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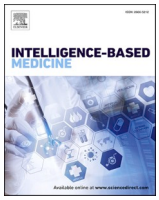

Features and eigenspectral densities analyses for machine learning and classification of severities in chronic obstructive pulmonary diseases

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ABSTRACT

Chronic Obstructive Pulmonary Disease (COPD) has been presenting highly significant global health challenges for many decades. Equally, it is important to slow down this disease's ever-increasingly challenging impact on hospital patient loads. It has become necessary, if not critical, to capitalise on existing knowledge of advanced artificial intelligence to achieve the early detection of COPD and advance personalised care of COPD patients from their homes. The use of machine learning and reaching out on the classification of the multiple types of COPD severities effectively and at progressively acceptable levels of confidence is of paramount importance. Indeed, this capability will feed into highly effective personalised care of COPD patients from their homes while significantly improving their quality of life.

Auscultation lung sound analysis has emerged as a valuable, non-invasive, and cost-effective remote diagnostic tool of the future for respiratory conditions such as COPD. This research paper introduces a novel machine learning-based approach for classifying multiple COPD severities through the analysis of lung sound data streams. Leveraging two open datasets with diverse acoustic characteristics and clinical manifestations, the research study involves the transformation and decomposition of lung sound data matrices into their eigenspace representation in order to capture key features for machine learning and detection. Early eigenvalue spectra analyses were also performed to discover their distinct manifestations under the multiple established COPD severities. This has led us into projecting our experimental data matrices into their eigenspace with the use of the manifested data features prior to the machine learning process. This was followed by various methods of machine classification of COPD severities successfully. Support Vector Classifiers, Logistic Regression, Random Forests and Naive Bayes Classifiers were deployed. Systematic classifier performance metrics were also adopted; they showed early promising classification accuracies beyond 75 % for distinguishing COPD severities.

This research benchmark contributes to computer-aided medical diagnosis and supports the integration of auscultation lung sound analyses into COPD assessment protocols for individualised patient care and treatment. Future work involves the acquisition of larger volumes of lung sound data while also exploring multi-modal sensing of COPD patients for heterogeneous data fusion to advance COPD severity classification performance.

1. Introduction

In the UK, Chronic Obstructive Pulmonary Disease (COPD) accounts for 1 in 8 patients attending Emergency Care due to the sudden worsening of the condition that is known as an "Exacerbation Event" (EE). The NHS manages 1.2 million patients with COPD and, unlike communicable diseases, it is expected to grow by 40 % by 2030 with annual costs exceeding £2.5 billion (NHS, 2023). There is also an expectation of nearly 2 million undiagnosed people who are living with COPD [1].

COPD is a broad term for respiratory conditions that limit airflow [2] and systematic inflammatory responses [3]. COPD is partially reversible and manageable depending on the accurate classification of its severity levels. These are pivotal in effective clinical management and intervention [2]. Currently, the 2 million undiagnosed people with COPD in the UK are identified only after experiencing an acute EE [1]. With the current advances in Artificial intelligence (AI), we are enabled to benchmark the deployment of machine classifiers which advance COPD's diagnosis, prognosis, and severity identification for supporting personalised healthcare of large numbers of patients in a scalable manner. Thus, the primary objective of this pioneering study is to

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develop machine learning classifiers of COPD severities and assess their respective performances. This paper sets out the background setting of COPD and medical diagnosis, lung differences in health and COPD before reviewing the literature for computational classification of lung pathologies and COPD and its distinct severities. Then, we review our lung sound analysis by exploring the eigenspectra of COPD audio-transformed representative matrices and their features versus COPD severities prior to supervised machine learning and classification results of COPD severities from given audio signals. Our new findings and our perspectives of future research work are discussed in our conclusions.

1.1. Background

COPD is a debilitating respiratory condition which is characterised by the overdistention of air spaces distal to the terminal bronchioles, leading to the destruction of alveolar septa, alveolar enlargement, and limitation of expiratory airflow [4]. It is a significant public health concern, which substantially impacts affected individuals' quality of life and health outcomes. This background discusses the diagnostic methods and the intricate dynamics of lung function in healthy individuals compared to those with COPD. It focuses on lung sounds, including adventitious sounds, as indicators of the disease's presence and eventual progression.

COPD diagnosis primarily relies on spirometry, a highly recommended technique by the Global Initiative for Chronic Obstructive Lung Disease [2]. Spirometry involves assessing important lung metrics, including Forced Vital Capacity (FVC), which measures a complete forced exhale, Forced Expiratory Volume in 1 s (FEV1), and the FEV1/FVC ratio. In COPD diagnosis, the FEV1/FVC ratio must be below 0.70. Furthermore, and according to the GOLD criteria [5], COPD severities are categorised in the following way:

1. **Mild:** $FEV_1 > 0.80$
2. **Moderate:** $0.50 < FEV_1 < 0.80$
3. **Severe:** $0.30 < FEV_1 < 0.50$
4. **Very Severe:** $FEV_1 \leq 0.30$

During spirometry, patients are instructed to exhale forcefully and rapidly. Spirometry is useful for diagnosing and monitoring COPD as an objective metric for airway obstruction. Additionally, COPD severity is assessed using the "ABE" categorisation, which considers symptoms, their impact on patients, and the history of exacerbations. This assessment relies on either the COPD Assessment Test (CAT) score or the Modified Medical Research Council (mMRC) Dyspnoea Scale [6].

However, some patients may face challenges in performing forceful exhalation due to various factors, which may potentially affect the accuracy of FEV1 measurements as an indicator of lung condition [7].

In addition to spirometry, another method to aid in COPD diagnosis and assess its severity is Computerised Tomography (CT), which is more invasive. However, the National Institute for Health and Care Excellence (NICE) recommends using CT primarily to rule out other potential diagnoses [8].

COPD is primarily associated with several risk factors, the most prominent ones including smoking and exposure to environmental lung irritants, such as air pollutants. These may include Sulphates, Nitrates, Ozone gases and Suspended Particulate Matter [2]. Additional risk factors include susceptibility to lung infections and genetic predisposition, notably Alpha-1 antitrypsin deficiency (AATD) [2]. Understanding these risk factors is crucial for the early detection and prevention of COPD.

