COMP8831-S1-2025 - Machine Learning

Cough Detection Using Audio Spectrogram Transformer and 1D CNN

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Abstract

Coughing is a key symptom of many respiratory diseases, and early detection of its type can significantly aid in diagnosis. Advances in machine learning (ML) and deep learning (DL) offer a promising solution by enabling the automated detection of cough-related conditions. By training models on a variety of cough sounds, it becomes possible to perform early disease detection using edge devices, reducing the need for immediate doctor consultations. In New Zealand, where securing a healthcare appointment is often challenging due to limited availability and long wait times, such technology can be particularly impactful. These models can assist medical professionals in prioritizing patients based on the severity of the detected condition. This project implements cough detection from audio recordings using two models: the Audio Spectrogram Transformer (AST) and a 1D Convolutional Neural Network (CNN). Both models were trained and evaluated on a dataset of 9,716 two-second audio clips containing cough and non-cough events. The AST model achieved an accuracy of 93%, outperforming the 1D CNN, which achieved 90%. These models form the foundation for future work in classifying specific types of coughs to support remote healthcare diagnostics.

Keywords: Audio Spectrogram Transformer, 1D CNN, Health Acoustic Event Detection, Cough Detection

1. Introduction

Health acoustic events like cough, stridor, wheezing, and snoring carry crucial information that can help doctors accurately diagnose various diseases—particularly respiratory conditions. Among these, coughing is a key acoustic event that plays a vital role in identifying illnesses such as asthma, COPD, pneumonia, bronchitis, and tuberculosis. According to statistics, COPD affected 213 million people globally in 2021, resulting in 3.65 million deaths, making it the fourth leading cause of death that year [1]. Pneumonia, another

severe illness, led to 4 million deaths in 2025 [2]. Tuberculosis and asthma have also caused a significant number of fatalities worldwide [3].

While COPD and asthma are serious conditions, they are not airborne and do not pose a direct risk to those living with the patient. In contrast, tuberculosis and pneumonia are airborne diseases, making early detection and patient isolation critical for preventing their spread.

In New Zealand, diagnosis of these diseases typically requires consultation with a general practitioner (GP). However, access to GP appointments is often delayed, which can lead to worsening of the condition. Recent statistics show that only 36% of patients are able to secure a same-day or next-day appointment, while over 20% wait more than a week. In rural and coastal areas, telehealth GP appointments have an average wait time of 7–13 working days, with a median of 9 days [4]. This underscores the urgent need for a cough detection system that can assist in identifying diseases early and accurately.

Numerous studies have explored the use of machine learning (ML) and deep learning (DL) models for cough detection, as discussed in Section 2. In this project, we use two DL models: 1D CNN and Hugging Face's AST (Audio Spectrogram Transformer) to identify cough sounds. The models are trained on audio samples from the COSWARA and FluSense datasets, and their performance is evaluated using various metrics.

2. Related works

Many studies were conducted for the detection of cough using ML and DL methods. In [5] proposed Coswara, a publicly available dataset of cough, breath, and voice sounds collected via crowdsourcing to aid in COVID-19 diagnosis. The study extracted acoustic features and used a random forest classifier, achieving a baseline accuracy of 66.7% in classifying nine respiratory sound categories. This work demonstrates the potential of using machine learning on respiratory audio signals as a scalable and low-cost screening tool for respiratory diseases. For feature extraction, the authors used various feature extractors such as MFCCs,Spectral contras etc and each 500 ms audio segment was represented by a 28-dimensional feature vector.

In [6], authors developed an AI-based mobile application to perform preliminary COVID-19 diagnosis using cough audio recordings. The system uses MFCC features and a binary classifier combining machine learning and deep learning techniques, trained on hundreds of crowdsourced samples. The model achieved over 90% sensitivity and specificity, providing a scalable, non-invasive pre-screening tool for resource-constrained settings.

CoughMotion, a CNN-based cough detection model was proposed in [7] that combines audio and IMU (inertial measurement unit) data collected from modified Sony wireless earbuds. The architecture includes three branches: one for audio processed via a VGGish CNN using mel-spectrograms, and two separate 1D CNN branches for gyroscope and

accelerometer data. The preliminary study involved 90 cough samples from a single participant, showing a visible correlation between audio and IMU signals. While no quantitative accuracy results are presented, the design and early insights motivate further investigation into multimodal cough detection using wearable devices.

