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RESEARCH ARTICLE

Deep Transfer Learning for Chronic Obstructive Pulmonary Disease Detection Utilizing Electrocardiogram Signals

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethical Review Board of Sakarya University Medicine Faculty under Application No. 16214662/050.01.04/70.

ABSTRACT The motivation of this research is to introduce the first research on automated Chronic Obstructive Pulmonary Disease (COPD) diagnosis using deep learning and the first annotated dataset in this field. The primary objective and contribution of this research is the development and design of an artificial intelligence system capable of diagnosing COPD utilizing only the heart signal (electrocardiogram, ECG) of the patient. In contrast to the traditional way of diagnosing COPD, which requires spirometer tests and a laborious workup in a hospital setting, the proposed system uses the classification capabilities of deep transfer learning and the patient's heart signal, which provides COPD signs in itself and can be received from any modern smart device. Since the disease progresses slowly and conceals itself until the final stage, hospital visits for diagnosis are uncommon. Hence, the medical goal of this research is to detect COPD using a simple heart signal before it becomes incurable. Deep transfer learning frameworks, which were previously trained on a general image data set, are transferred to carry out an automatic diagnosis of COPD by classifying patients' electrocardiogram signal equivalents, which are produced by signal-to-image transform techniques. Xception, VGG-19, InceptionResNetV2, DenseNet-121, and ''trained-from-scratch'' convolutional neural network architectures have been investigated for the detection of COPD, and it is demonstrated that they are able to obtain high performance rates in classifying nearly 33.000 instances using diverse training strategies. The highest classification rate was obtained by the Xception model at 99%. This research shows that the newly introduced COPD detection approach is effective, easily applicable, and eliminates the burden of considerable effort in a hospital. It could also be put into practice and serve as a diagnostic aid for chest disease experts by providing a deeper and faster interpretation of ECG signals. Using the knowledge gained while identifying COPD from ECG signals may aid in the early diagnosis of future diseases for which little data is currently available.

INDEX TERMS Biomedical signal analysis, chronic obstructive pulmonary disease, deep transfer learning, ECG signal classification, stockwell transform, wavelet transform.

I. INTRODUCTION

Chronic Obstructive Pulmonary Disease is characterized by an airflow limitation that is not fully reversible. It is one of the leading causes of morbidity and mortality in both industrialized and developing countries because it significantly affects both the lungs and the heart [1], [2]. Since COPD is mostly caused by smoking cigarettes often and for a long time, symptoms usually show up when the disease has already gotten worse. Thus, early COPD detection is clinically important.

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The primary goal of this research is to diagnose COPD utilizing deep transfer learning methods and a simple heart signal in a practical and safe way, before the disease becomes incurable. Another contribution of this research is to classify time series heart data without requiring domain knowledge or a feature selection algorithm, as opposed to conventional machine learning methods and feature extraction schemes. A transfer learning technique is presented that employs the learned characteristics of pre-trained networks to categorize the scalograms produced from ECG time series signals of COPD and healthy subjects. Methods for automatic detection of COPD using ECG signals with a from-scratch model and pre-trained convolutional neural networks (CNNs) such as Xception, VGG-19, InceptionResNetV2, and DenseNet-121 are being worked on.

Firstly, the collected ECG signals of patients are converted from the time series domain to frequency-domain equivalent scalogram images using Wavelet and Stockwell transform. Afterward, to classify the scalograms, the power of pre-trained deep networks is utilized by transferring and fine-tuning. This is the first published work on COPD detection using ECG data utilizing deep transfer learning. And this will also help the COPD diagnosis to be completed quickly since ECG signals are fairly simple to record in a typical healthcare facility or practically any household.

According to the Global Initiative for Chronic Obstructive Lung Disease (GOLD) criteria, COPD is defined as; forced expiratory volume in 1 second (FEV1) divided by forced vital capacity (FVC) being smaller than 0.70 [1]. Today, a classical COPD diagnosis is made by using some clinical applications like spirometer tests, static lung volumes, exercise testing, ECG, echocardiography, computed tomography (CT), and magnetic resonance imaging (MRI). The majority of these procedures can be performed with considerable effort in a hospital or well-equipped medical facility. To effectively interpret the spirometer, CT, and MRI, well-trained experts with the necessary skills and expertise are required. This time-consuming and effort expensive condition may discourage future COPD patients from seeking hospital care while the disease is progressing. As a result, it is clear that early, practical, and safe diagnosis of COPD disease is extremely beneficial to human health. This goal serves as the impetus for our research.

The structure of the article is as follows: In Section II, the nature of the ECG signal, its link with COPD, and the methodologies of deep learning are discussed. The third section describes the system design, data collection, data production, wavelet and Stockwell transform methods, deep transfer learning strategies, limitations and experimental setup utilized in this research. Comparative findings from the various experimental configurations are reported in Section IV. The fifth section covers the benefits and potential future applications of the research. The conclusion describes the best performing models and how the knowledge and experience obtained in this work may be applied to other illness detection or classification problems besides COPD.

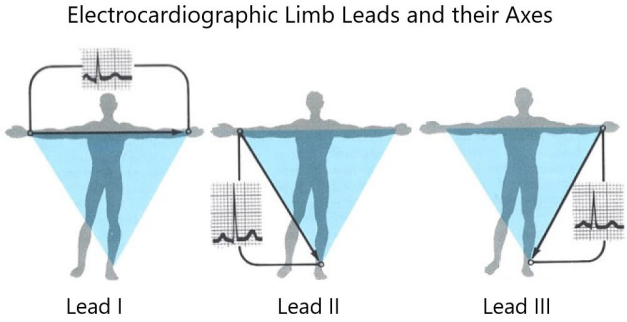

FIGURE 1. Placement of the ECG electrodes in Lead I-II-III.

II. BACKGROUND AND RELATED WORK

Not much research has been conducted on the use of ECG for COPD detection. Thus, we conducted a research to demonstrate the usefulness of heart signal data in COPD diagnosis [3]. After gathering ECG signal data from the individuals with and without COPD, twenty four distinct ECG characteristics were derived in the time domain. Since the ECG is a biological signal and does not have a normal distribution, the Mann-Whitney U test was employed to examine whether the ECG characteristics of the patient and control groups were substantially different. If the value received from the test result is not statistically significant, the result is considered significant, indicating that there is a difference between the groups. The research concluded that the ECG signal can be used as a discriminator for COPD disease. Consequently, we presented a new COPD diagnostic approach employing a rule-based machine learning method utilizing an ECG signal [4]. According to the classification results of the decision tree method, the disease condition may be diagnosed with 93.89 percent accuracy. Following this result, we aimed to improve the classification result using deep learning rather than traditional machine learning techniques, and we began research to diagnose the disease in question using deep learning.

To begin at the beginning, an electrocardiogram is a graphical representation of the electric waves generated by the heart during cardiac action. It provides information on the pace, rhythm, and shape of the heart. Using electrodes placed on the skin, an ECG graphs the electrical activity of the heart as a function of time. Fig. 1 depicts the placement of the electrodes in Lead I-II-III on a patient's body. These electrodes detect the tiny electrical changes caused by depolarization and repolarization of cardiac muscle throughout each cardiac cycle (heartbeat).

Fig. 2 illustrates the three principal components of an ECG. P wave represents the depolarization of the atria, QRS complex represents the depolarization of the ventricles, and the T wave represents the repolarization of the ventricles.

