CatBoost Implementation on ConvNeXt for Respiratory Disease Detection Using Limited Imbalanced Lung Sounds

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**Abstract.**  Lung diseases are responsible for a significant number of deaths. Growing air pollution exacerbates the situation, which is often overlooked by patients. To address this problem, this paper explores a deep learning model for detecting lung disease through lung sounds. A dataset of respiratory sound recordings from patients, provided by the ICBHI 2017 challenge with various but limited and imbalanced lung conditions, was used to train the classification model. The proposed model is a gradient-boosted decision tree using CatBoost to classify features extracted from log-mel spectrograms of each recording using ConvNeXt. The label of dataset was then divided into 2 classes and 3 classes, based on the categorize of lung disease. The suggested model trained with time domain augmentation on audio of full dataset and feature domain augmentation using SMOTE to improve variation on imbalanced and limited dataset resulting in 96,1% for average score of specificity and sensitivity, 96,3% for F1-score on 2 classes, and 87,8% and 90,3% for average score and F1-score respectfully on 3 classes. Other boosting algorithms, such as LightGBM and XGBoost, are used for comparison with the proposed model, which is inferior to proposed model.

**Keywords:** CatBoost, ConvNeXt, Augmentation, SMOTE, log-mel spectrogram

# INTRODUCTION

Lung diseases are responsible for a significant number of deaths. According to the World Health Organization (WHO), about 3, 1.6, 1.4 million people die each year from COPD, lung cancer, tuberculosis respectively. Growing air pollution exacerbates the situation by increasing the number of people suffering from respiratory diseases [1]. These common respiratory diseases refer to as the "big five," are tuberculosis, lung cancer, acute lower respiratory tract infections, asthma, and chronic obstructive pulmonary disease [2]. Professional and experienced medical staff are required for an accurate and comprehensive diagnosis. However, the availability of qualified medical resources is limited. Thus, it is crucial to build an automated diagnosis system. Subjects with respiratory disease will have observable symptoms on their lungs during respiratory cycle that could be the object of diagnosis for the patient. The audio comes from recorded patient’s respiratory system during certain duration where the sound of air passing through lungs happened during breathing. With improvement in machine learning models on classification task, there is a possibility to build health care assistant for medical professionals equipped with various tools to help to diagnose the disease of patient’s sample respiratory audio. This classification model can be built using machine learning or deep learning [3, 4]. This study's audio dataset was gathered from patients with both healthy and diseased respiratory systems, including COPD (Chronic Obstructive Pulmonary Disease), URTI (Upper Respiratory Tract Infections), LRTI (Lower Respiratory Tract Infections), bronchiectasis, bronchiolitis, pneumonia, bronchitis, and asthma. This dataset is unbalanced, with fewer examples of some illnesses than others. This mismatch has an impact on the model's generalization and leads to overfitting because it can only guess the label with large amounts of data. On majority of related previous works, the classification was carried out using deep learning models with various way, including the feature extraction process of data that varies where some used log-mel spectrogram and MFCC feature, and augmentation techniques were including time domain frequency, such as adding white noise, and shifting audio pitch, and on frequency domain augmentation using SpecAugment and RepAugment. The splitting of audio also differs, where some research used official ICBHI split included in the dataset with ratio 60:40 for train and test respectfully, and others used 80:20 ratio. This paper develops a boosting model with a decision tree to classify the dataset, as the previously known method performs well on the imbalance dataset [5]. The audio dataset is divided into three parts: training, validation, and testing with ratio of 60:20:20 with stratification to ensure the difference of labels between audio recognized by model. Training data consisting of log-mel spectrogram extracted feature by ConvNeXt is used to fit into CatBoost model, while testing data is used to evaluate model performance. Before being used to train the model, audio data is preprocessed with several steps, such as normalization, log-mel spectrogram extraction, and padding. Normalization is performed to ensure that all audio data is on the same scale. Then primary feature will be extracted which is log-mel spectrogram, and applied cyclic padding before fed into ConvNeXt to get secondary feature which will be used as main feature for prediction.