Lung dynamics in healthy individuals exhibit gender-based differences. Studies have shown that women generally have 10–12 % lower lung volume than males [9]. Furthermore, lung compliance, a critical measure of lung function, is influenced by anatomical differences such as smaller airway diameter, lung volumes, maximum expiratory flow and diffusion surface in women compared to men [10]. These anatomical disparities are crucial in respiratory function, particularly during women's pregnancy. But it is worth noting that lung size, rather than gender, appears to be the primary determinant of functional implications.

In contrast to healthy lungs, COPD, characterised as obstructive pulmonary disease, leads to increased lung volumes caused by trapped air, increased airway resistance on exhalation and decreased expiratory flow rates. Emphysema, a subtype of COPD, is further characterised by increased lung compliance with reduced carbon monoxide diffusion capacity [11]. The disproportionate decrease in Forced Expiratory Volume per second (FEV1) compared to the Forced Vital Capacity (FVC) is a hallmark of COPD [11].

Lung auscultation serves as an invaluable diagnostic tool, offering critical insights into the health of both the respiratory and cardiovascular systems. Notably, there exist distinct differences in lung sounds between healthy individuals and those grappling with the complexities of COPD. In individuals with COPD, a careful examination may reveal decreased breath sounds and the presence of adventitious lung sounds, such as crackles (Bickley and Szilagyi, 2017). These crackles, characterised by their discontinuous and non-harmonic nature, indicate early inspiratory changes often associated with COPD (Bickley and Szilagyi, 2017). Moreover, a more ominous sound in lung auscultation emerges in coarse crackles, bearing a distinct popping quality which persists throughout inspiration and expiration (Bickley and Szilagyi, 2017). Though often linked to COPD, these coarse crackles can also signal the presence of other diseases, including pneumonia (Bickley and Szilagyi, 2017).

In addition to crackles, wheezes represent another type of adventitious lung sound frequently associated with conditions like COPD and asthma [12]. Unlike crackles, which are sudden and transient, wheezes exhibit a continuous, harmonic quality lasting approximately 250 ms. These sounds are attributed to airway turbulence, often induced by excess mucus. While crackles are categorised as transient signals due to their abrupt nature, wheezes are classified as harmonic sounds.

Furthermore, it is essential to acknowledge the intricate interplay between COPD and other lung diseases and comorbidities. COPD characteristics often overlap with other respiratory conditions or diseases, such as Asthma or Congestive heart failure [13]. This coexistence highlights the multifaceted and complex nature of COPD. It underscores the need for a comprehensive diagnostic approach to discern the complexity of symptoms, including specific lung sounds that may be present in affected individuals.

In summary, this background section has outlined the critical differences in lung dynamics between healthy individuals and those with COPD and the role of gender, lung size, and anatomical factors. It has also emphasised the importance of understanding the risk factors associated with COPD and the significance of lung sounds, including adventitious sounds that can be used as diagnostic markers.

Further, accurate classification of COPD severity is crucial for appropriate treatment planning, monitoring disease progression, and improving patient outcomes. Our proposed method aims to provide clinicians with a reliable, non-invasive tool for assessing COPD severity. This shall potentially enable earlier interventions and more personalised care strategies for COPD patients in the near future. While further clinical validation would be required, this approach could complement existing diagnostic methods and greatly support clinical decision-making in COPD management.

Diagnosing and Classifying COPD and other lung diseases pose intricate challenges, which prompt extensive research efforts to explore various methods and techniques for precise computational and automated assessment. Upon reviewing the existing literature, it becomes evident that diverse approaches are employed. These also highlight the persistent challenges encountered in this field. In this, let us delve into the classification of respiratory conditions initially before narrowing it down to COPD literature later.

Recent advancements in deep learning have shown promising results in COPD severity analysis. Huang et al. [14] provided a comprehensive overview of deep learning algorithms which are used for lung sound analysis, while they emphasised the significance of artificial intelligence in this field. Further, their review focused on various components of deep learning-based lung sound analysis systems, including Abnormal Sound Detection and Respiratory Disease Recognition, public datasets, denoising methods, and state-of-the-art approaches for converting lung sounds into two-dimensional spectrograms.

In a related study, Sabry et al. [15] presented a discussion on the elements of sound-based lung disease classification using machine learning algorithms. Their work highlighted the importance of feature extraction, selection, and classification techniques in developing accurate models for lung disease recognition.

Palaniappan et al. [16] embarked on the classification of respiratory health conditions by analysing breath sound signals. Their work stands out due to its notable classification accuracies. Additionally, they employed a Bandpass filter with a 150–200 Hz range and harnessed a Support Vector Machine, which excels in classifying non-linear sound signal data.

Similarly, Altan et al. [17] embraced a deep learning methodology, utilising 3D-second-order difference plots to analyse respiratory sounds. Their approach underscored the potential of non-linear signal analysis and high-order statistics, further emphasising the need for research into denoising techniques to enhance information extraction. They also conducted signal processing with low and high pass filters on segmented audio sections.

Likewise, Rocha et al. [18] worked on the automatic classification of adventitious respiratory sounds. Their study highlighted the challenges arising from variable event durations, calling for a more profound exploration of the underlying causes of misclassifications and strategies to mitigate them.

Transitioning to the COPD Identification and Severity Classification domain, Li et al. [19] introduced a groundbreaking approach based on CT-based radiomics feature analysis for COPD identification and severity staging. While their methodology showcases advancements in image-based diagnosis, it prompts a need for comprehensive evaluations, considering the clinical impact and potential ethical considerations linked to reliance solely on imaging features.

On the other hand, Isik et al. [20] delved into COPD classification using Artificial Neural Networks (ANNs). They considered 15 feature input parameters such as age, gender, airway obstruction metrics and pathology metrics, which explored the multifaceted nature of COPD and achieved effective results with their ANNs.

In contrast, Cheplygina et al. [21] explored the application of Multiple Instance Learning (MIL) for COPD classification, emphasising the utilisation of weakly labelled data. Nevertheless, they concluded that further research is required to generalise and test the method under other datasets and clinical settings for COPD classification.

Concurrently, Siddiqui and Morshed [22] concentrated on severity classification using heart rate and oxygen saturation sensor measurements. However, the measurement criteria were obtained from documented clinical literature, and the performance measures were compared to the same data cluster results as data without clinical annotation.