All of the waves in an ECG signal and the intervals between them have a predictable time duration, a range of acceptable amplitudes (voltages), and a typical morphology. Any deviation from the normal trace is potentially pathological

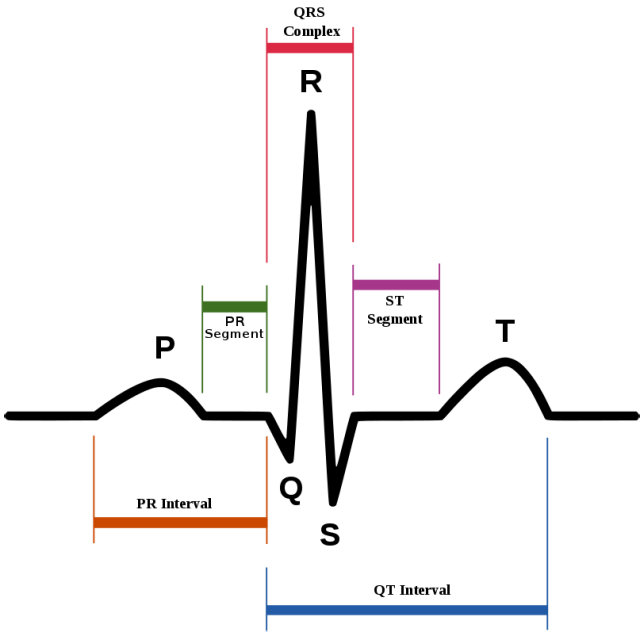

FIGURE 2. Segmentation of an ECG signal.

and therefore of clinical significance. ECG analysis offers a variety of beneficial uses, including activity recognition, biometric identification, patient screening, and diagnosis. Due to its non-invasive nature and low cost, the ECG is the most popular and essential diagnostic tool for the assessment of almost all diseases in clinical routine. Until very recently, most of the reported approaches in the literature for classifying the ECG signals solely relied on extracting hand-crafted features from the ECG [5], [6], [7], [8], [9]. This is performed by utilizing either traditional feature extraction algorithms or human expert knowledge. The extracted features are then fed either to generative or discriminative models to predict or classify the ECG signals. Support vector machines (SVMs) are widely utilized with hand-crafted features that have generated acceptable results among these approaches [10]. In this research, the extracted feature quality has the greatest influence on the reliability and performance of the classification approach.

Consequently, it is always sought to extract the disease's most representative, critical, dominant, and relevant characteristics. In addition, the ECG signal characteristics are highly subject-dependent, and the extraction of useful features often needs an in-depth understanding of the domain. Conventional feature extraction was regarded as an intrinsic component of ECG pattern classification. Recent research has demonstrated, however, that deep neural networks may do feature extraction straight from the data. Other techniques, such as the wavelet transform, discrete Fourier transform, and cosine transform, have also been utilized in the literature to extract characteristics from ECG signals in both the time and frequency domains [11].

One of the recent applications of deep neural networks is the classification problem in time series data. Time series classification problems that specifically deal with a large amount of data are used in various applications in health care systems, bioinformatics, activity recognition, etc. Diverse techniques, including deep belief networks, conditional and gated restricted Boltzmann machines, autoencoders, recurrent neural networks, HMMs, and CNNs, have been utilized and developed in the literature to address various time series data classification problems similar to ECG classification [12], [13]. The framework for deep learning enables the network to discover the optimal characteristics for a specific task. There have been several documented applications of deep transfer learning in health informatics [14], [15], [16], [17], [18], [19], [20], [21], [22], [23]. Specifically, deep learning experiments with ECG signals include the diagnosis of arrhythmia [24], [25], congestive heart failure [26], atrial fibrillation [27] and other cardiac disorders. In these investigations, deep learning outperformed conventional methods and offered additional benefits, including the elimination of the necessity for feature extraction, feature selection, and de-noising.

A. CORRELATION BETWEEN COPD AND ECG SIGNAL

There are a number of studies whose objectives are to investigate the relationship and association between respiratory function and ECG characteristics in patients with chronic COPD and to identify the ECG results that may indicate the presence of COPD [6], [7], [28]. The major findings of these studies are:

- QRS amplitude in Lead-I was significantly correlated with airflow limitation determined by FEV1/VC.
- QRS amplitude in Lead-I emerged as an independent variable related to COPD according to the multivariate analysis.
- When suspecting ECG changes in COPD, a modest increase in heart rate, a vertical P-axis, a small P-wave in v1, small QRS amplitudes, a QRS-axis that is vertical or slightly deviant (usually to the left) and clockwise rotation of the precordial (horizontal) QRS transition zone are observed.

COPD disease indirectly affects the heart conditions, and corresponding heart abnormalities can be detected by trained physicians. Some of these heart abnormalities include:

- Reduced lung conductivity as a result of hyperinflation
- Increase of anteroposterior chest diameter (increase of distance between heart and chest electrodes)
- Replacement of diaphragm downwards
- Chest electrodes' staying above because of replaced diaphragm
- Hypertrophy and dilation of the right ventricles dependent on pulmonary hypertension
- Vertical heart as a result of diaphragm and heart replacement downwards.

It is plausible to assume that each of these pathophysiological mechanisms could affect the heart and the electrical

conduction of the thorax. Consequently, physical anomalies influence the nature of the ECG signal as follows:

- P wave verticalization's growing beyond +60°
- At the point where the P wave axis hits 90 degrees, a straight P wave develops in the Lead-I sign
- Verticalization of the P wave is correlated with obstructive lung function. Near the inferior vena cava, a pericardial ligament links the right atrium to the diaphragm. While the diaphragm descends and gradually flattens, the right atrium descends and the P wave transforms vertically. The verticalization of the P wave on the electrocardiogram (ECG) is one of the most significant indications observed during COPD surveillance.
- Low peak-to-peak amplitude. The decrease in conductivity of the lungs as a result of hyperinflation and the increased distance between the chest electrodes and the heart causes this situation.
- As a result of the replacement of the diaphragm downwards and thus the verticalization of the heart, the QRS axe's verticalization and shifting to the right.
- Stenosis of QRS complex, due to left ventricular non-usage atrophy and low voltage
- Loss of R progression in the anterior
- Heart verticalization due to the diaphragm being replaced downwards
- The chest electrodes' staying relatively above because of the diaphragm being replaced downwards
- Atrial arrhythmias (seen especially in the decompensation period of COPD)
- QS wave (between V1-V3) at right precordials
- T wave's becoming more evident, especially if P wave is high.

Several investigations involving COPD patients have revealed characteristic alterations in their ECG signals. Studies have revealed that the P axis is useful for detecting COPD, and the verticalization of the P wave has been proven to correlate with COPD. In addition, a larger P wave in Lead-III than in Lead-I has been reported as a screening marker for emphysema [29]. Recent reports [30], [31], [32], [33] indicate that a vertical P axis greater than 60 is a helpful marker for COPD. Lead-I frequently displays a low QRS voltage in COPD patients [31]. "Lead-I sign" refers to a Lead-I QRS amplitude smaller than 0.15mV [34], [35]. The frontal plane of the QRS axis is almost perpendicular in Lead-I of COPD patients, and this results in a low QRS amplitude in Lead-I. The low voltage of QRS in Lead-I is caused by the insulating effect of hyperinflated lungs and by the lower position of the heart with respect to the electrode placement. These investigations suggest that the anomalies described in the ECG signal of a COPD patient are useful diagnostic criteria for COPD.

B. DEEP LEARNING

Deep learning belongs to the class of machine learning methods. It is a specialized form of representation-based learning in which a network learns and constructs intrinsic features from each successive hidden layer of neurons. The term "deep" is derived from the numerous hidden layers in the Artificial Neural Network (ANN) structure. The structure of the neural network is depicted in Fig. 3.

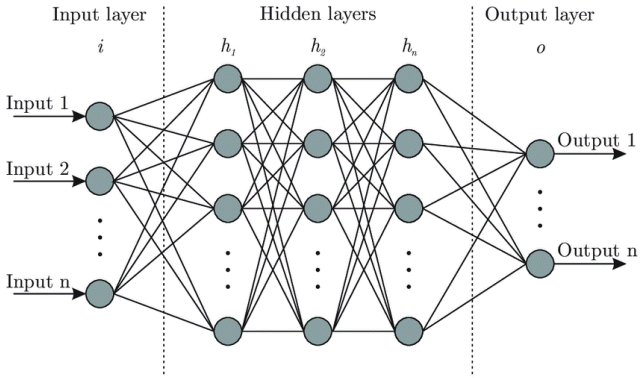

FIGURE 3. Traditional artificial neural network structure.

Every neuron or node (nerve cell) is connected to each neuron in the next layer through a connection link. A nerve cell is made up of axon (output), dendrites (input), a node (soma), nucleus (activation function), and synapses (weights). The activation function in the artificial neuron acts as the nucleus in a biological neuron whereas the input signals and its respective weights model the dendrites and synapses, respectively. Fig. 4 illustrates the artificial neuron structure.

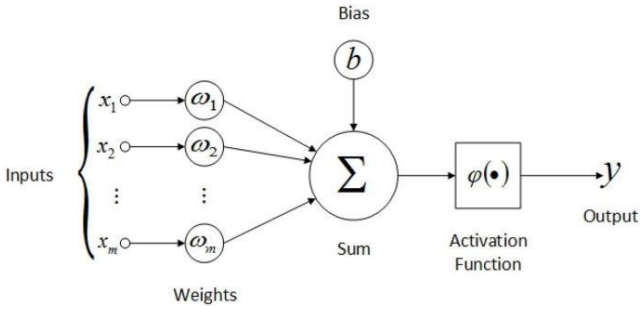

FIGURE 4. Artificial neuron structure.