The reason for the selected models comes from the fact that ConvNeXt is a recently constructed convolutional neural network model that performs well on a variety of image recognition tasks. This model employs an efficient neural network design and can be trained with very minimal data [6]. For multiclass classification of respiratory disorders, proposed model ConvNeXt block is used for feature extraction and become the data inferred by boosted decision tree that replaces dense layer, similar to Deep Convolutional Neural Network (DCNN) on related work [7]. The proposed boosting algorithm is CatBoost, a powerful boosting algorithm capable of handling unbalanced data sets. This technique classifies data using an ensemble of decision trees. CatBoost is trained on training data from which features were extracted with the ConvNeXt model to find out if the features output is suitable for the classification. This model was intended for categorical data, however in this experiment, it was used on continuous numerical data to answer whether this model could manage the classification smoothly. The ability of boosted decision trees is evaluated in this experiment to produce an efficient model for system limited compatibility by using lightweight model to train on new sample data and to run for patient’s diagnosis assistance. The model selection is backed by previous works using same dataset with different approach, where log-mel spectrogram extracted from audio with DCNN models such as various ResNet versions outperformed other features such as MFCC and gammatone spectrogram, and other models such as CNN and LSTM [8-10].CatBoost as boosted decision tree model is chosen due to efficiency of the model and fair performance, compared to Linear Discriminant Analysis and bagged decision tree as lightweight model, with highest performance on f1-score metric on 93.61% [8].

This paper explains the experiment in four sections, where research flow and explanation of experiment steps to build classification model is included in methods. Results and discussion chapter contains the model’s outcome based on metrics and the explanations that can be inferred from the results, and the parameters of model used. Finally, the conclusions sum up the paper with future works for improvement.

# METHODS

The method used in this experiment starts from the data preparation stage, then goes into the augmentation and development of the proposed model and other boosting models as a comparison model after goes to the evaluation stage of each model. The experimental flow of the proposed model is explained in **FIGURE 1.**

The dataset used is data from ICBHI 2017 which includes recorded lung sounds from 126 subjects with 920 recorded samples from various electronic stethoscopes, namely AKGC417L, Meditron, Litt3200, and LittC2SE. Each subject can produce more than one sample with different tools, which can lead to an imbalanced dataset, which in this case occurs with COPD. Of these various tools, the cause of the imbalance dataset is the AKGC417L tool, all 646 data recordings are included in COPD disease, plus the Litt3200 tool with 60 recordings and all of them are in the COPD category, most tools also have recordings of lung sounds with COPD disease. This resulted in data that around 86 percent were included in this disease. Apart from that, patients with LRTI and Asthma disease classes are also included in the minority class because subjects suffering from LRTI disease are only found on the Meditron device and Asthma only on the LittC2SE device.

The audio and class labels are then prepared by changing the labels using the one-hot encoding method to become training material for the model. After that, we visualize the class distribution on the dataset. The picture below shows there are still significant disparities, especially in the COPD disease class which falls into the Unhealthy category in the 2 classes system and Chronic in the 3 classes system. The imbalanced data can be interpreted from data distribution in **FIGURE 2.**

A diagram of a sound system

Description automatically generated

A white and blue rectangular object with black text

Description automatically generated**FIGURE 1**. Experiment flow

**FIGURE 2**. Dataset class distribution

There is still little data on certain classes of diseases classified as imbalance. In the next model development, categories were combined according to previous research to compare with proposed model. This combination consists of 2 classes consisting of Healthy and Unhealthy which consist of all diseases. This dataset has huge imbalance on unhealthy data that has more than 800 samples. Data is also categorized into 3 classes consisting of Healthy, Chronic Disease consisting of COPD, Asthma, and Bronchiectasis, and Non-Chronic Disease consisting of URTI, LRTI, Pneumonia and Bronchiolitis. The distribution is dominated by chronic disease for COPD disease.

