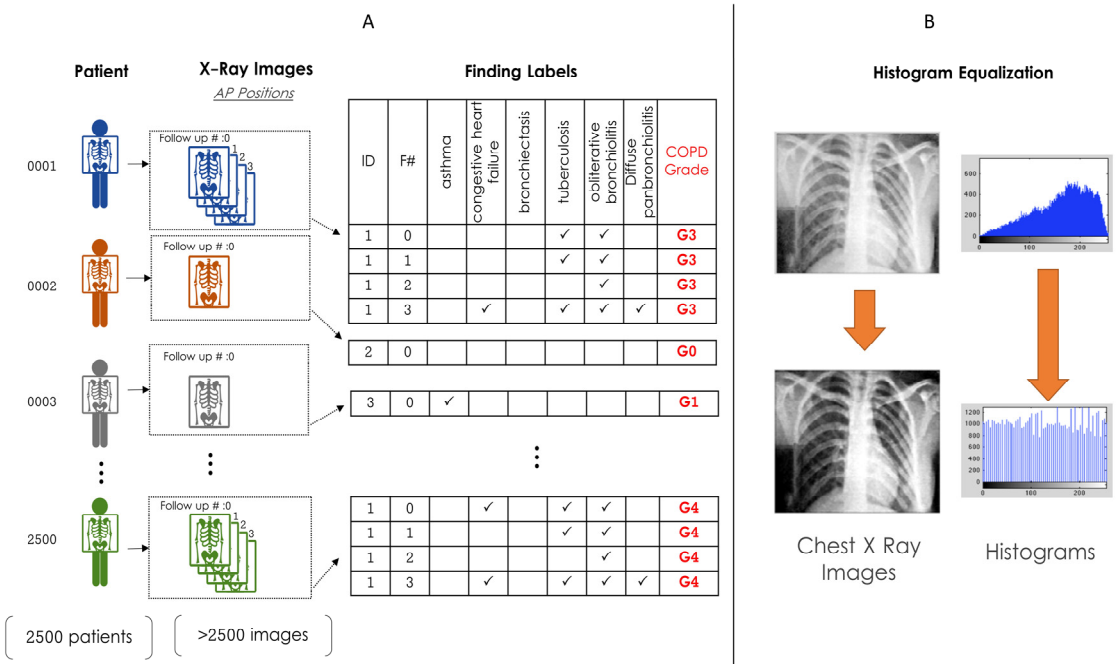

Figure 1. The formation scheme of the dataset. A) A representative data table showing the stages of COPD and accompanying diseases. B) Histogram equalization process to be applied to each image

2.3. Deep Convolutional Neural Networks-DCNNs

A paper by Yann LeCun and his colleagues, which proposed the use of artificial neural networks in computer vision, was rejected from a leading conference in 2008. At the time, it was generally believed that computer vision could not be solved entirely with artificial neural networks, and that there needed to be stages designed by hand. It was assumed that a problem related to object recognition could not be solved simply by using images and labels. Concerns about displacing the skills of programmers in computer vision with a general learning technique procedure are thought to have contributed to this situation [50].

Approaches to object recognition use machine learning methods as a basis. In order to improve the performance of these methods, larger datasets should be collected, and better techniques should be used to avoid overfitting. Before the idea of deep convolutional networks, the datasets used in computer vision (e.g. NORB [51], Caltech-256 [52], etc.) contained relatively few examples, numbering in the tens of thousands. For simple recognition problems, models that use data techniques derived from these relatively small datasets (augmented) have achieved human-like performance and surpassed human performance in traffic sign classification [53].

However, since real-world objects exhibit considerable variability from these datasets, larger training datasets are required to achieve high accuracy in recognizing these objects with computer vision [50]. Recently, it has become possible to create such datasets. ImageNet [54] consists of 15 million labeled images from 22,000 categories, while LabelMe [55] consists of hundreds of thousands of images that have been segmented. Convolutional neural networks have demonstrated high success rates in object recognition and image classification within these datasets [50,56].

To learn (classify) thousands of objects from millions of images, enormous learning capacity

models are required. However, the tremendous complexity of object recognition necessitates predicting the difficulties that will be encountered in classifying such a large number of categories using traditional methods. Therefore, to solve such a problem with classical methods, one must have a lot of prior knowledge. However, deep convolutional neural networks (DCNNs) are able to automatically learn this prior knowledge while solving these types of problems. These networks, whose depths and widths can be changed to control their capacities, make strong and mostly accurate assumptions about the nature of images (i.e., the regularity of statistics and pixel dependencies). As a result, compared to standard feedforward neural networks with layers of similar sizes, DCNNs are easier to train since they have much fewer connections (locally-connected) and parameters [50].