Further, Roy and Satija [23] proposed a Mel Spectrogram Snippet Representation learning framework for COPD severity detection while they incorporated deep learning frameworks. What is noteworthy regarding this work is that YAMnet was used as a base for transfer learning from existing data to facilitate sound classification.

Furthermore, to address the need for efficient and lightweight models, Roy and Satija [24] developed a novel lightweight inception network (RDLINet) for respiratory disease classification using lung sounds. Their model achieved high accuracy while maintaining a low computational footprint, which makes it suitable for deployment in resource-constrained environments.

In a recent study, Roy et al. [25] proposed a triple-scale self-operational neural network (Pulmo-TS2ONN) for pulmonary disorder detection using respiratory sounds. Their approach incorporated a triplet time-frequency feature set extraction method and demonstrated improved performances in classifying various pulmonary disorders.

Moreover, Guo [26] sought to uncover the predictive value of clinical data, blood test indexes and ventilation function test indexes for distinguishing COPD severities. This presented a promising nomogram modelling approach. Nevertheless, the standard blood test data's limitations may not fully represent the entire spectrum of systematic inflammatory blood biomarkers for assessing COPD classifications.

Convolutional Neural Networks (CNN) may also be suitable for COPD identification using diverse data inputs. In this, Nguyen and Pernkopf [27] utilised a CNN for crackle detection using audio signal data. However, they highlighted the issues of limited data while acknowledging the adopted transfer learning strategies for their CNN, which exhibited improvement in the F1 scores. In comparison, Wu et al. [28] developed a CNN for COPD identification by integrating CT scans of 3D airway trees and lung field morphologies, displaying CT and CNN's potential role in COPD identification.

Recent advancements in deep learning have shown promising results in COPD severity analysis. Altan et al. [29] proposed a novel method using deep learning on multi-channel lung sounds for COPD severity analysis. Their approach, which utilised convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, achieved high accuracy in classifying COPD severity levels. In a related study, Altan et al. [30] developed a computerized analysis system for COPD using deep learning techniques. They employed a hybrid deep learning model which combines CNNs and bi-directional LSTMs, while demonstrating improved performance in COPD detection and severity assessment when compared to traditional machine learning methods. These studies highlight the potential of deep learning approaches in enhancing the accuracy and reliability of COPD severity classification using lung sound analyses.

The above studies collectively showcase various methodologies and data types, underscoring the intricate nature of COPD diagnosis and classification. Nevertheless, many of these studies operate with limited data, while some of them boosted their machine learning performance results by adopting transfer learning strategies. Consequently, further research using larger datasets is indispensable to generalise the approaches mentioned earlier while transfer learning knowledge can still be adopted.

Another theme for analysing respiratory audio is the need for a noise reduction strategy. Several studies above utilised filters to remove heart sounds and other artefacts from the respiratory audio, with Altan et al. [17] highlighting more research in denoising methods to reduce information loss.

In addition, no literature on COPD severity classification of an ordinal nature using machine learning has been found. It entails COPD grading from mild to severe and misclassification. Therefore, using metrics that incorporate abstract distances from a targeted class may advance research into COPD severity classifications.

In the next section, we will state and describe the data used in this early research work and provide the foundation of the mathematical theories used in this study.

2. Data holdings

This study utilised two datasets: The Respiratory Database @TR Dataset [31] used throughout our study; and the ICBHI Respiratory Database [32] in the second phase of our study. The system the experiment was run on was a Linux-6.1.58 with 12.7 Gb RAM.

2.1. Respiratory Database @TR dataset

The Respiratory Database @TR Dataset [31] contains recordings of

42 patients with five categories of COPD. These categories are COPD0, COPD1, COPD2, COPD3, and COPD4, where COPD0 are people with symptoms and at risk of COPD, while the other four categories follow the GOLD COPD severity guidelines from low to very severe (as was outlined in section 1.1). Each patient has 12 recordings from different auscultation locations. The breakdown of recordings per condition and recordings selected is based on a ≥20-s filter. The counts of conditions used for the training and test datasets are displayed in Table 1.

2.2. The ICBHI Respiratory Database

The ICBHI Respiratory Database [32] contains 920 recordings of auscultations of people with multiple conditions. Audio samples shorter than 20 s are excluded, as 20 s duration are extracted from the included audio samples. Therefore, each audio sample that was included contained multiple breathing cycles. Table 2, below shows the breakdown of the conditions for the whole database and the counts for selected audio used in creating the projection matrix.

In summary, two respiratory datasets are utilised in this study. But they are both imbalanced. Audio samples were selected based on containing 20 s of audio, as multiple breathing cycles were captured for analysis while the audio length remained constant.

A bandpass filter with a frequency range of 200–1500 Hz was applied to remove heart sounds and other low-frequency noise while preserving the relevant lung sound information applied to all samples. This range was selected based on previous studies which have shown it effective in isolating respiratory sounds from other physiological noises [16,17].

The Respiratory Database @TR Dataset is utilised for data exploration of Eigenspectral Analyses and COPD Severity Classification. The ICBHI Respiratory Database is utilised only for COPD severity classification.

3. Eigenspaces, Singular Value Decomposition and STFT

This study leverages eigenspace analysis to uncover key patterns in lung sound fields, a technique widely applied across scientific disciplines. We employ this approach to identify essential characteristics and distribution of lung sound signals for data exploration of COPD severities.

The eigenspace framework enables us to distil crucial features from the complex lung sound data. By focusing on eigenvectors and their corresponding eigenvalues, we can isolate the most influential components of the sound field, revealing underlying structures that may not be immediately apparent in the raw data. Mathematically, eigenspaces are defined by the equation $A\vec{v} = \lambda\vec{v}$ is a linear transformation, $\vec{v}$ is an eigenvector and λ is the corresponding eigenvalue [33].

Singular Value Decomposition (SVD) plays a pivotal role in our analysis, since it facilitates the decomposition of the lung sound field matrix into its constituent components. This decomposition allows us to extract and prioritise the salient features for our data exploration and COPD severity classification. The SVD of a given matrix A is defined by $A = U\,\Sigma\,V^T$, where U and V^T are orthogonal matrices and Σ is a diagonal matrix of singular values.

Our methodology incorporates a Short-Time Frequency Transform (STFT) as an initial processing step to provide spectrograms of the pulmonary audio [34]. This transform segments the audio signal into windowed sections and converts them to the frequency domain, providing a time-frequency representation of the lung sounds. We then apply SVD to this transformed data, enabling us to capture both temporal and spectral characteristics of the lung sounds efficiently.