## DATA AUGMENTATION

This study applied time-domain augmentation techniques using the Audiomentations library to enhance data variation across all disease classes before training the model. Various methods were used to diversify and improve the training data, including adding Gaussian noise to the audio with varying amplitudes, time stretching to alter playback speed without affecting pitch, pitch shifting within a semitone range, and time shifting the audio signal forward and backward. For the initial comparison of boosting algorithms, the entire ICBHI dataset was augmented using the Audiomentations library to balance the training set. Rather than applying each technique individually, all augmentations were performed simultaneously to avoid data leakage, ensuring that the model does not learn from original features validation or testing data during training. Meanwhile in the second experiment, augmentations were only applied to the training data to prevent data leakage. Further augmentation was done using SMOTE (Synthetic Minority Oversampling Technique) on features extracted by ConvNeXt before classification with a boosted decision tree.

## PREPROCESSING

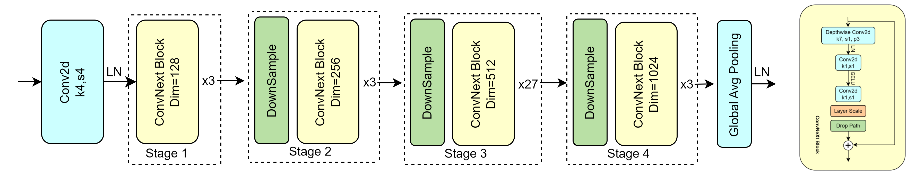
The audio must be converted to numerical format which represents rich feature of the audio to make both augmented and original raw audio data identifiable by model. Therefore, Short Time Fourier Transform (STFT) is first used to process the audio waveform to generate the dataset, which is using Discrete Fourier Transform (DFT) to gain time and frequency information of signal. The sample rate used matches the audio's native sampling rate, and the resampling type is kaiser fast from the resampy library. Following that, a mel filter with 50 mel bins is used to generate the mel spectrogram, which is then transformed to log scale. The number of time frame is fixed to 1660, and cyclic padding is used to fix the length of the spectrogram for all data, adjusting to the average original length of the log-mel spectrogram of all audio data. The number of parameters is selected carefully depending on the tradeoff between feature dimension and limitation of memory to avoid curse of dimensionality. In this experiment, whole audio feature without segmentation of cycles is processed to find out whether the model can infer the disease from data with minimal information. The outcome of the process produces data with dimension (n, 50, 1660, 1) with n represents number of 3 dimensions data, then duplicated across 3 channels to be fit into ConvNeXt model.

## MODEL

The proposed model is a modification of base version of ConvNeXt which was frozen to continue its classification by CatBoost to categorize audio data for 2 and 3 classes respectively. The ConvNeXt model is used and set to untrainable so that the parameters in the model are not updated during the training process. The goal is to apply feature extraction from ConvNeXt to the Log-mel spectrogram so that it can be more easily differentiated by the next model, namely CatBoost. This approach allows ConvNeXt to function as a powerful feature extractor, while CatBoost is used to perform classification based on the extracted features. ConvNeXt was chosen because it has a higher efficiency level than several pretrained CNN such as ResNet and EfficientNet. By combining ConvNeXt's capabilities in visual representation of Log-mel spectograms as the feature extractor and CatBoost's speed in classification task, this system is expected to produce more optimal performance than earlier studies. Meanwhile, CatBoostClassifier, which is based on a decision tree, and suitable for this case because imbalance data can be handled by this model by preventing overfitting using Bayesian estimators [11] and can be trained more efficiently compared to deep learning models. ConvNeXt is a model of a convolution network that was designed to address the computational resources needed to to predictions accurately. Inspired by Vision Transformer, ConvNeXt adopts similar concept to weighted sum operation on self-attention mechanisms by processing images using depth-wise convolutions on image patches [6]. It is used primarily as a feature extractor to produce feature representations from input images. It was trained using the ImageNet dataset, which is one of the largest and most extensively used for image recognition tasks. Using ConvNeXt transfer learning, the model may use previously obtained information, improving the accuracy and efficiency of the feature extraction process. The proposed version of ConvNeXt for this experiment is the base version which consists of four stages, with number of stacked downsample layer and ConvNeXt block at 3:3:27:3. This model has 89 million parameters with 261 number of layers, and number of channels 128, 256, 512, 1024 for each block which produces feature of each data with dimension of (1,1024). This model has some modification of previous DCNN models to reduce layers It uses GELU (Gaussian Error Linear Units) on formula (1) as activation function of the convolution network where Φ(x) is cumulative distribution function for Gaussian distribution.