2.4. Differentiating COPD from Other Lung Diseases

In order to design a deep convolutional neural network model that will predict the stages of COPD, which is the aim of our model, it is necessary to distinguish between COPD and comorbid diseases. For this purpose, modules for planned disease differentiation and visualization of lesion sites are shown in Figure 2.

Module-1, shown in Figure 2, has labels to indicate the classes (7 different diseases) that will be the output of the deep convolutional neural network. The properties and weights of the classes at the output of Module -1 become the input of Module-2. The details of these modules are explained in the following subheadings.

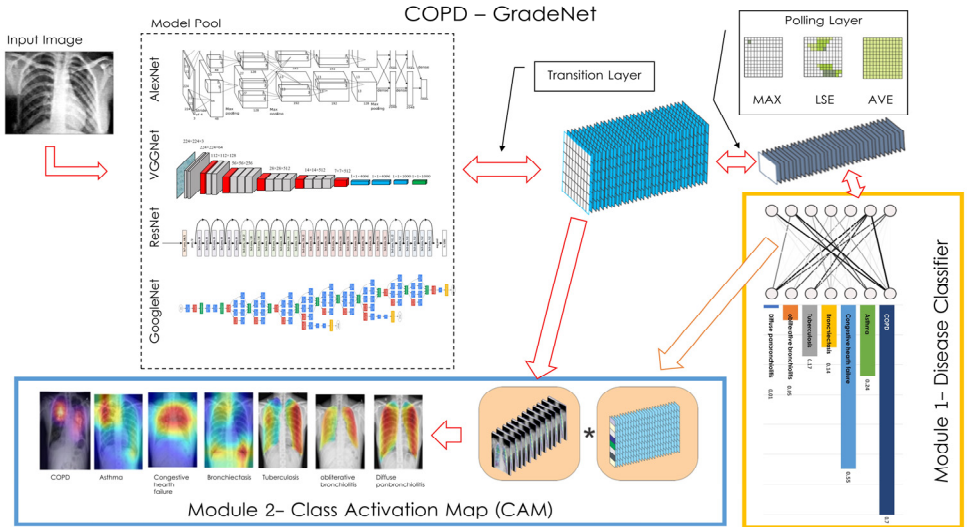

Figure 2. Modules of the COPD-GradeNet model (Module 1 & Module 2)

2.4.1. Model Pool

The learning processes of deep convolutional neural networks are affected by costs such as time and hardware, so in order to facilitate the learning process, the transfer learning technique based on the principle of reusing the information obtained from past tasks will be applied [57]. Because fine-tuning a network with transfer learning is often much faster and easier than training a network with weights randomly started from scratch. We predict that COPD-GradeNet will be successful with the use of this technique, which provides high classification performance using a small number of training images [58-60]. Since it is not known in advance which trained network will have high performance, the model pool consists of 4 networks such as AlexNet [50], GoogLeNet [61], VGGNet-16 [62],

ResNet-50 [63], which have proven themselves in the literature. The models can be trained by removing the final classification layers of these networks and adding the classification layer suitable for the purpose of COPD-GradeNet (Figure 2).

2.4.2. Module 1&2- Disease Classifier

In the classification of diseases, the development of a standard terminology is very important in terms of epidemiological studies, calculations of healthcare costs, and national/international comparisons of diseases, and according to a study [64] done to make this standard classification by machines, deep learning networks make great contributions to the solution of multi-label classification problems. provides. In a study [65] conducted to evaluate the classification performance of COVID-19 using two different datasets of labeled chest X-ray images of 16 different deep learning models, AUC 0.83-0.89 for the CheXpert dataset and AUC 0.983-0.988 for the COVID-19 Image Data Collection dataset. reported to have excellent performance. In the same study, it was reported that even a certain amount of shallow network models used approached high performance. From this point of view, we think that it will be possible to find a suitable deep mesh model according to the complexity of the problem to be solved as a result of the COPD-GradeNet model.