By rigorously selecting 20-s audio samples, we ensure the capture of multiple breathing cycles, enhancing the reliability and comprehensiveness of our analysis. This approach allows us to construct a robust feature space that forms the foundation for our machine-learning classifiers.

The significance of this eigenspace-based approach lies in its ability to efficiently identify and extract the most relevant features from complex lung sound data. With the focus on these key characteristics, we can develop more effective and interpretable machine-learning models for COPD severity classification.

Regarding computational complexity, the Big O notation for our proposed method is primarily determined by the SVD operation, which has a time complexity of $O(mn^2)$ for an $m \times n$ matrix, where $m \geq n$. The STFT, performed as a pre-processing step, has a time complexity of $O(n \log n)$ for each window, where n is the number of samples in the window. The total number of Floating-Point Operations (FLOPs) for the SVD is approximately $2mn^2 + 2n^3$ for an $m \times n$ matrix.

It is worth noting that while these computational complexities might seem high, the dimensionality reduction achieved through eigenspace analysis often leads to significant improvements in subsequent processing steps, potentially offsetting the initial computational cost. Moreover, the interpretability gained through this approach can provide valuable insights into the underlying structure of the lung sound data, which may not be readily apparent with other methods.

Table 1
COPD Severity Dataset audio counts with selected training/testing sets.

Severity	Count	Selected	Training	Testing
COPD0	72	63	51	12
COPD1	60	48	45	3
COPD2	84	60	45	15
COPD3	84	71	57	14
COPD4	204	145	111	34
Totals	504	387	309	78

Table 2
Conditions in the ICBHI Respiratory Database with selected samples.

Condition	Count	Selected
Asthma	1	1
Bronchiectasis	16	16
Bronchiolitis	13	13
COPD	793	757
Healthy	35	30
LRTI	2	2
Pneumonia	37	37
URTI	23	21
Totals	920	877

4. Eigenspectral densities exploratory analysis

In this initial phase of the study, we investigated the eigenspectral probability distributions which are derived from COPD audio recordings for data exploration. This is specifically for categorising them by severity and recording locations. Our primary hypothesis asserts that the eigenspectral distributions corresponding to different severity levels may exhibit observed differences. We also examined the question of independence concerning the recording locations of COPD audio signals. In contrast, the alternative hypothesis posits a statistically significant dependence between recording locations and severity levels. The extraction of eigenspectral distributions, or densities, from audio samples, involves the employment of the spectrogram technique, followed by SVD. Subsequently, we perform a random sub-sampling procedure, selecting 20 %[35] of each SVD component's elements. This sub-sampled data undergoes an eighth-root transformation purposely designed to generate the eigenvalue spectra with normal and interpretable trends [36]. Histograms of 50 bins are visually depicted as eigenspectral distributions in the subsequent Figs. 1 and 2 below. These represent the generated eigenspectral under severities and locations recordings, respectively.

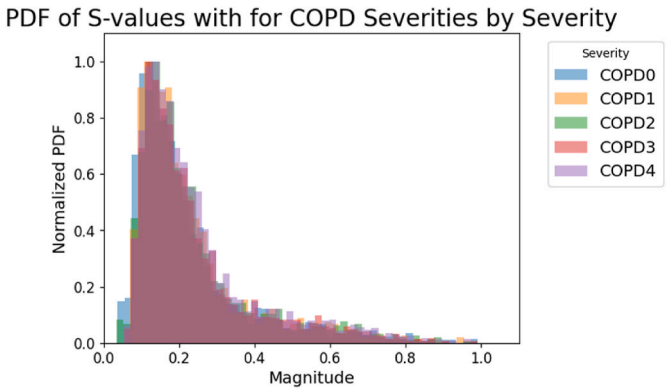

Fig. 1. PDF of Singular S-Values for COPD by severity.

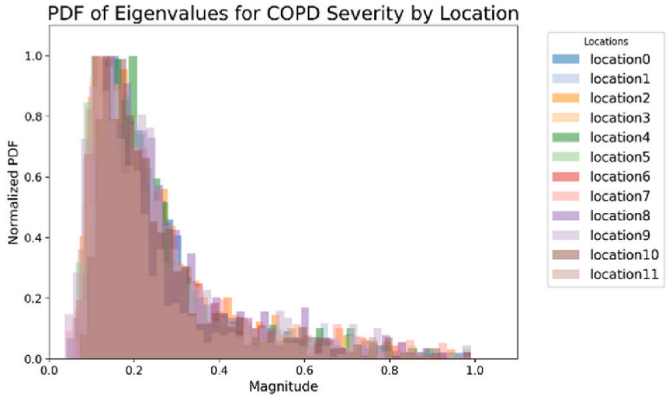

Fig. 2. PDF of Singular S-Values for COPD by location.

4.1. Severities

Normalised spectral densities have been computed against severities using the labelled experimental data from the Respiratory Database @TR. Further, these refer particularly to the generated Σ singular matrix with its S-values following the SVD transform of the matrix $\boldsymbol{X}$. The densities under the five severities are depicted in Fig. 1, below.

Following the above, the generated eigenspectral densities, representing Σ manifest their subtly different distribution trends, against severities respectively. Nonetheless, they fall under an overall common trend.

In the computational exploration of COPD severities through eigenspectral analysis, our work leveraged a suite of software libraries to process and analyse the transformed auscultation audio data. The core of our computational framework was built upon Python version 3.10, Librosa and SciPy. These libraries were practical in facilitating the signal processing of spectral analysis required in our study. The computational process commenced with the extraction of the S, U, and V^T matrices from the audio data, which are essential components for the eigenspectral density analysis. The execution times for this phase varied depending on the COPD severity category and the number of samples processed. The CPU times noted in accord with the various severities versus samples used are illustrated in Table 3 below:

4.2. Locations

The same approach is adopted for severities for computing the spectral densities against locations, which are the various patient auscultation points of the chest at which audio signals are observed, using the same labelled experimental data. Again, these particularly refer to the generated Σ matrix following the SVD transform of the matrix $\boldsymbol{X}$. They are depicted in Fig. 2 below.

Table 3
CPU times.