(1)

It also follows transformer by replacing batch normalization on ResNet model with layer normalization for each residual block. ConvNeXt also uses separate downsampling layers, which were added between stages where spatial resolution is changed to commit stabilized training, forming a model as **FIGURE 3** [12].



**FIGURE 3**. ConvNeXt base architecture

CatBoost is one of the boosted tree algorithms optimized for categorical data, which follows the principle of gradient boosting [8]. Gradient boost itself is a boosted algorithm which combines Gradient Descent mechanism and boosting and incorporates fitting an ensemble model in a forward stage-wise fashion. It makes use of binary decision trees as base predictors. Observing data with samples , where is a vector of features and response feature, which can be binary or encoded as numerical features (0 or 1). Sample are independently and identically distributed according to some unknown distribution . The goal of the learning task is to train a function which minimizes the expected loss, where is a smooth loss function and is a testing data sampled from the training data .

In a greedy manner, the algorithm for gradient boosting constructs iteratively a sequence of approximations . From thre previous approximation is obtained in an additive process, such that , with a step size and function , which is a base predictor, is selected from a set of functions G to reduce or minimize the expected loss of

Often, the minimization problem is approached by the Newton method using a second-order approximation of at or by taking the negative gradient step [9]. For this experiment where all the data are numerical, CatBoost's ordered boosting mechanism is employed to prevent prediction shift. This mechanism addresses overlap between training data for base models and data used for gradient calculation by randomly permuting the dataset in each iteration and using only the data preceding each example in the permutation for training.

In this case, the CatBoost model is selected with iteration parameters of 1000 epochs, learning rate 0.1, tree depth 6, and MultiClass loss function. The multiclass loss function is used to predict the class of several trained labels. This model uses leaf-wise growth concept involves iteratively selecting the leaf that offers the highest potential gain, while also ensuring that the trees remain balanced and regularized to prevent overfitting. This differs from the more commonly used "level-wise" strategy in regular decision trees. This model stores a set of scores or values associated with each class at each leaf, which are used to make the final predictions. This function makes it possible to calculate the first and second derivatives, and from there the distance between the ideal prediction and the average gradient on the leaf, as is the case with other loss functions [10]. Many iterations allow the model to learn deeply, while a moderate learning rate facilitates careful learning without significant risk of overfitting. The relatively shallow tree depth of 6 is sufficient to capture complex patterns in the data without introducing excessive complexity. The same parameter is applied to other boosting models to compare them fairly.

## METRICS

In cases where the main priority is to minimize diagnostic errors, especially to reduce false positives in specificity and false negatives in recall as well as how precisely the model can correctly guess a disease (precision) in precision, the F1 score metric is used, and specificity is very relevant as a comparison of model performance in classifying each class. There is another metric from the dataset publisher named ICBHI score to compare the result of model, which comes from the average of sensitivity and specificity. This formula is used to create Average score, to get a thorough value that represents a model capability to detect the disease, instead of accuracy score that only compares correct predictions to all predictions and will be useful only when data distribution is equal for each label.