DeepCough3D, a lightweight deep learning model based on 3D CNNs was introduced in [8]to classify cough sounds for COVID-19 diagnosis. Using the COUGHVID dataset (comprising 20,975 cough recordings), the model takes in log-Mel spectrograms and is optimized for real-time mobile applications. The authors propose a compact architecture with fewer parameters while achieving an accuracy of 95.2% and F1-score of 0.952 on the test set. The results demonstrate the model's suitability for low-resource environments and edge devices without compromising diagnostic performance.

In [9] a lightweight and efficient variant of the Audio Spectrogram Transformer (AST), called FastAST, for classifying cough sounds. Using a curated dataset of 6,881 cough samples from the COUGHVID corpus (labeled as wet or dry), the authors convert audio to log-mel spectrograms and feed them into a convolution-free transformer architecture. The model achieves a test accuracy of 93.4% and AUC of 97.1%, outperforming standard CNN and LSTM baselines. FastAST uses patch-wise attention and fewer parameters, making it suitable for deployment in low-resource settings. The results highlight the potential of transformer-based models for real-time, high-performance cough classification tasks.

In [10], a novel approach for COVID-19 detection using Audio Spectrogram Transformer (AST) applied to cough audio recordings is presented. The authors convert audio into log-mel spectrograms and feed them into a Transformer-based model without convolutional layers. Trained on 3,847 cough samples, the AST model achieves a test accuracy of 94.2% and AUC of 95.8%, significantly outperforming baseline CNN models. The architecture includes positional embeddings, patch-based attention, and a classification head suitable for binary COVID-19 status prediction. This work demonstrates the potential of transformer-based models in real-time, non-invasive health diagnostics.

Based on the promising results demonstrated by both CNN and transformer-based models in prior studies, we have selected 1D CNN (IDCNN) and Hugging Face's Audio Spectrogram Transformer (AST) for our experiments on cough sound classification.

3. Methodology

The proposed methodology involves four key stages: data collection, data preprocessing, model training, and evaluation. The workflow integrates two publicly available datasets (Coswara and FluSense), prepares the data for training, and fine-tunes a pretrained Audio Spectrogram Transformer (AST) model and ID CNN for binary classification (cough vs. non-cough). The overall process is illustrated in Figure 1.

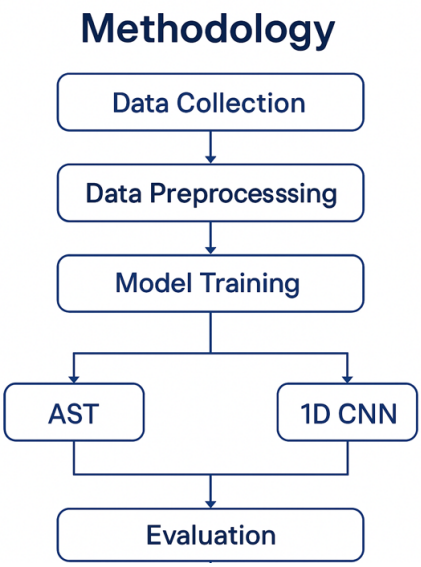


Figure 1: Methodology pipeline for cough detection

- **Data Collection:** Audio samples were obtained from the Coswara dataset, which contains labeled cough recordings from human subjects, and the FluSense dataset, which provides real-world cough sounds captured in hospital environments.
- **Data Preprocessing:** All audio files were converted to mono channels, split into 2-second segments, resampled to 16kHz, and zero-padded where necessary to ensure uniform length. Data augmentation techniques such as pitch shifting, time shifting, and Gaussian noise injection were applied to check the improvement of the model in generalization.
- **Model Training:** The AST model pretrained on AudioSet was fine-tuned using the processed cough and non-cough data. Training experiments were conducted with different batch sizes and early stopping enabled to avoid overfitting. An additional experiment with data augmentation was included to assess its impact. 1D CNN was trained from scratch and the same experiments were performed on the model.
- **Evaluation:** Performance was evaluated using accuracy, precision, recall, and F1-score from classification reports. Confusion matrices were used to visualize the model's ability to distinguish cough from non-cough events.

3.1 Dataset

For this study, cough and non-cough audio samples were sourced from the Coswara and FluSense datasets.