Computational Times		
Severity	Number of samples	CPU time (s)
COPD0	63	1.30
COPD1	48	0.93
COPD2	60	1.27
COPD3	71	1.44
COPD4	145	2.91
Totals	387	7.85

Similar observations are noted for each spectral density, representing Σ as manifesting various distribution trends against various recording locations. Again, they represent an overall common trend although with their slight and subtle distinctions.

In order to evaluate our hypotheses, we employed the Kruskal-Wallis Test, a practical statistical methodology for discerning the presence of statistical independence among variables. Specifically, we applied this test to investigate the relationship between severity levels and recording locations within the context of eigenspectral distribution. The results of the Kruskal-Wallis Tests are presented in Tables 4 and 5. Remarkably, both sets of tests related to severity levels and recording locations yield p-values that fall substantially below the predetermined significance level of $\alpha = 0.05$. Consequently, we accepted the null hypothesis, which ultimately concludes that the distribution of eigenspectral densities demonstrates significant independence amongst the groups concerning severity levels as well as recording locations.

In summary, when the Kruskal-Wallis test yields a p-value below $\alpha = 0.05$, it suggests that statistically significant differences among groups likely exist. However, the test alone does not provide information regarding distinct groups. Subsequent analyses are imperative for identifying the specific groups manifesting disparities. As we reflect on these findings, it becomes apparent that the relationship between recording and respiratory sound characteristics is complex.

Our research significantly advances the understanding of the complex interactions within acoustic environments, particularly highlighting how spatial factors influence acoustic attributes. Building on the insights from our analysis of Eigenspectral distributions, the next phase of our study will focus on the classification of COPD severity levels. Our previous findings have demonstrated a clear distinction among the severity level distributions, indicating that the medians of these groups are significantly different. This differentiation is crucial for the accurate classification of COPD severity. However, a challenge remains: Despite these significant differences, further advanced analytical techniques are needed to enhance the discriminatory power of our classification model, in this case, the utilisation of eigenspaces for a projection matrix to enhance features understanding. Enhancing our model is essential for improving the accuracy of COPD severity identification, which ensures that our approach remains robust in various clinical scenarios. This step is vital for developing a more effective diagnostic tool that can lead to better patient outcomes.

The computational times for this aspect of the study varied depending on the location category and the number of processed samples. The average number of samples per location was 32, and the average Eigenspectral extraction CPU time was 0.91 s, with the total

Table 4
Kruskal-Wallis test of COPD severity groups.

Kruskal-Wallis Test by Severity Levels		
Component	Statistic	P-Value
S Values	11189.3	0.0
U Vectors	1005.8	0.0
V^T Vectors	915.6	0.0

Table 5
Kruskal-Wallis test of COPD location groups.

Kruskal-Wallis Test by Location Groups		
Component	Statistic	P-Value
S Values	109.8	0.0
U Vectors	261825.4	0.0
V^T Vectors	1769.6	0.0

time of processing all 387 samples being approximately 10.90 s.

5. COPD severity classification

Accurate COPD severity assessment is vital for effective clinical management. This part of the study proposes a novel approach to COPD severity identification by analysing the eigenspectral of lung audio signals. Given the challenge of limited data availability within the Respiratory Database@TR dataset [31], our study draws upon the ICBHI Respiratory dataset [32] to augment our data.

The respiratory audio samples we employ undergo a multistep transformation process. Firstly, we filter out heart rate interference using a bandpass filter of 200–1500hz on each sample and transform it into spectrograms with the STFT. The ICBHI Respiratory dataset spectrograms are then organised into a matrix, which serves as SVD input to extract unique respiratory characteristics from multiple respiratory health conditions. From the SVD, we derive a projection matrix by combining the left matrix vectors and the singular values.

This projection matrix plays a pivotal role in our research methodology. It facilitates the transformation of the filtered spectrogram COPD severity audio samples into a subspace, a critical step in our pursuit of accurate classification using machine learning. We harnessed the power of four distinct machine-learning algorithms to classify and identify COPD severity classes effectively. This approach allows us to transfer insights gained from various respiratory conditions and healthy audio-sound characteristics to the context of COPD severity assessment.

In the following sections, we delve into the technical details of our methodology, present experimental results, and discuss the implications of our findings. Our research aims to set a benchmark of accurate and robust COPD severity assessment, ultimately benefiting future clinical practice and patient care.

5.1. Eigenspace projection and features

The projection process, which involves the V^T matrix enables the capture of the variations in the attributes inherent in the respiratory audio data from the Respiratory database and the corresponding singular values and culminates in constructing a pivotal projection matrix. This one is denoted as follows:

$$P = X \bullet \mathrm{V} \bullet \Sigma^{+}. \tag{9}$$

Where P is the projection matrix, X the original matrix of stacked flattened spectrograms. V signifies the matrix of eigenvectors that capture the variance, Σ^{+} is the pseudo-inverse of the singular matrix Σ. Notably, the pseudo-inversion of Σ refers to the Moore-Penrose (1955) inversion of a rectangular matrix of *Rank p=max (n,m)* under the earlier introduced SVD transformation, shown in equation (4).

Integrating eigenvalues into the projection matrix draws inspiration from the work of Albiges et al. [37] and Javaheri and Sicilian [38].

Albiges et al. [37] assert that eigenvalues are pivotal in discerning disparities among conditions of healthy individuals, those with chronic obstructive pulmonary disease (COPD), and those with pneumonia. These conditions could be manifested under the eigenvalue spectrum structures, leading to the classifications of respiratory conditions. Their findings are complemented by Javaheri and Sicilian's [38] research on breathing patterns, which reveals insights into the relationship between lower forced vital capacities (FVCs) and the concurrent increase in respiratory rates and decrease in tidal values. These distinct characteristics may closely correlate with the combined manifestation of the V matrix, the V^T matrix transposed, which captures the variance of the eigenvalue spectral density together with Σ^{+} on the eigenspace's strength characteristics. This matrix P encapsulates the most significant basis vectors of the selected samples from the ICBHI dataset of breathing sounds, representing the directions and magnitudes in the eigenspaces which contain maximum information. By projecting new samples onto this feature space, P accentuates essential features that are most discriminative while suppressing less informative ones, often associated with noise or irrelevant variations.

However, it is essential to note that while our approach draws inspiration from these pioneering works [33,39], it diverges in a vital aspect. The referenced studies utilised rank reduction techniques, whereas our method takes a different path with a focus on all the reordered characteristics, which is indeed a departure from the rank reduction approach [33]. This strategic alteration aims to enhance linear classification, moving away from rank reduction in the projection stage, as the filtered audio seeks to remove unwanted noise only.