Since the ANN structure is receptive to translation and shift deviation, the CNN has been developed as an extension of the ANN. CNN's architecture ensures translation and shift invariance. Fig. 5 illustrates a generic CNN network structure. It consists of convolution, pooling, and fully connected layers and is a feed-forward network. It is a deep neural network whose convolutional layers alternate with subsampling layers.

CNN is best described in terms of its two steps: the alternating convolutional and subsampling stages and the classification stage. The convolution layer convolutes the input with a set of filters, like producing feature maps. These feature maps are further reduced by subsampling. The classification stage is then given the kernels or supervised features of the top convolution filters and subsampling.

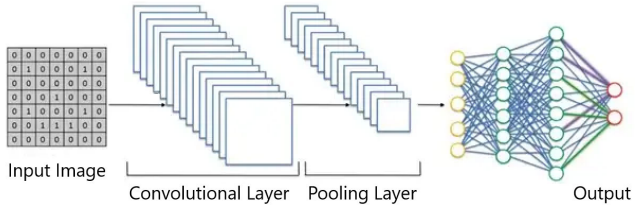

FIGURE 5. Generic CNN structure.

With labeled source data, filters are fine-tuned to produce supervised features. CNNs are capable of ignoring minor positional variations, i.e., they seek patterns not only in a specific image position but also in moving patterns. As in many other domains, deep learning techniques employed in recent years continue to show excellent performance in the field of medical image processing [24]. Deep learning models have been used successfully in many areas, such as detection, segmentation, and classification of medical data. Analysis of images and signals is obtained with medical imaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT) and X-rays with the help of deep learning models. As a result of these analyses, detection and diagnosis of diseases such as diabetes mellitus, brain tumors, skin cancer, and breast cancer are provided with convenience [36], [37].

Researchers encounter one of their greatest challenges when assessing and dealing with medical data in the restricted quantity of available datasets. Typically, the amount of medical data obtained from COPD patients is quite limited. At this point, deep transfer learning is the optimum solution [38].

The greatest benefit of transfer learning is that it enables training with fewer datasets at a lower cost. The knowledge gained by the pre-trained model on a large dataset is transferred to the model to be trained. A pre-trained model is a network that has been trained on a large benchmark dataset to solve a comparable problem to the one researchers wish to solve. Due to the computational expense of training such models, it is a standard strategy to import and employ models from published literature, as in the case of this research.

Transfer learning tries to create a framework for leveraging previously learned information to tackle new problems that are similar to those previously encountered, more quickly and efficiently. Additionally, the pre-trained network can be retrained using the task-specific data by fine-tuning one or more of its layers. The distributions of the source and target problems may differ or be the same, as may the labels of the source and target problems. Both the source and target problems in this research have different distributions and labels.

III. MATERIALS AND METHODOLOGY

This section describes the proposed system architecture, dataset, signal-to-image transformation methods, deep transfer learning structure, and experimental setup utilized in this research. For the purpose of finding a solution to the COPD detection problem, it is divided into five phases.

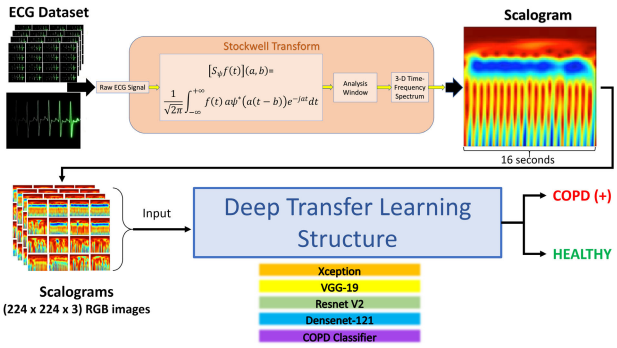

FIGURE 6. Overview of the system design with stockwell transform.

- Phase of data collection: ECG raw data from two groups of individuals were collected in the hospital. In total, 96 hours of uninterrupted data collection occurred over the course of several days.
- Data conversion phase: Using frequency analysis techniques, raw ECG signals are converted into frequency domain equivalent scalogram images that can be used as input for deep learning algorithms. Scalograms are designed to be compatible with the input size of CNNs so that they can be incorporated into CNN architectures.
- Phase of data preparation: Generating and preparing image data for use in distinct CNN structures (training, validation and test data)
- Transfer Learning phase: Adapting and analyzing the pre-trained networks and trained-from-scratch model for COPD detection problem.
- Evaluation phase: Evaluating the proposed system's results and performance.

A. SYSTEM ARCHITECTURE

In this research, a system is developed that uses easily accessible heart signals and the power of deep transfer learning to diagnose COPD. Without requiring an additional medical exam, the proposed system will determine whether the signal's owner has COPD and the severity of their condition. As described in Section II, it is a well-studied and established fact that the ECG signal and COPD are correlated [2]. As a result of its interactions with all body organs, the ECG signal contains disease-related information.

In order for deep learning techniques to detect disease signs in the ECG signal, the heart signals of the patients are divided into 16-second and 32-second segments and converted to image format ($224 \times 224 \times 3$ RGB images) using signal frequency analysis techniques, the Wavelet Transform and the Stockwell Transform. Deep neural networks are fed this image dataset as input. Frequency analysis is utilized to improve the discrimination of the ECG signal's important signs. Fig. 6 and Fig.7 illustrate an overview of the proposed

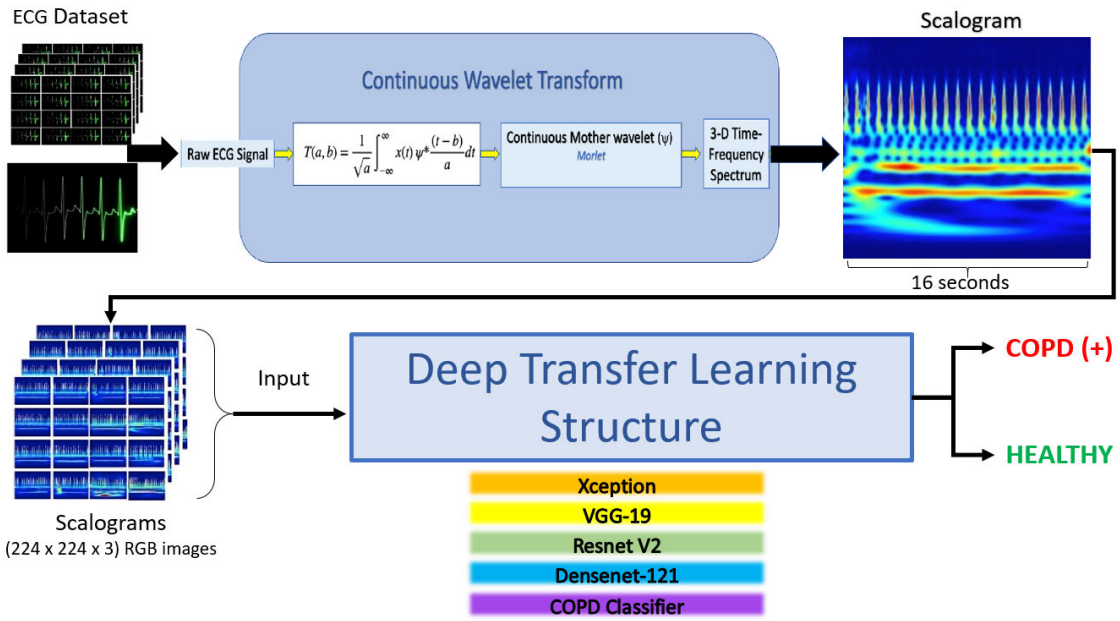

FIGURE 7. Overview of the system design with wavelet transforms.

system design, which incorporates Wavelet and Stockwell Transforms.

B. DATASET

In the Sleeping Laboratory of Sakarya Hendek State Hospital, our chest diseases expert physician obtained ECG recordings of all of the subjects. Electrocardiograph SOMNOSCREEN Plus PSG was utilized to record ECG signals at 256 Hz sampling rate. The device was regularly calibrated prior to each recording. In accordance with GOLD (Global Initiative for Chronic Obstructive Pulmonary Disease) standards [37], our chest diseases expert physician examined 12 subjects using a respiratory function test system and diagnosed each as "COPD" or "Healthy" after obtaining their medical records. Utilizing a Vitalograph Alpha spirometer, the respiratory function test was conducted.