- **Coswara** is a curated, crowdsourced dataset developed to support research in audio-based COVID-19 diagnosis. It contains audio recordings of respiratory sounds including coughs, breathing, and speech, collected from participants worldwide. Each

recording is accompanied by metadata such as age, gender, health status, and symptom details, enabling rich analysis. The dataset is labeled and suitable for training supervised machine learning models, especially in tasks like cough classification or respiratory disease detection. It has been widely used in research for extracting features like MFCCs and training deep learning models including CNNs and transformers.

- **FluSense** is a real-world dataset collected from hospital waiting areas using a custom-built edge-computing platform to monitor influenza-like illness symptoms. It includes time-stamped audio events such as coughs and speech, along with environmental and crowd metadata. While the dataset protects privacy by not storing intelligible speech, it provides detailed labels and annotations useful for supervised learning. FluSense has been instrumental in developing models for passive health monitoring and disease surveillance. Its structure supports training of deep learning architectures like 1D CNNs and audio transformers for cough detection tasks.

The number of samples from each dataset is given in table 1. From the Coswara dataset, cough sounds were directly used, while non-cough samples were selected from categories such as speech, breathing, counting, and sentence reading. In the case of the FluSense dataset, cough sounds were again used as-is, whereas non-cough samples were derived from segments labeled as silence and speech.

Table 1: Class distribution in Coswara and FluSense datasets

Class	**Coswara**	**FluSense**
Cough	2313	2481
Non-Cough	1488	3435

3.2 Data Preprocessing

Data preprocessing is a crucial step in training any model, as it ensures that the input data is consistent and structured, preventing confusion during learning. The following preprocessing steps were applied in this project to standardize the audio data.

- Converted all audio recordings to mono-channel format to ensure consistency across samples and reduce computational complexity.
- Split long audio recordings into 2-second segments to standardize input length for fixed-size model inputs.
- Resampled all audio clips to a 16kHz sampling rate to match the expected input format of pretrained models and reduce data size.
- Applied zero-padding to audio clips shorter than 2 seconds to maintain uniform input dimensions required for batch processing.

The final dataset count of audio clips is shown in 2,after resampling, mono conversion , and segmentation into 2-second durations for uniformity.

Class	Count
Cough	4,793
Non-Cough	4,923
Total	**9,716**

Table 2: Final dataset distribution after preprocessing

3.3 Model Architecture

3.3.1 Hugging Face AST Architecture

Figure 2: AST Model Training Pipeline

The flowchart illustrates the step-by-step pipeline used for training an audio classification model using the AST (Audio Spectrogram Transformer). The process begins with loading the audio dataset, followed by splitting it into training, validation, and test sets to enable proper model development and evaluation. The AST feature extractor is then loaded to

transform raw audio into a format suitable for the AST model.The AST feature extractor processes raw audio waveforms and prepares them for input into the Audio Spectrogram Transformer (AST) model. It converts the audio into log-Mel spectrogram features, which represent the frequency content of the sound over time. A log-Mel spectrogram is a visual representation of sound that shows how the energy of different frequency bands changes over time, using a scale that mimics human hearing. It is created by converting audio into short chunks, applying a Mel filter to capture key frequencies, and then using a logarithmic scale to highlight important patterns for the model to learn.Additionally, it performs normalization to standardize the input values, improving model stability and learning. The extractor also handles resampling to a consistent sampling rate (e.g., 16 kHz), ensuring uniformity across all audio samples. This preprocessing step is essential for aligning the input format with what the AST model expects during training and inference. Preprocessing of the audio data includes tasks like mono conversion, resampling, splitting into 2-second clips, and zero-padding. After preprocessing, the audio data is converted into a PyTorch-compatible format to be used for model training.

Once the data is ready, a pretrained AST model is loaded, and evaluation metrics such as accuracy or F1-score are defined to monitor performance. Training arguments are configured, including the use of early stopping to prevent overfitting by halting training when performance stops improving. The model is then trained using the training set while being validated against the validation set. Finally, the trained model is evaluated on the test set, and the results are analyzed using a confusion matrix and a summary report to assess the effectiveness of the classification task.