(3)

F1-score is a measure that combines precision and recall, providing a balanced view of a model's ability to correctly identify certain classes. F1-score provides a composite value between precision and recall, which is useful in cases where the balance between false positives and false negatives is critical. The precision, recall (sensitivity), and specificity formula can be seen below. Specificity prioritizes the context of false positives, the greater the level, the smaller the score. This is important to prevent misdiagnosis of certain diseases. For the results, the average specificity for each disease class is used.

(4)

(5)

(6)

# RESULTS AND DISCUSSION

The feature extraction from log-mel spectrogram using ConvNeXt used parameter of batch size 32 to meet the memory constraints and to meet the limited dataset to prevent local minima by make the gradient noisier, because of the limited data on dataset and leads to random updates for the gradient. ConvNeXt base version is deployed in this paper for achieve greater performance and prevent underfitting based on the simplicity of the model that tiny version has and completed the feature extraction task more efficiently than large and huge model. Based on the first experiment methods to find if the boosted trees can be used in this spectrogram as sequential data, for each dataset, performance of CatBoost excels compared to other boosting algorithms, such as XGBoost and LightGBM. CatBoost implements symmetric trees which perform better than leaf-wise trees on LightGBM and depth-wise trees on XGBoost. The parameter used for CatBoost resulting model training on best iteration at 78, indicating the poor performance of CatBoost by overfitting to learn from the data and to predict the class label correctly. Further results can be seen in **TABLE 1** for the first flow of experiment which classify on two classes and three classes. On the two classes classification, the data has more variation since it includes audio feature from more labels of disease. Meanwhile on three classes, it has smaller variation on label, yet still be used on classification task in prior assumption that diseased and healthy lung sound has significant difference such as crackle and wheeze sound on unhealthy class, and chronic and non-chronic disease with the intensity and the pattern.

**TABLE 1.** Results for first augmentation flow experiment

| Model | Task | Precision | Recall | Specificity | F1-score | Average score |
| --- | --- | --- | --- | --- | --- | --- |
| CatBoost | 2 classes | 0.940 | 0.997 | 0.926 | 0.933 | 0.961 |
| XGBoost | 0.930 | 0.926 | 0.851 | 0.889 | 0.889 |
| LightGBM | 0.870 | 0.923 | 0.777 | 0.821 | 0.850 |
| CatBoost + SMOTE | 0.940 | 0.997 | 0.926 | 0.933 | 0.961 |
| XGBoost + SMOTE | 0.940 | 0.927 | 0.926 | 0.933 | 0.961 |
| LightGBM + SMOTE | 0.870 | 0.923 | 0.777 | 0.821 | 0.850 |
| CatBoost | 3 classes | 0.920 | 0.803 | 0.867 | 0.893 | 0.835 |
| XGBoost | 0.910 | 0.759 | 0.829 | 0.868 | 0.794 |
| LightGBM | 0.910 | 0.827 | 0.848 | 0.878 | 0.837 |
| CatBoost + SMOTE | 0.890 | 0.940 | 0.867 | 0.878 | 0.903 |
| XGBoost + SMOTE | 0.890 | 0.845 | 0.829 | 0.858 | 0.837 |
| LightGBM + SMOTE | 0.910 | 0.827 | 0.848 | 0.878 | 0.837 |

By using additional data augmentation in the time-domain with augmentation techniques on Audiomentations library, and applying SMOTE in the feature domain, this method is expected to enhance the classification task on the limited lung audio dataset. This approach is effective because training with high-variation data results in more generalized models, reducing bias. This method is proposed to address the issue of overfitting, which is a common problem with limited datasets where model only can truly predict the majority label. For the result, on the CatBoost model for 3 classes classification, the average score which relies on specificity and sensitivity increased by 8.18% with increased sensitivity by 14.54% and stagnant specificity, but there is some trade off since there is a decrease in precision and f1-score by 3.26% and 1.61%, respectively. This decrease shows early sign that SMOTE is not suitable for this task, since the ability of model to predict positive class is weak due to incorrect label of extracted data from augmentation. For the second augmentation method as commonly accepted classification rule where test and validation set should be hidden from training process by doing time domain augmentation is done only on training dataset. The result reported at **TABLE 2** proves the first flow research hypothesis, where overfitting happens. This is because of the low score of specificity where model could not predict correctly on minority class, thus resulting in low true negatives and assume that data belongs to majority label. The high score of recall but low score in specificity in this report also shows that the model guesses too much data of correct prediction on majority label, and as the result the pattern of data of minority label is poorly identified by the model.