The ECG signals obtained from two groups of individuals are utilized: six recordings from COPD patients and six recordings from healthy individuals. The duration of each subject's record is approximately eight hours without interruption. Six male subjects have been diagnosed with "COPD," while two female and four male subjects have been diagnosed with "Healthy" in the control group. During the consultations, all participants gave their informed consent for the use of their data. ECG signal data collected from the subjects is in 1-dimensional format: amplitude (millivolts, mV) vs. time (seconds, s) (seconds, s). In Fig. 8 and 9, 4 second long representatives of two ECG categories are plotted.

After gathering the raw ECG data, Wavelet and Stockwell transform based time-frequency representations of the ECG signals, scalograms are created to be able to feed the deep neural networks with two-dimensional images. Scalograms

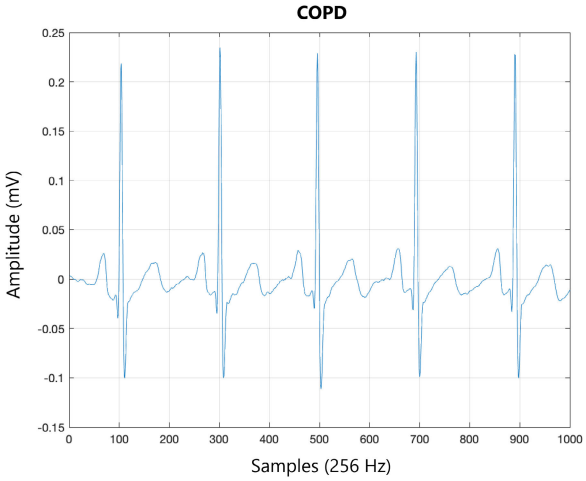

FIGURE 8. ECG signal of a person with COPD, 4 seconds.

are the absolute value of ECG signal's Continuous Wavelet Transform (CWT) and Stockwell Transform (ST) coefficients. Some ECG signal segments (16 seconds, 256 Hz) and their transformed equivalents (scalograms) for "COPD" and "Healthy" subjects are depicted in Fig. 10 and Fig. 11, respectively.

The periods chosen for the scalograms should contain sufficient R-peaks for locating the pattern's characteristics and be ones in which the features can be observed. In this context, 16 seconds and 32 seconds were selected as periods with medical significance, and it was determined that these periods would be suitable for experimental purposes. Consequently, two versions of the datasets are created. The ECG data of

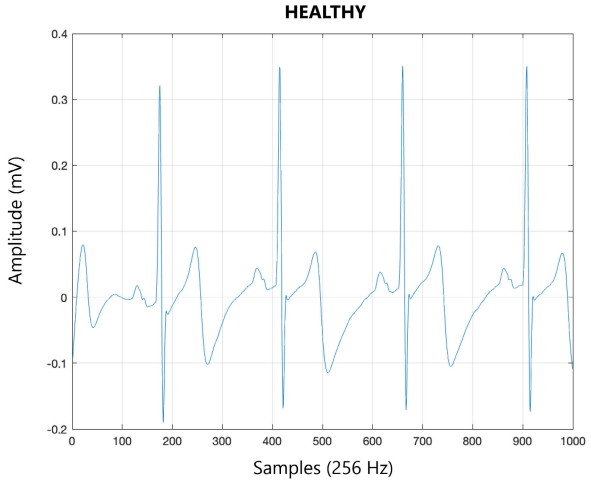

FIGURE 9. ECG signal of a healthy person, 4 seconds.

TABLE 1. Quantities of data labeled as "COPD" and "Healthy".

Dataset name	Epoch period	COPD labeled recordings	Healthy labeled recordings	Total quantity
DataSet-A	16 seconds	10906	10976	21882
DataSet-B	32 seconds	5453	5488	10941

each subject is split into segments of 16 seconds (Dataset-A) and 32 seconds (Dataset-B) and categorized as ''COPD'' or ''Healthy.'' The data quantities and labels for DataSet-A and DataSet-B are displayed in Table 1.

C. SIGNAL-TO-IMAGE TRANSFORM METHODS

In this research, two well-established signal frequency analysis techniques are used to convert the ECG data of the subjects into an image format so that they can be utilized in the deep learning architecture. Since it has been hypothesized and investigated that the ECG signal itself carries the signs of COPD, it is essential to process and extract the signals for accurate classification.

Time-frequency analysis is typically employed to process local characteristics in non-stationary signal processing. Popular methods for feature extraction include the Short-Time Fourier Transform, Gabor Transform, Wigner-Ville distribution, Hilbert-Huang Transform, Wavelet Transform, and Stockwell Transform [39]. Despite their individual benefits, the majority of time-frequency representation techniques result in an unsatisfactory time-frequency distribution of non-stationary signals due to low resolution, cross-term interference, and other problems. In recent years, a number of signal processing techniques, such as the Wavelet Transform and Stockwell transform, have been proposed to address these problems.

Wavelet Transform has been utilized extensively for feature extraction. The Stockwell Transform is a technique for time-frequency spectral localization that combines Wavelet Transform and Short-Time Fourier Transform characteristics. In light of this context, the Wavelet Transform and Stockwell Transform are the preferred signal-to-image transformation methods for the proposed system. This research examines techniques for detecting COPD using images (scalograms) derived from the Wavelet Transform and the Stockwell Transform coefficients of ECG signals. To ensure compatibility with the employed CNN architectures, scalograms are generated as RGB images scaled to 224 $\times$ 224 pixels. Generative Adversarial Networks (GAN) or any other data augmentation methods were not used in this research because, as seen in Fig. 10 and Fig. 11, the distinctions between the two classes are not particularly clear, and we did not wish to lose or obscure the distinguishing characteristics of the data through augmentation.

1) WAVELET TRANSFORM

The Wavelet Transform (WT) technique is used to process ECG signals whose constituent frequencies vary over time. To efficiently classify ECG signals, a tool with high precision in both the frequency and time domains is required, allowing us to determine at what frequencies the signal oscillates and when these oscillations occur. The WT meets both of these conditions. WT is resistant to the noise in the signal. In addition, it is a tool that provides a representation of a signal by letting the translation and scale parameters of the wavelets vary continuously. The frequency domain properties of wavelets are used to design a filter bank in which each wavelet at increasingly larger scales (more dilated) passes a narrow, lower band of frequencies from the input signal.

Time domain procedure of the Wavelet Transform is to use wavelets of different scales, translate them over an interval along an input signal, and correlate the wavelet with the input at each of these scales and translations. Low-frequency components (longer period) are detected by larger scale wavelets, whereas higher-frequency components are detected by smaller scale wavelets [11]. This procedure generates a frequency-appropriate time resolution for each frequency. For slow oscillations, long epochs are utilized, while shorter epochs are used for faster oscillations. Due to the continuous nature of the ECG signal, this research employs the Continuous Wavelet Transform (CWT), a variant of WT for continuous signals.

When analyzing multiple signals in frequency vs. time, the filters are pre-computed once, and the filter bank is then passed as input to CWT for improved computational efficiency. Three parameters are used in that filter bank: signal frequency, signal length (sample size), and the wavelet bandpass filters per octave (voices per octave). The signal frequency is 256 Hz, with 4096 samples (256 Hz $\times$ 16 s) and 8192 samples (256 Hz $\times$ 32 s) for the signal length, and 12 voices per octave. In order to solve the problem of knowledge loss in the temporal domain, WT uses a time-localized oscillatory function as the mother wavelet. The Morlet wavelet is used as the mother wavelet. The wavelets are visualized in time and frequency with the help of