The aim of a classifier model is to assign one or multiple labels to each instance in a sample space [66]. Most classification problems associate each instance with only one class [67]. This is referred to as a multiclass classification problem, where an instance belongs to only one of multiple classes. However, there are many classification problems in which each instance can be associated with one or more classes. Such problems are known as multilabel classification problems [67]. For example, each patient can be simultaneously diagnosed with multiple classified diseases, which is an instance of a multilabel classification problem. Since COPD, which is the disease the COPD-GradeNet model is trying to solve, is often seen with other diseases [3], it is necessary to distinguish these diseases before staging COPD. The patterns of the identified 7 different diseases can be seen simultaneously in a person's lung X-ray, so a multilabel classification approach will be used instead of a multiclass classifier model. This will allow for overlapping between different diseases, and predictions will be made separately for each disease instead of making a single final prediction.

The deep learning network created in the disease classifier module should have approximately 2500 preprocessed lung X-ray images as training input. The process for creating the database of these images, including how the other 6 diseases that can be seen with COPD will be labeled and how preprocessing will be applied, has been explained above. After these stages, a deep learning classifier model will be designed to predict the class of these diseases, which have been labeled by expert physicians based on X-ray images (Figure 3). The predicted class labels and pre-determined COPD stages can be used as input for the task of coloring the lesion regions in the next stage (Figure 2).

The activation function used in the output layer that concerns Module-1 will be the sigmoid function. Thus, the values calculated between (0,1) for each of the 7 diseases will also indicate the probability of having that disease (Figure 3).

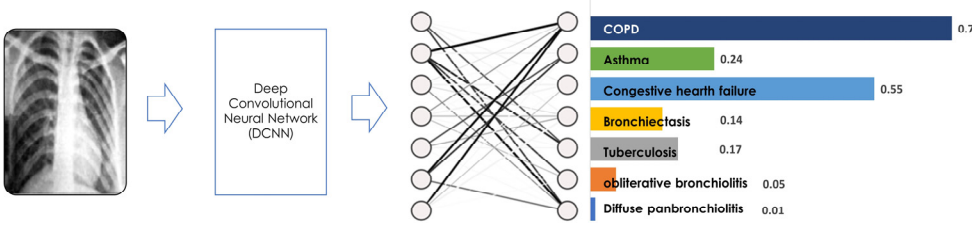

Figure 3. Module-1: A diagram showing the input image, the deep network, and the output layer consisting of 7 neurons

At this stage, it is impossible to know in advance what ratios of examples with diseases accompanying COPD will be in the dataset. The situation where at least 3 of the 6 diseases accompanying COPD are below 5% can be considered as an important risk criterion. In order to solve this problem, the risks that will arise from data insufficiency can be minimized by using a multiclass classifier model that separates 3 groups as "COPD", "not COPD" and "at least one of the other diseases" instead of modifying the multi-label classifier model, since only COPD staging is aimed to be performed in the next stage according to the objectives of COPD-GradeNet model, and there will be no internal evaluation on other diseases.

In the COPD-GradeNet model, after the disease classification process is completed, the regions belonging to that disease will be colored on the X-ray. In this coloring process, the original image will be used in the form of grayscale and only the area corresponding to the disease will be colored. Thus, it will be ensured that the radiologist focuses on the area where the disease is located.

The block diagram of the entire model to be developed for COPD-GradeNet is roughly shown in Figure 4. In this diagram, the COPD image is transferred to another classifier for COPD staging from 7 images, which have been colored (weighted) with respect to the regions related to the disease as the output of Module-2. The outputs of Module-3 consist of 5 classes: patients without G0 COPD, and stages determined according to the severity of COPD between G1 and G4.