Subsequently, the projection matrix is a fundamental tool for projecting COPD severity samples into a novel subspace, as articulated in $S = P^T \bullet A$. Here, S denotes the transformed COPD severity sample, P^T Represents the transpose of the projection matrix P, and A symbolises the COPD severity audio sample, which is pre-processed by a bandpass filter and transformed into spectrograms, for facilitating the exploration and analysis of COPD severity based on Eigenspectral in the ensuing stages of this the ongoing research programme.

5.2. Machine learning and severity classification

Four machine learning algorithms are applied to the transformed audio of the COPD severity dataset. We opted for a Training/Testing split ratio of 80:20. The training and testing set numbers have been previously noted in Table 1. The classification is conducted twice, firstly on the spectrograms without projection, as shown in Table 6, and secondly on the projected spectrograms, S, in Table 7, for a comparison of the results. As the datasets are imbalanced, the class weights are passed to the machine learning algorithms. This study opted for class weighting over other balancing techniques, such as oversampling or undersampling, to preserve all available data while addressing the imbalance issue. This method is particularly suitable for our relatively small dataset, where losing samples through under-sampling could significantly impact model performance.

The machine learning algorithms employed in this study encompass Random Forest, Gaussian Naïve Bayes, Support Vector and Logistic Regression Classifiers. As an ensemble method, Random Forest constructs multiple classification trees and amalgamates their outputs to yield the results [40]. The Gaussian Naïve Bayes classifier operates as a probabilistic classification model, while the Support Vector Classifier serves as a boundary classifier, aiming to delineate class boundaries using a hyperplane [41]. Lastly, Logistic Regression for multiclass classification operates as another probabilistic classifier that predicts class membership using a one-versus-the-rest approach for each class [42].

The classification evaluations in this study employed several metrics, including Accuracy, Precision, Recall, F1-Score, Kappa [43], and weighted Kappa. The use of weighted Kappa is particularly relevant in this context as the target classes represent values of an ordinal variable. To further assess the models' performance, a detailed classification examination per class is conducted using ROC curves [41,44].

Table 6
COPD severity classification results without projection to feature subspace.

Without Projection						
	Accuracy	Precision	Recall	F1-Score	Kappa	Weighted Kappa
Random Forest	52.6 %	30.3 %	31.3 %	27.3 %	0.22	0.47
Naïve Baye	53.8 %	56.2 %	52.0 %	47.69 %	0.40	0.35
Support Vector	55.1 %	48.6 %	50.8 %	47.7.3 %	0.39	0.46
Logistic Regression	48.7 %	42.5 %	48.3 %	42.6 %	0.30	0.45

Table 7
COPD severity classification results with projection to feature subspace.

With Projection						
	Accuracy	Precision	Recall	F1-Score	Kappa	Weighted Kappa
Random Forest	59.0 %	56.8 %	39.1 %	40.8 %	0.36	0.37
Naïve Bayes	43.5 %	35.0 %	23.6 %	0.20 %	0.06	0.08
Support Vector	75.6 %	70.7 %	69.3 %	67.7 %	0.65	0.65
Logistic Regression	71.8 %	64.5 %	65.0 %	62.8 %	0.60	0.64

6. Results and discussion

6.1. COPD severity classifications

The outcomes of the COPD severity classification based on eigenspectral feature spaces are presented below for comparison. The result of the classification without projection is shown in Table 6.

Table 7 displays the results of the COPD severity classification with projection into subspace to assist on class separation.

Tables 6 and 7 present the classification results for models without projection and those with projection, respectively. In the absence of projection, the classifiers performed poorly. Specifically, the Logistic Regression model achieved an accuracy of 48.7 %, with a Precision of 42.5 %, Recall of 48.3 %, and F1-Score of 42.6 %. Similarly, the Random Forest model exhibited an accuracy of 52.6 %, with Precision, Recall, and F1-Score values of 56.2 %, 52.0 %, and 47.69 %, respectively. Support Vector and Logistic Regression models demonstrated 55.1 % and 48.7 % accuracy, respectively. Upon applying projection into the breathing subspace, improvements were observed for some classifiers. While the Random Forest model still performed modestly, it exhibited an accuracy of 59.0 %, with Precision, Recall, and F1-Score values of 56.8 %, 39.1 %, and 40.8 %, respectively. Equally, Naïve Bayes achieved an accuracy of 43.5 %, with Precision, Recall, and F1-Score values of 35.0 %, 23.6 %, and 20.0 %, respectively. However, the Support Vector model showed significant improvement with an accuracy of 75.6 % and robust Precision, Recall, and F1-Score values of 70.7 %, 69.3 %, and 67.7 %, respectively. Likewise, Logistic Regression demonstrated an accuracy of 71.8 %, with Precision, Recall, and F1-Score values of 64.5 %, 65.0 %, and 62.8 %, respectively. Overall, the classifiers with projection generally showed improvements in accuracy and performance metrics, particularly evident in the substantial enhancement of the Support Vector model notwithstanding the Logistic Regression. The weighted Kappa values provide insights into the agreement beyond chance, with both models displaying varying degrees of agreement. The observed variations underscore the impact of the projection into the breathing subspace on model performance. Looking at the results of the best-performing models, the SVC with linear kernel and the Logistic Regression, specifically by checking their Receiver Operating Curves (ROC) and Area Under Curves (AUC), are shown in Fig. 3.

Further, the evaluation of the SVC and Logistic Regression models, the AUC for the One versus Rest classification across different classes reveals distinctive performance metrics (Fig. 4). For the Support Vector Classifier, the AUC values for each class indicate varied discriminatory capabilities. Class 1 exhibits the highest AUC at 96, indicating excellent discrimination, followed by Class 0 with an AUC of 93. Class 4 and Class 2 demonstrate respectable AUC values of 90 and 94, respectively, suggesting good discriminatory capabilities. However, Class 3 lags with an AUC of 78, implying a comparatively lower discriminative ability.

In contrast, the Logistic Regression model displays a similar trend but with nuances. Class 1 achieves the highest AUC at 96, akin to the SVC results. However, Class 0 shows a slightly lower AUC of 92, indicating robust discriminatory performance. Classes 4 and 2 maintain respectable AUC values of 90 and 77, respectively. Class 3 mirrors the lower discriminatory trend observed in the SVC results, with an AUC of 78.