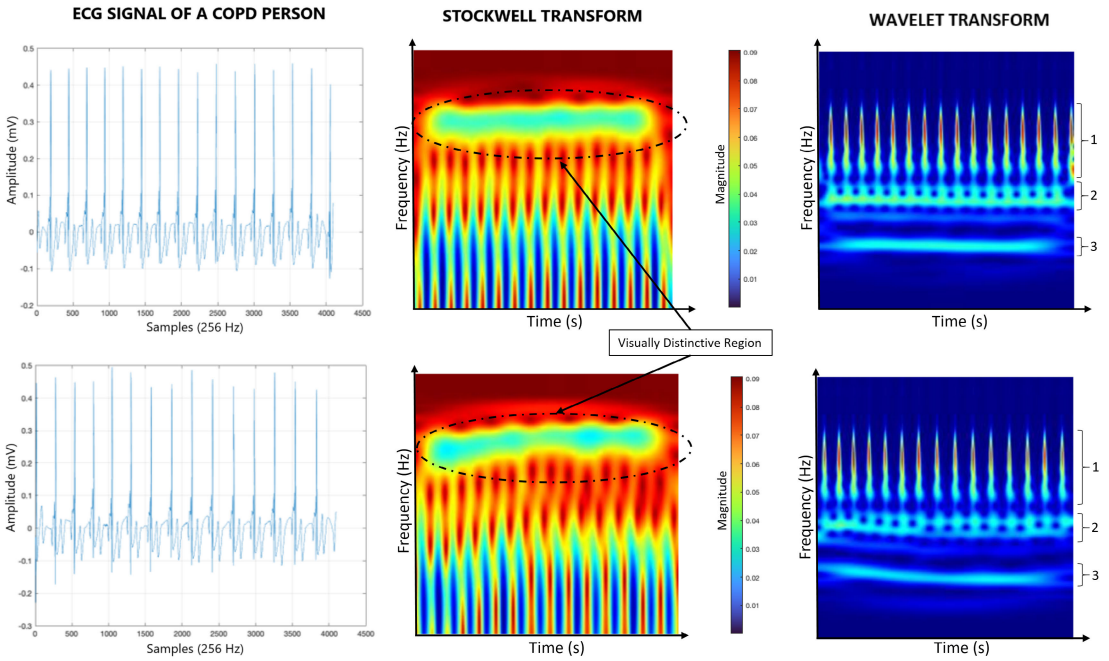

FIGURE 10. A COPD person's ECG signal, Stockwell and Wavelet scalograms. In the wavelet transform scalograms, three distinct groups of area can be observed. In the upper portion of the Stockwell transform scalogram, a yellow region indicates a frequency change intensity that is moderate. When compared to the next figure of a healthy person, these are the distinguishing signs of a COPD person's heart signal transformations.

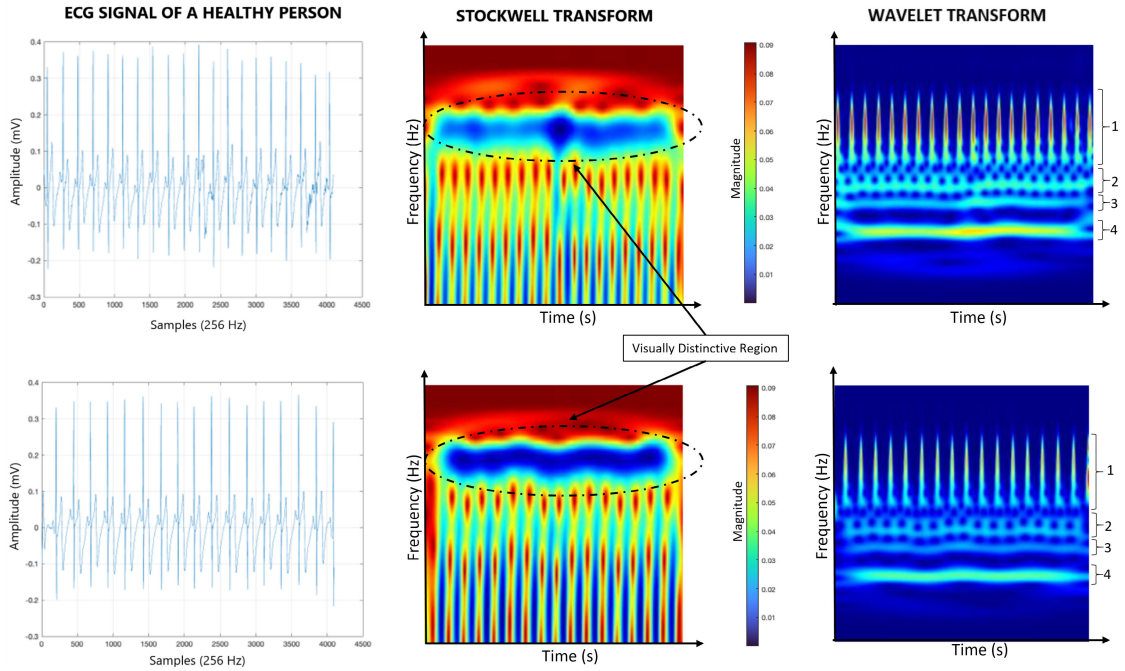

FIGURE 11. A healthy person's ECG signal, Stockwell and Wavelet scalograms. Observable in the wavelet transform scalograms is the addition of a new area as the fourth one. A blue region in the upper part of the Stockwell Transform scalogram indicates a low frequency change in intensity.

the filter bank. Fig. 12 depicts a scalogram of an ECG signal segment (16 seconds, 256 Hz) generated by the WT method, as well as 16 randomly selected samples from DataSet-A.

WT enables us to explore the frequency domain features of the ECG signal as an image by formatting the output as a scalogram image and then taking advantage of

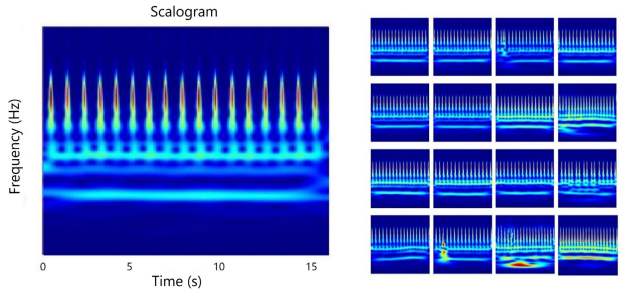

FIGURE 12. Scalograms of ECG signals (Wavelet transform).

deep image classification techniques. Similar to the time-frequency domain, the CWT provides a description of a signal in the time-scale domain, allowing the representation of temporal features at multiple resolutions. This is achieved by decomposing the signal into dilated (scale) and translated (time) versions of a prototype wavelet. High scales translate into long, slow wavelets equivalent to narrow, low-frequency filters, while lower scales produce shorter, faster wavelets equivalent to wider, higher-frequency filters. CWT achieves an ideal balance of time and frequency resolution: slow trends are represented with a high frequency resolution and a low time resolution, while fast components are well defined in time but less in frequency. Such inherent multi-resolution characteristics make CWT highly successful at detecting and representing singularities, so it has been widely utilized in ECG analysis [40].

For accurate ECG classification, the combination of waveform shape and timing interval features is critical. This is expected, as there are arrhythmic beats whose proper classification depends more on timing properties than on waveform shape. The WT has been demonstrated as a tool for effectively isolating relevant properties of the waveform morphology from the noise, baseline drift, and amplitude variance of the original ECG signal [40], [41]. It is seen that groups using the down-sampled WT of the ECG signal as their feature set rather than the original waveform have demonstrated high classification accuracy. Using wavelet decomposition for classification also reduces calculation time significantly [42].

2) STOCKWELL TRANSFORM

The Stockwell Transform (ST) is derived from the Continuous Wavelet Transform. By combining the advantages of STFT and WT, Stockwell et al. proposed it [43], which has attracted significant interest in a number of scientific and engineering fields, such as bioinformatics, biomedical imaging, optics, and signal processing. It stands out because it offers frequency dependent resolution while still having a clear connection to the Fourier spectrum. It employs a window whose width decreases with frequency and provides resolution that is frequency-dependent. This transformation includes both amplitude and phase spectrum information [44].

It is a technique that involves both STFT and WT but falls into a different category. Stockwell Transform provides notable results in property extraction in the presence of noise. This makes Stockwell transform suitable for accurate detection and classification of signal differences. It has an explicit physical interpretation and usefulness for medical applications. The time-frequency spectrum of the modulated signal is focused. This time-frequency analysis technique provides a three-dimensional graph of a signal in terms of its energy, or magnitude, over time and frequency [45]. The Stockwell transform stands out because it offers frequency dependent resolution while still having a clear connection to the Fourier spectrum. Additionally, it can be thought of as a phase-corrected WT, giving time-frequency analysis more precise information about the local properties of a signal. However, its signal analysis ability is restricted in the time-frequency plane [39] and this is observable in our experimental results. Experiments were conducted with the following parameters: a signal length of 16 or 32 seconds, a maximum frequency of 60 Hz, and a sampling frequency of 256 Hz. Fig. 13 shows a scalogram of an ECG signal (16 seconds, 256 Hz) generated by the ST technique and 16 randomly selected samples from DataSet-A.