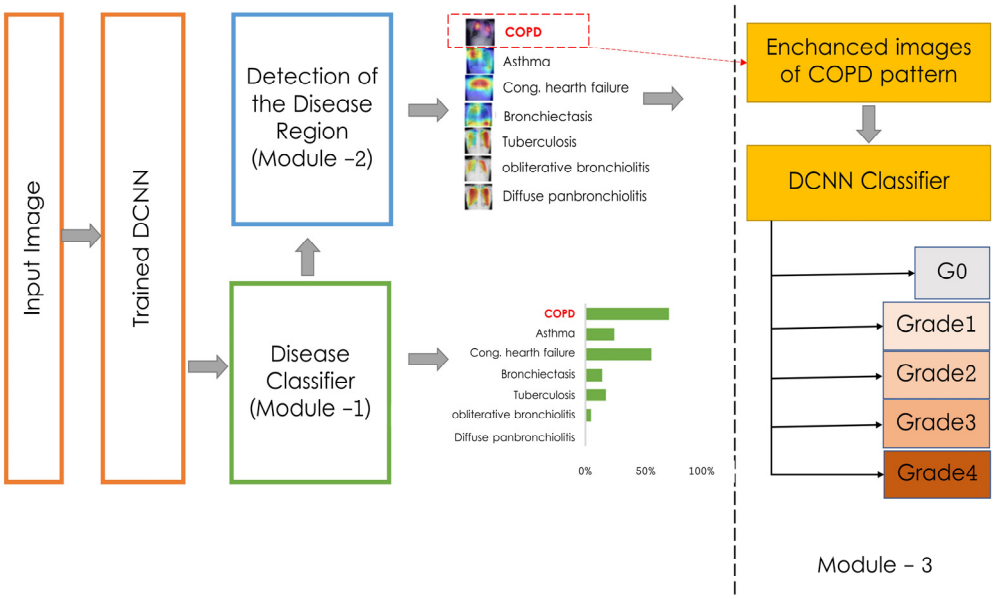

Figure 4. Transfer of the image related to COPD from the localized images, which are the output of Module-2, to Module-3

2.4.3. Module 3 – Prediction of COPD Stage

In Module-2, the effects of non-COPD diseases on the X-ray images will be removed by weighting the regions related to COPD. This way, the COPD staging task will be executed in a healthy manner. Similar to Module-1, a model pool will be created with AlexNet [50], GoogLeNet [63], VGGNet-16 [62], and ResNet-50 [63] networks that have completed training on large datasets for the DCNN model that will perform COPD staging. The model that performs the best with transfer learning approach from these networks will be selected and the classification problem will be solved for COPD

staging. Transfer learning-based DCNNs have been successfully used in fields such as bioinformatics [68], biomedical image processing [69], recommender systems [70], autonomous vehicle technology [71], natural language processing [72]. Transfer learning aims to enable systems to quickly adapt themselves to new situations, tasks, and environments. It provides machine learning systems with the ability to leverage auxiliary data and models to help solve target problems when there is only limited data available in the target domain. The technique of transfer learning makes these systems more reliable and robust, ensuring that the machine learning model achieves its expected performance [73,74].

3. DISCUSSION

The lack of sensitive diagnostic tests, especially for early stages of COPD, leads to insufficient diagnosis of a treatable disease. With our proposed COPD-GradeNet, it is believed that early diagnosis, which will allow possible treatments, will be greatly contributed, especially by being able to classify Grade1 from lung X-rays.

The advantages that deep learning models like COPD-GradeNet can provide are as follows:

More Accurate and Reliable Results: Deep learning methods enable accurate prediction of disease levels by analyzing and learning from large amounts of data, resulting in more accurate and reliable results.
Fast and Automatic Analysis: Deep learning algorithms make data analysis fast and automatic, allowing for faster detection of COPD levels.

Personalized Treatment: Deep learning algorithms can help create personalized treatment plans by accurately detecting the disease level. This can improve the effectiveness of the treatment.

Reduced Risk of Death: Deep learning methods can analyze various features used to predict COPD levels and can predict the patient's risk of death. This can increase the patient's chances of survival by enabling earlier intervention in the treatment plan.

Data-Driven Decision Making: Deep learning methods provide an objective approach to decision-making by analyzing large amounts of data. This helps doctors make data-driven decisions and contributes to better management of disease levels.

4. CONCLUSION

This study being a theoretical model proposal, no experimental results have been presented. The model to be developed integrates a series of techniques for the automatic use of the progression of future Chronic Obstructive Pulmonary Disease (COPD) with Deep Convolutional Neural Networks (CNNs). By laying out the theoretical foundations of COPD-GradeNet, the potential impact on early diagnosis services and resource optimization in primary healthcare has been emphasized when implementing the model. Any specific limitations related to the model's performance have not been discussed. Consequently, the importance of leveraging deep learning for COPD diagnosis has been underscored, and further validation and testing are encouraged to assess the real-world applicability of COPD-GradeNet. Future data-driven studies are recommended to explore the integration of the model into clinical practice for improved COPD management.

5. ACKNOWLEDGEMENTS

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