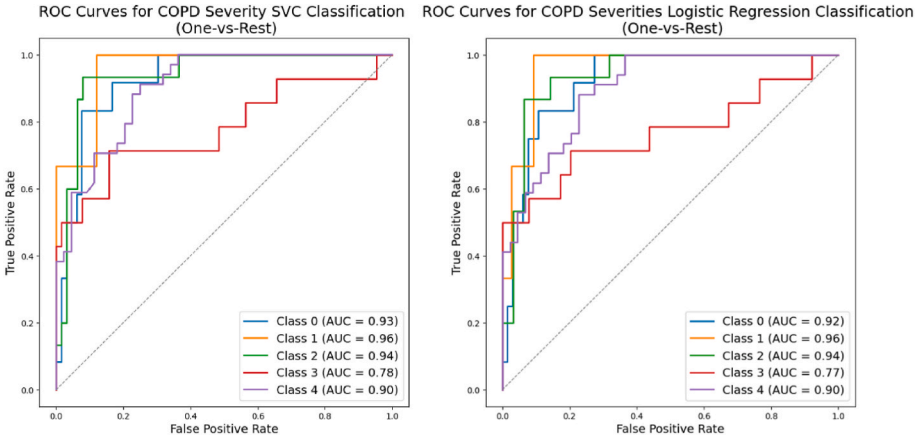

Fig. 3. Roc curves of the SVC and the logistic regression models.

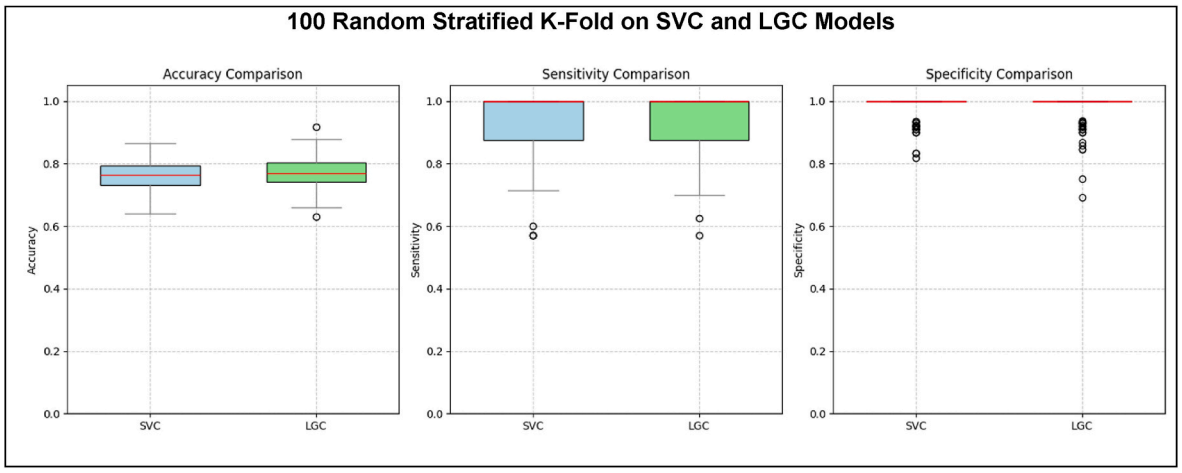

Fig. 4. Boxplots of average, sensitivity, and specificity of 100 random trials of stratified K-fold on the SVC and LGC models.

These AUC values provide valuable insights into the extracted models' ability to distinguish between different classes concerning COPD severities. The consistently high AUC for Class 1 suggests a robust discriminatory capacity across both models. The nuanced variations in AUC values across other classes highlight the models' differing abilities to discriminate between specific groups.

This study performed a parameter sensitivity analysis for the SVC and LGC models to optimise their performance. For the SVC, we explored different values of the regularisation parameter 'C', finding that lower values yielded better results. This suggests a larger margin and potentially increased generalisation benefited our COPD severity classification task. For the LGC, we compared the L1 and L2 regularisation methods while discovering that L1 regularisation outperformed L2. This indicates that feature selection and sparsity were advantageous for our dataset, which is potentially due to the high-dimensional nature of the audio features. These parameter choices were made based on the models' respective performances.

These findings contribute to a comprehensive understanding of the models' discriminative power across various classes, underscoring the importance of class-specific evaluation metrics in assessing the performance of machine learning models.

The computational CPU time of the SVD of the grouped breathing audio was performed, which took 37.8 s for 877 samples. This step was crucial for decomposing the audio data into its constituent eigenvectors and eigenvalues, thereby enabling the identification of features that characterise the different COPD severities. The projection of these samples into the eigenspace, a critical step for the classification of COPD severities using machine learning algorithms, CPU-time was completed in a mere 1.9 s for 387 samples.

The classification performance was evaluated using a comprehensive set of metrics to assess the models' capabilities [45]. The assessment of the stability and reliability of our best-performing models, SVC and LGC, led us to conduct 100 randomised tests using stratified k-fold cross-validation (k = 5). We report the mean and 95 % confidence intervals for each COPD severity class's accuracy, sensitivity, and specificity.

The results with the mean results of the 100 random stratified K-fold results are shown in Table 8 below and Fig. 4 shows the distribution of results as a box plot for the SVC and LGC models metrics accuracy, sensitivity, and specificity.

The results of 100 random stratified k-fold cross-validations for COPD severity classification demonstrate robust performances for both the SVC and LGC models. Both classifiers achieved a mean accuracy of 77 %, with the SVC showing a slightly higher upper bound of the 95 % confidence interval at 86 %, when compared to the LGC's 84 %. Both models exhibited excellent sensitivity, with a mean of 93 % and an upper confidence interval reaching 100 %. This indicates a strong ability to correctly identify positive cases across COPD severity levels.

Table 8
Results for the 100 random stratified K-fold COPD severity classification of the SVC and LGC models.