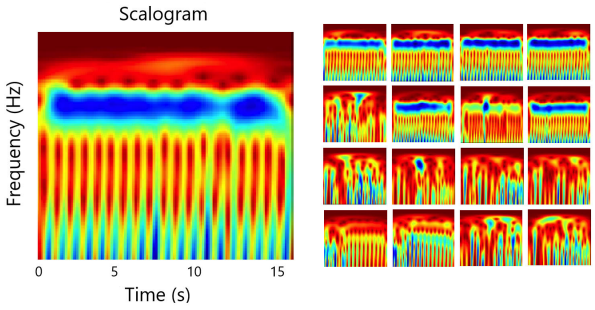

FIGURE 13. Scalograms of ECG signals (Stockwell transform).

D. TRANSFER LEARNING STRATEGY

COPD data is inherently difficult to collect from many people due to the nature of the problem. Therefore, we have limited participants for acquiring ECG signal data categorized as COPD positive or healthy. Deep transfer learning, which is known to be an appropriate approach for small sets of samples [17], [27], [46], [47], is therefore considered to be employed in this research. Transfer learning is an approach that utilizes the weights of the convolutional layers, which are defined by the source task, without re-training the network [5], [46]. The fine-tuning involves utilizing a network initialized with pre-trained weights and partially re-training it on the target task. In the context of deep learning, fine-tuning a deep network is a common strategy to learn both task-specific deep features and the methodology to extract global features present in every image, such as general shapes. Usually, the fine-tuning strategy allows more trainable weights at the top of the network because those

convolutional layers extract more abstract and high-level information compared to the first layers, where local features are learned. In the experiments, the effects of three main strategies are investigated: training from scratch, transfer learning, and transfer learning by fine tuning.

Using these strategies, it is shown how well the advanced CNN architectures for image classification work. A train-from-scratch strategy (named "COPD Detector" from this point on) is adopted by taking after well-known CNN architectures. The major techniques that CNNs employ for image classification are, training the CNN from scratch or re-purposing the pre-trained models, known as Transfer Learning [47] and Fine-Tuning [41]. While re-purposing the pre-trained models, the original classifier layers are replaced with new ones that fit the classification problem solved in this research. Five distinct CNN models are worked on according to each of the three transfer learning strategies below. A schematic representation of these strategies is shown in Fig. 14.

- Train the entire model: The architectures of the pre-trained models are used, and they are trained using DataSet-A. This is the training-from-scratch model, so the larger dataset on hand is used, and considerable computational power and time are expended for this strategy.
- Train some layers and leave the others frozen: A frozen layer means that it does not change during the training. As mentioned before, lower layers refer to general and problem-independent features, while higher layers refer to specific and problem-dependent features. Here, that dichotomy is played by choosing how much to adjust the weights of the network. Since there is a relatively small amount of data in DataSet-B, more layers are kept frozen to avoid overfitting. In contrast, when the relatively larger DataSet-A is used, it is tried to improve the model by training more layers to the new task since overfitting is not an expected problem there. Both DataSet-A and DataSet-B are used in this strategy.
- Freeze the convolutional base: This case is an extreme example of the train/freeze trade-off. The fundamental idea is to maintain the convolutional base in its original state and then feed the classifier its outputs. Pre-trained models are employed as fixed feature extraction mechanisms, which is effective when the dataset is small or when the pre-trained model solves a classification problem that is highly similar to the target classification problem, both of which are applicable to this research. Both DataSet-A and DataSet-B are used in this strategy.

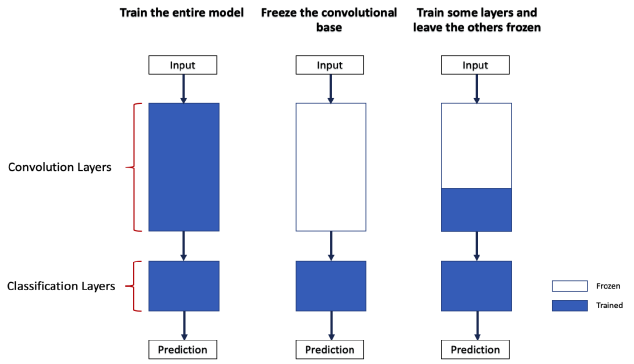

FIGURE 14. Transfer learning and fine-tuning strategies.

E. EXPERIMENTAL SETUP

This research is conducted using a variety of convolutional neural networks (CNNs), each of which utilizes a distinct learning strategy. All the experiments were performed via the Google Colaboratory Compute Engine (TPU) infrastructure in the Python programming language, using Keras and TensorFlow as backends. Xception, VGG-19, InceptionResNetV2, DenseNet-121 and COPD Detector are employed for the ECG signal classification task. These deep CNNs used in this research were originally designed to classify images into 1000 categories. Here, it is preferred to leverage the performance of these four well-known CNNs that have been trained on large data sets for conceptually similar tasks. Three extra layers are added on top of these CNNs to reduce the number of classes from 1000 to 2, as there are only two classes involved in the COPD identification problem (COPD and Healthy). Dense (512), Dense (32), and Dense (2) are the three layers that have been added. The Table 2 provides a listing of the CNNs used and their primary specifications.

TABLE 2. The CNNs used in this research, and their basic specs.

CNN Name	Parameters	Depth	Input Size
InceptionResNetV2	55,873,736	572	(299, 299, 3)
Xception	22,910,480	126	(299, 299, 3)
VGG-19	143,667,240	26	(224, 224, 3)
DenseNet-121	8,062,504	428	(224, 224, 3)
COPD Detector	2,797,665	14	(224, 224, 3)

Hyperparameters: All the CNNs utilized in this research share certain hyperparameters in common. After a series of trials, it is attempted to balance the hyper-parameters to achieve the best precision and accuracy. The CNNs were compiled using the "Adam" method of optimization. The learning rate is a hyper-parameter that controls how much the network's weights are modified. When using a pre-trained model, it is preferable to utilize a low learning rate because higher learning rates increase the danger of losing previous information. In the experiments, the learning rate is kept at 0.001. Choosing the proper number of epochs is also essential. Reducing the number of epochs results in under-fitting, whereas increasing the number of epochs leads to over-fitting. In the experiments, the training lasted between 5 and 40 epochs with a batch size of 32.

F. LIMITATIONS

It is necessary to acknowledge three limitations of this research. The first is that not all of the patients with COPD underwent diagnostic imaging such as chest computed tomography and echocardiography. Our physician (an expert in chest disease) diagnosed patients based on respiratory function tests and clinical history. These medical workups were also used to exclude patients who had heart diseases and lung diseases other than COPD. Second, since other conditions such as pericardial effusion could possibly affect QRS amplitude, to avoid confounding variables, patients with other conditions that could cause low QRS voltage are excluded. Consequently, the remaining 12 subjects' data are utilized for the research. The third limitation is that ECG data from six COPD patients and six healthy people is used, totaling 12 subjects. The recording period for each subject is 8 hours without interruption. Hence, a transfer learning strategy is used to compensate for the limited number of subjects. Further studies with large numbers of subjects with COPD are also being planned for experimentation in future work.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, the outcomes of various training strategies and experimental setups are provided. One important point should be made before delving into the experimental results. The best way to evaluate the effectiveness of the training is to have the network classify data it has never encountered. To maintain subject-independent validation results for each transfer learning model, cross-validation is used in this research.

Cross-validation involves dividing data into training and validation sets, and then repeating this process multiple times with different splits of the data. This helps to provide a more robust estimate of how well a model generalizes to new data. 12-fold cross-validation was utilized in the training and testing procedures. During this step, the dataset is divided into 12 folds, with each fold including data for every subject. While 11 folds are used for training and validating the model, the last fold is concealed and is only used to evaluate the test set accuracy of the model. The procedure is repeated such that each fold serves as the test set. This approach increases the computational cost but improves the result's significance. The results for accuracy in the tables are the averages of the values for accuracy at each fold. For each transfer learning strategy, performance metrics including sensitivity, specificity, precision, F1 Score, validation accuracy, and test set accuracy are also reported to provide a clear and objective measurement of each strategy's effectiveness.

To completely evaluate the effectiveness of the models, it is required to choose an appropriate evaluation index based on the below metrics. Regarding the classification task of the CNNs, the following metrics are recorded:

- correctly classified COPD signals: True Positives, TP
- incorrectly classified COPD signals: False Positives, FP
- correctly classified Healthy signals: True Negatives, TN
- incorrectly classified Healthy signals: False Negatives, FN.

Sensitivity, specificity, precision, F1 score, validation accuracy, and test set accuracy values of the experiments are computed to evaluate the models. The sensitivity, also called recall, refers to how well a model detects stress among the true stress events. The specificity shows the ability of the experiment to correctly generate a negative result for people who don't have COPD. The precision represents the ratio of the number of true positives to the number of cases in which a model predicted stress. The F1 score represents the mean of sensitivity and precision.