**TABLE 2.** Results for second augmentation flow experiment

| Model | Task | Precision | Recall | Specificity | F1-score | Average score |
| --- | --- | --- | --- | --- | --- | --- |
| CatBoost | 2 classes | 0.770 | 0.914 | 0.554 | 0.734 | 0.690 |
| XGBoost | 0.800 | 0.917 | 0.629 | 0.773 | 0.739 |
| LightGBM | 0.850 | 0.851 | 0.703 | 0.777 | 0.773 |
| CatBoost + SMOTE | 0.700 | 0.903 | 0.257 | 0.580 | 0.478 |
| XGBoost + SMOTE | 0.830 | 0.920 | 0.703 | 0.812 | 0.786 |
| LightGBM + SMOTE | 0.770 | 0.914 | 0.554 | 0.734 | 0.690 |
| CatBoost | 3 classes | 0.610 | 0.690 | 0.658 | 0.674 | 0.654 |
| XGBoost | 0.570 | 0.641 | 0.620 | 0.630 | 0.612 |
| LightGBM | 0.640 | 0.694 | 0.696 | 0.695 | 0.681 |
| CatBoost + SMOTE | 0.640 | 0.758 | 0.677 | 0.718 | 0.688 |
| XGBoost + SMOTE | 0.640 | 0.713 | 0.677 | 0.695 | 0.676 |
| LightGBM + SMOTE | 0.590 | 0.643 | 0.639 | 0.641 | 0.627 |

The huge drawback of the result from previous flow is also the evidence that data leakage is happening. The pattern of the validation and test data is still causing overfitting, though already processed through heavy augmentation. SMOTE on feature domain augmentation also still improves the model, although not as much as the previous one. This concludes that SMOTE does work by increasing the performance of model, but due to the different natures of dataset including the way of labelling or diagnosing the spectrogram of patient’s lung sound, it can be someway misleading the model into false label, the disease diagnosis in this case. Furthermore, the proposed model which is CatBoost implemented on ConvNeXt overall still works best compared to another boosting methods. The nature of symmetric trees where each split is based on same condition makes the model more specific in considering the class of the feature. Due to weak result from fair classification flow, it can be considered that the model’s inability to predict entire new data is the reason the models still need improvisation by feeding more precise data with more resource to compute the spectrogram and capture the information needed to learn by the model, based on former related experiment results.

# CONCLUSIONS

In this study, exploration on the implementation of CatBoost in ConvNeXt architecture model to classify lung diseases based on recording of patient’s lung sound is concluded. ConvNeXt became the feature extractor of logmel spectrogram data is successfully reduce the dimension before inferred by boosted decision tree. This study also highlights the CatBoost performance compared to another boosting algorithms, XGBoost and LightGBM. Additionally, the use of data augmentation techniques such as Audiomentations and SMOTE further improved the model's performance on experiment by helping the model from seeing closer to the pattern, but at the consequence of misleading in context of predicting lung disease.

The high values of the created model which reaches highest average score at 96,1 % with CatBoost with SMOTE at 2 classes is the simulation with rich variation of data on training dataset created by heavily augmented test and val data, thus only valid for model comparison purpose. With SMOTE increasing some cases and decreasing some performance of model on random trend, it can be concluded that SMOTE is not suitable for the accurate assistant for deployment, because of low performance when tested on blind test data experiment. The next model results of high sensitivity and low specificity suggests that the model is only good at predicting majority label, but only because compared to little test data of minority label. Further different augmentation and cycle annotation is expected to increase the capability of the model of classifying the data.

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