Results of 100 Random Stratified k-Fold COPD Severity Classification						
Model	Average		Sensitivity		Specificity	
	Mean	95 % IC	Mean	95 % IC	Mean	95 % IC
SVC	77 %	86 %	93 %	100 %	97 %	100 %
LGC	77 %	84 %	93 %	100 %	90 %	100 %

The SVC demonstrated superior specificity, with a mean of 97 % and a confidence interval of 100 %, compared to the LGC's of 90 %. We selected these performance metrics on their ability to comprehensively assess classification performance, particularly with imbalanced datasets [46]. Mean and 100 % upper bound, suggest the SVC's capability to correctly identify negative cases. These findings underscore the models' effectiveness in distinguishing between different COPD severity levels, with the SVC showing a marginal advantage in overall performance.

7. Further discussions

This research aimed to leverage artificial intelligence in healthcare and benchmark it with machine learning approaches, which were satisfactorily performed in detecting COPD severities. The methodology can be summarised as follows.

1. **Data Pre-processing and Transformation**: We began by processing respiratory audio samples, removing heart rate background interference, and converting them into spectrograms uses the STFT. The dataset is organised into a matrix for SVD.
2. **Singular Value Decomposition (SVD)**: We utilise SVD to extract unique respiratory characteristics from the data. From this, we derive a pivotal projection matrix that plays a crucial role in our subsequent analysis.
3. **Eigenspace Features Projection**: The projection matrix is constructed by incorporating eigenvalues and eigenvectors from the SVD process. This step draws inspiration from previous research on respiratory conditions and diverges from conventional rank reduction approaches.
4. **Subspace Transformation**: The projection matrix facilitates the transformation of the COPD severity samples, capturing crucial basis vectors representing the high-variance directions in the eigenspace.

This transformation highlights discriminative features while suppressing noise and irrelevant variations.

5. **Machine Learning Classification**: We apply four machine learning algorithms to classify COPD severities. Data is split into training and testing sets for evaluation, focusing on comparing classification performance with and without projection onto the eigenspaces.
6. **Machine Classification Metrics**: Our evaluation includes various metrics for comparing classification without and with the projection method.

The potential impact of this research is significant. A future, more accurate and automated COPD severity classification system can assist healthcare professionals in making critical, informed decisions. This can lead to earlier interventions by clinical and nursing professionals with personalised treatment plans. These are expected to improve patient outcomes, benefiting from smart clinical practice and patient care. Our ultimate goal here is to contribute to the development of reliable COPD diagnostics and prognostics in the future. This will undoubtedly and positively impact the lives of COPD patients and the healthcare community as a whole.

Our study represents an early promising advancement in classifying COPD severities using Artificial Intelligence (AI). Our methods are enhanced by the application of SVD and the projection matrix to lung respiratory audio signals for the classification of COPD severity. Note also that this innovative approach incorporates the concept of transfer learning, which draws valuable insights from one distinct dataset and applies it to another. Our results underscore the substantial contribution of this methodology to the precise categorisation of COPD severity levels, carrying promising implications for clinical practice and healthcare management. The ability to accurately differentiate between COPD severity categories holds profound consequences for clinical decision-making and healthcare administration. The potential for future integration of our method into medical practice equips healthcare professionals with a valuable tool to inform treatment plans and interventions. Early detection and understanding of the various severities from *mild, moderate, and severe to very severe* conditions has the potential to facilitate proactive medical strategies, thereby reducing hospitalisations and enhancing overall patient outcomes in the near future.

Moreover, our research foundational framework is currently at a benchmarking work stage for developing portable and non-invasive diagnostic and prognostic tools for COPD severity assessments. However, it is imperative to acknowledge the limitations inherent in our study at this moment in time. The relatively modest size of our dataset for model training and testing raises questions about the generalizability of our findings to broader populations. The absence of external validation datasets further obscures the actual robustness of our models on unseen data. In addition, the classifiers' performance might be susceptible to the quality of audio recordings, external noise, and variations in auscultation practices.

As we look ahead, the future research path opens up promising opportunities for us. Scaling up the dataset to encompass a more diverse and extensive sample size holds the potential to fortify the classifiers' reliability. Our models can be better equipped to tackle genuine clinical scenarios by incorporating real-world noise and variability in audio recordings. Additionally, more knowledge discovery and explainable AI could support further research in understanding COPD and respiratory audio, especially with extra clinical and demographic variables, such as age, height, chest size and smoking history, leading to a more comprehensive evaluation of COPD severity audio signals.

8. Conclusion

This study marks a noteworthy advancement in COPD severity classification through auscultation audio signals. By leveraging knowledge transfer techniques, we have achieved notable improvements in classification accuracy, underlining the potential of this approach for practical implementation in clinical settings. Identifying critical features within principal components of the eigenvectors adds depth to our understanding of the intricacies involved in COPD severity assessment and diverges from rank reduction methods. However, it is essential to acknowledge this study's early stages and limitations. The relatively modest size of our dataset may pose challenges to the broader generalisations of our findings. The absence of external validation datasets further underscores the need for caution in interpreting the robustness of our models on unseen data. External factors such as audio recording quality, ambient noise, and variations in auscultation practices could influence classifier performance.

Future research avenues should prioritise scaling up the dataset to encompass a more diverse and extensive sample size. This expansion can enhance the reliability of classifiers and better simulate real-world clinical scenarios, accounting for variations in audio recordings.

Nonetheless, this study brings in novel benchmarks for addressing lung respiratory signals through targeted pre-processing and transforms to relevant feature spaces such as the representative eigenspaces of the audio signals Discrete Fourier Transform matrices to discover the best performing AI algorithms which understand and distinguish subtleties amongst the various types of progressing severities of COPD. Thus, future research efforts are warranted to address existing limitations and propel the field towards more robust and clinically applicable solutions. Our team is indeed on the journey towards enhancing diagnostics and prognostics precisions for detecting the nuanced features of COPD severity using AI, together with future-generated larger volumes of data in our laboratory activities with the participation of more cohorts of COPD patients in our region and beyond.

CRediT authorship contribution statement

Timothy Albiges: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **Zoheir Sabeur:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Banafshe Arbab-Zavar:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis.

Ethics statement

We, the authors of this submitted paper entitled: "Features and Eigenspectral Densities Analyses for Machine Learning and Classification of Severities in Chronic Obstructive Pulmonary Diseases", are the sole contributors of this research work, which has been conducted at Bournemouth University. The research work has been conducted under the approval of Bournemouth University Ethics Committee under **reference number 49385**.

All authors have read and approved the final draft of this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Bournemouth University Ethics Committee approved this study; Reference number 49385.

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