The primary metrics are test set accuracy and validation accuracy. When comparing models with very similar accuracy metrics, sensitivity, specificity, precision, and F1 score must all be taken into account because the comparison must be examined as a whole.

TABLE 3. Performance of the train-the-entire-model strategy (10 epochs) with stockwell transform.

CNN	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
Xception	95.80%	97.60%	97.50%	96.60%	96.70%	96.70%
VGG-19	98.40%	79.80%	82.90%	90.00%	90.10%	89.10%
ResNetV2	97.20%	97.60%	97.50%	97.30%	97.10%	97.40%
DenseNet-121	94.40%	88.80%	89.30%	91.80%	93.00%	91.60%

TABLE 4. Performance of the train-the-entire-model strategy (10 epochs) with wavelet transform.

CNN	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
Xception	99.60%	98.60%	98.30%	98.90%	99.10%	99.90%
VGG-19	100%	0%	50.00%	66.66%	50.00%	50.00%
ResNetV2	99.80%	86.90%	85.60%	92.10%	92.50%	85.50%
DenseNet-121	94.80%	99.50%	99.40%	97.20%	97.60%	90.20%

A. TRAIN-THE-ENTIRE-MODEL STRATEGY

All layers of the four distinct networks are trained with signal-to-image transformed ECG data (scalograms), adapting only their input and output parameters. Training all of the layers requires a significant amount of GPU resources and time. Performance metrics of this strategy are given for the input data transformed by ST in Table 3, and for the input data transformed by WT in Table 4. Observations indicate that the strategy is effective at classifying COPD and healthy signals. Unexpectedly, the VGG-19 model categorized all test set data as healthy when fed WT data as input. This unacceptable scenario has been investigated, and it will also be covered under the subsection titled Train Some Layers and Leave the Others Frozen. To give a hint, there are five convolutional blocks in VGG-19, and when more than three of them are trained, classification becomes problematic. Consequently, the Xception model trained with WT data and the Inception-ResNetV2 model trained with ST data appear to outperform other models.

TABLE 5. Performance of the freezing the convolutional base strategy (10 epochs) with stockwell transform.

CNN	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
Xception	94.40%	90.60%	90.90%	92.60%	93.20%	92.50%
VGG-19	85.60%	99.00%	98.80%	91.70%	92.50%	92.30%
ResNetV2	86.40%	85.00%	85.20%	85.80%	85.70%	85.70%
DenseNet-121	89.20%	90.40%	90.20%	89.70%	90.85%	89.80%

TABLE 6. Performance of the freezing the convolutional base strategy (10 epochs) with wavelet transform.

CNN	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
Xception	98.60%	74.60%	75.10%	85.20%	85.10%	91.30%
VGG-19	95.20%	99.30%	99.10%	97.10%	97.50%	97.40%
ResNetV2	85.90%	77.10%	74.50%	79.80%	81.00%	79.20%
DenseNet-121	74.50%	99.60%	99.30%	85.10%	88.60%	88.40%

B. FINE-TUNING STRATEGY

Fine-tuning of a convolutional network is a process that must be continuously enhanced and maintained. As a starting point in this research, two fine-tuning sub-strategies are examined in the direction of the proposed strategy. ''Freezing the convolutional base'' and ''Training only a subset of layers while leaving the rest frozen'' sub-strategies will be explained and investigated in this part.

1) FREEZING THE CONVOLUTIONAL BASE

As its name suggests, the convolutional bases of the pre-trained networks are frozen and just the top classification layers of each network are trained with signal-to-image transformed ECG data. The term frozen here refers to the layers/convolution blocks remaining exactly as they were in their original state. The computational cost (GPU usage and processing time) is lower in comparison to the Train-the-Entire-Model Strategy because not all of the layers are trained from scratch. Based on Table 5 and 6, the results of this strategy are likely to succeed, but inferior to those of the first strategy. Although the performance degradation in InceptionResNetV2 is noticeable when both ST and WT are used, the best performer in this substrategy is VGG-19 which uses WT data as its input and has 97.40% test set accuracy and 97.50% validation accuracy.

2) TRAINING SOME LAYERS AND LEAVE THE OTHERS FROZEN

In that sub-strategy, some layers are getting trained, including the top and experimentally selected ones below the top, the others are left frozen. The VGG-19 structure, which has the highest score of the previous sub-strategy, is worked on in this sub-strategy with the WT data as its input.

Several adjustments for fine-tuning are tested in this particular section to get the best results. For example, it is investigated how it affects the classification results if the convolution blocks of the VGG-19 structure are made trainable in a certain order. In Table 7, the number defining each experimental case refers to the number of convolution blocks made trainable during the experiment. As an example, CNN stated as ''Fine-Tuning 3'' corresponds to three convolution blocks made trainable starting from the top of the CNN, but all the other layers were left frozen. Performance metrics for this sub-strategy are given in Table 7. As shown in the table, as the number of convolution blocks increases, accuracy and other performance metrics also improve. When only one convolution block is trainable, validation and test set accuracies are 97.00% and 97.80%, respectively; when three blocks are trainable, they are 98.90% and 99.10%. However, there is a saturation point. Since the VGG-19 network has a total of five convolutional blocks, it is anticipated that the network's performance will be comparable to the VGG-19 train-the-entire-model strategy when four blocks are made trainable. When we attempted it, we achieved the expected outcomes. The results of Fine-Tuning 4 were unsatisfactory as VGG-19 train-the-entire-model strategy. Consequently, Fine-Tuning 3 model has the best performance metrics in this strategy.

TABLE 7. Performance of the train some layers and leave the others frozen strategy (10 epochs) with wavelet transform.

VGG-19	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
Fine-Tuning 1	95.30%	98.40%	97.80%	96.60%	97.00%	97.80%
Fine-Tuning 2	96.20%	96.90%	96.00%	96.10%	96.60%	98.70%
Fine-Tuning 3	98.60%	99.20%	98.90%	98.80%	98.90%	99.10%
Fine-Tuning 4	100%	0%	50.00%	66.66%	50.00%	50.00%

C. CUSTOMIZED NETWORK, TRAINING-FROM-SCRATCH STRATEGY

In addition to well-known and pre-trained CNN structures, one of the objectives of this research is to create a CNN structure with high performance in order to solve the COPD detection problem. Using as an example the VGG-19 structure that was relatively more effective in the previous experiments, a customized CNN structure was created and named ''COPD Detector'' in this sub-strategy. The general convolution layer structure of this custom network was inspired by VGG-19, and since Fine Tuning-3 produced the best results, we decided to use a structure with three convolution blocks. Network structure of COPD Detector is shown in Table 8.

COPD Detector is trained from scratch for multiple epochs, utilizing scalograms generated using both the ST and WT. Table 9 and 10 display the performance metrics for this sub-strategy for ST and WT, respectively. The COPD Detector is observed to compete with the other strategies in terms of every metric, achieving remarkable accuracy for a variety of epoch values. However, when the experiments are examined separately, it can be seen that using WT data is more efficient than using ST data in terms of classification performances. In terms of test set and validation set accuracy values, the 15, 25, and 35 epoch runs using WT data as input generate the highest-quality classification results.

TABLE 8. The network structure of the COPD detector.

Conv2D	(32, (3, 3)) input shape= (224,224,3)
Activation	Relu
MaxPooling2D	Pool Size= (2, 2)
Conv2D	(32, (3, 3))
Activation	Relu
MaxPooling2D	Pool Size= (2, 2)
Conv2D	(64, (3, 3))
Activation	Relu
MaxPooling2D	Pool Size= (2, 2)
Flatten	
Dense	64
Activation	Relu
Dropout	0.5
Dense	1
Activation	Sigmoid

TABLE 9. Performance of the COPD detector for different epoch values with Stockwell transform.

COPD Detector	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
5 epochs	90.00%	94.10%	94.10%	92.00%	92.00%	90.50%
10 epochs	90.30%	92.00%	92.20%	91.20%	91.10%	90.50%
15 epochs	86.60%	93.70%	93.50%	89.90%	90.00%	89.60%
20 epochs	92.10%	90.30%	94.00%	92.10%	91.90%	91.00%
25 epochs	92.30%	91.50%	91.90%	92.10%	91.90%	90.50%
30 epochs	93.60%	92.40%	92.80%	93.20%	93.00%	90.90%
35 epochs	93.10%	87.60%	88.70%	90.90%	90.40%	90.40%

TABLE 10. Performance of the COPD detector for different epoch values with wavelet transform.

COPD Detector	Sensitivity	Specificity	Precision	F1 Score	Validation Accuracy	Test Set Accuracy
5 epochs	97.70%	21.80%	49.30%	65.50%	55.00%	89.90%
10 epochs	94.70%	97.20%	96.30%	95.50%	96.10%	96.10%
15 epochs	97.90%	94.50%	93.30%	95.50%	96.00%	98.50%
20 epochs	87.00%	95.30%	93.50%	90.10%	91.60%	92.70%
25 epochs	96.40%	96.60%	95.70%	96.00%	96.50%	97.30%
30 epochs	93.80%	97.30%	96.40%	95.10%	95.80%	97.50%
35 epochs	96.50%	97.60%	96.90%	96.70%	97.10%	97.30%

D. COMPARATIVE ANALYSIS OF THE RESULTS

The results suggest that entirely trained Xception model, fine-tuned VGG-19 models, and COPD Detector model that trained for 15 epochs, achieve the best performance metrics over the rest of the CNNs. Since the dataset used in these experiments is balanced, meaning that each class is represented by an equal amount of data, and the majority of CNNs appear to perform well in terms of accuracy, sensitivity, specificity, precision, and F1 score as a whole, evaluation can be considered to have led to accurate conclusions. Using the combination of accuracy, sensitivity, and specificity as the criterion for selecting the top three models, the fully trained Xception model, the fine-tuned VGG-19 model, and the COPD Detector (trained from scratch for 15 epochs) stand out. In order to further assess these leading models, confusion matrices and accuracy values are shown in Table 11 and Fig. 15, respectively.

The best performance is obtained with a test set accuracy of 99.9%, a sensitivity value of 99.6%, and a specificity value of 98% for the Xception model, which is trained entirely with WT data as input. The Xception model provides superiority over the other 2 models in both the training and testing stages. The experimental evaluation also showed that the deep transfer learning structures provided over a 5 percentage point improvement over our previous study, a rule-based decision tree model with 93.89 percent accuracy. Thirty-four separate experiments investigating various approaches were conducted for this research, with 12 of them yielding better results than the prior decision tree model. It must be noted that, in the majority of experimental investigations for each model, it appears that using WT data as input yields better results than using ST data.

TABLE 11. Accuracy values of the best three CNNs.

CNN	Strategy	Validation Accuracy	Test Set Accuracy
Xception	Train the Entire Model	99.10%	99.90%
VGG-19	Fine-Tuning 3	98.90%	99.10%
COPD Detector	Trained-from-Scratch (15 epochs)	97.10%	97.30%

V. DISCUSSION

At present, deep learning is being used throughout the entire medical image processing workflow, with impressive results in a variety of medical image analysis applications. In order to improve the early diagnosis and treatment of COPD, the use of deep learning technology to detect COPD using ECG signals to aid medical physicians is of considerable significance.

The current research contributes to the possibility of a low-cost, rapid, and automated COPD diagnosis that can be used clinically in the near future, as COPD is being diagnosed using an ECG signal instead of more time-consuming procedures such as transporting the patient to the hospital for a respiratory function test, CT scan, or MRI. This is also convenient and crucial for keeping patients away from infection hotspots, especially during pandemic or epidemic periods.

It must be noted that we wanted to ensure that the results we observed were trustworthy and not the result of a specific architectural modification or technique. Therefore, we intentionally used four well-known and commonly used CNN model architectures with minimal modifications. With COPD Detector, five distinct CNN models are being investigated in total, and it is intended to research different deep network models, the selection of different hyper-parameters, loss functions, and optimizer functions to enhance the performance of COPD diagnosis. Future work may focus on developing more models structurally optimized for this task. Medical and computer scientists should also collaborate closely and employ their complementary expertise to confirm the utility of deep learning approaches.

The research also focuses on discovering possible Chronic Obstructive Pulmonary Disease related image biomarkers from scalograms derived from ECG signals. Although the

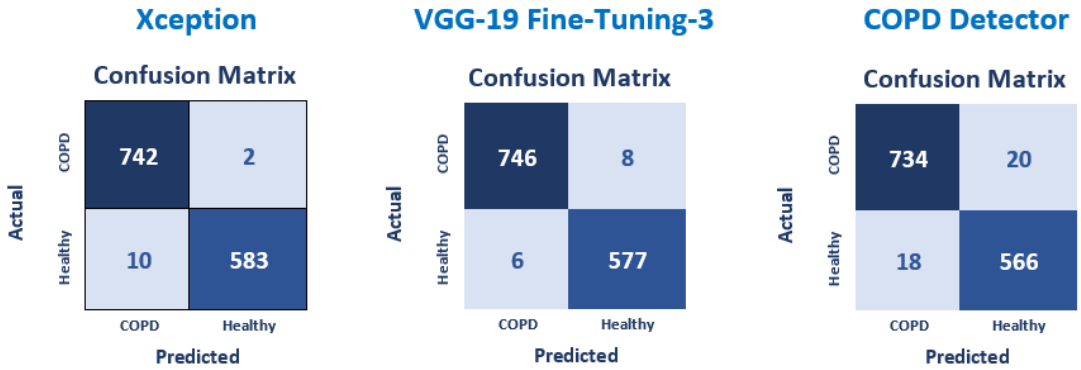

FIGURE 15. Confusion matrices of the best three CNNs.

ability of deep learning methods for image biomarker extraction is questionable due to the problem of interpretability, research suggests that it may be possible to discover new reliable bio-markers from ECG signal scalograms due to the fact that high classification results were achieved. Since the fine-tuned state-of-art CNNs rely on the evaluation of millions of parameters to extract the significant features, some of those may actually be image biomarkers, leading to a reliable result. This horizon is to be investigated in future research, possibly exploring other approaches such as Radiomics [48].

A more in-depth analysis requires much more patient data, particularly that of people suffering from COPD. One of the research's strengths is the use of AI to diagnose a fatal illness for which there is little human evidence. As previously noted, this research has some limitations that we want to resolve in the future. The subject pool is tiny, with 12 individuals. Although data augmentation could somewhat mitigate model overfitting and improve model performance, we will achieve better outcomes if we have access to additional data. To develop a larger dataset, we will continue to gather ECG data from COPD patients. Moreover, it is necessary to develop models capable of distinguishing COPD cases from other similar pulmonary or viral disease cases, such as pneumonia or emphysema.

To further facilitate early illness diagnosis, it will be beneficial to include the COPD detection system into mobile and embedded devices. A more promising approach for future studies would concentrate on identifying patients at the beginning phase of COPD, when they show almost no symptoms.

VI. CONCLUSION

The motivation of this research is that it introduces the first work on automated COPD diagnosis using deep learning and also utilizes the first annotated dataset in this field. As the disease progresses slowly and conceals itself until the final stage, hospital visits for diagnosis are uncommon. The medical goal of this research is to detect COPD using a simple heart signal before it becomes incurable. To address the COPD detection problem, we collected the ECG signals of 12 subjects, segmented them into 16 and 32-second long frames, transformed them to picture format using the signal transform methods, and then fed those images into CNNs. It is seen that Xception, fine-tuned VGG-19 and COPD Detector models give remarkable results while detecting COPD from ECG signals.

In addition to previous research in the literature, this paper makes two contributions. The first is, low-cost, rapid, safe and automatic detection of the COPD disease achieved using deep transfer learning. Since early prediction of COPD is vital to preventing the progression of the disease, the proposed method may give potential patients an opportunity to detect the disease at an early stage. The successful models can be put into practice and serve as a diagnostic aid for experts in chest diseases by providing objective and faster interpretation. It may be useful for medical decision-assisting tools to provide an extra option in challenging cases and can also be applied to achieve a first assessment of the likelihood of disease in patients with or without symptoms. Second, the findings suggest that future research should investigate the potential bio-marker behavior of the extracted features. The Xception model itself resulted in a performance that was nearly superior to other approaches that extracted features from non-medical images. This highlights the uniqueness of the extracted features and identifies them as potential biomarkers.

In future research, the knowledge and expertise obtained from this research could also be used for other illness detection or classification problems besides COPD. Our research is based on the premise that early diagnosis of COPD can reduce mortality rates throughout the world.

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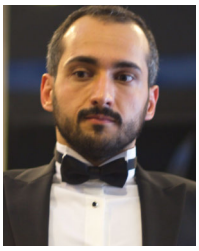

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