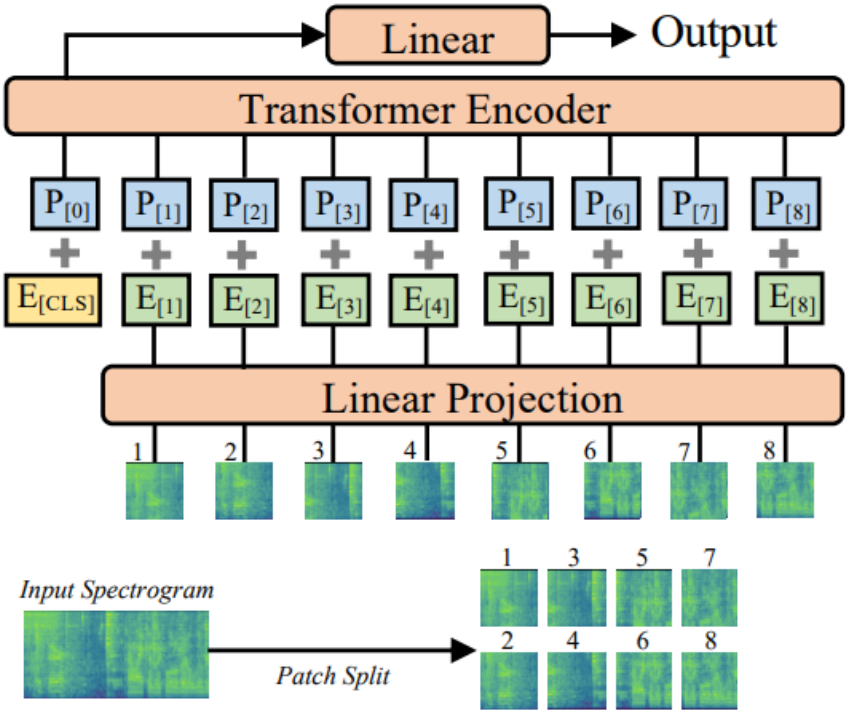


Figure 3: Architecture of Audio Spectrogram Transformer (AST) [11]

The Hugging Face Audio Spectrogram Transformer (AST) is a state-of-the-art model designed for audio classification tasks, built on the Vision Transformer (ViT) architecture. Unlike traditional audio models that operate directly on waveforms or use convolutional layers, AST processes 2D spectrogram representations of audio—typically log-Mel spectrograms—much like how ViT handles image patches. The model divides the spectrogram into fixed-size patches, embeds them, and feeds them into a Transformer encoder that captures long-range dependencies across time and frequency dimensions. AST is particularly effective in tasks such as sound event detection, acoustic scene classification, and speech-based emotion recognition due to its ability to model global context in audio signals.

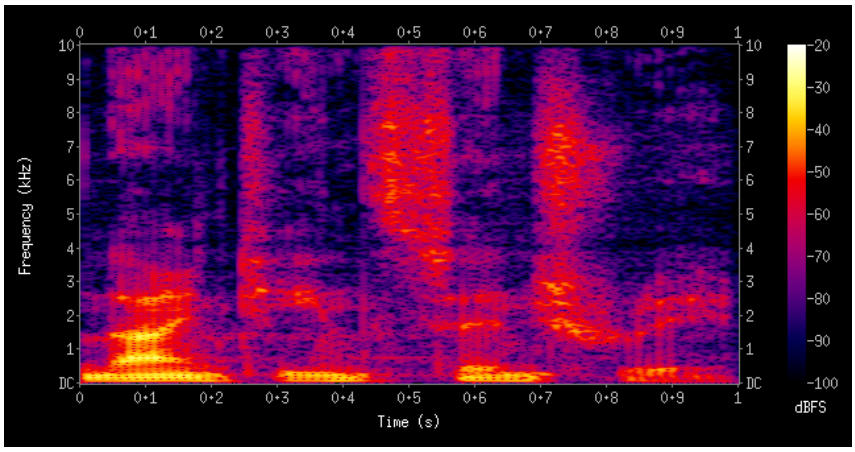


Figure 4: Spectrogram of an audio signal showing time-frequency representation in dBFS

Hugging Face provides a pretrained version of AST through the transformers library, allowing researchers and developers to fine-tune it on their own datasets with minimal setup. The model can be loaded with a few lines of code, using ASTForAudioClassification along with ASTFeatureExtractor to handle input preprocessing. Its compatibility with Hugging Face's Trainer API enables efficient training, evaluation, and integration of features like early stopping and metric tracking. By leveraging the pretrained weights learned on large-scale audio datasets such as AudioSet, users can achieve high accuracy even with limited labeled data. Overall, Hugging Face AST simplifies the process of deploying powerful audio classification models in real-world applications.

```
ASTForAudioClassification(
  (audio_spectrogram_transformer): ASTModel(
    (embeddings): ASTEmbeddings(
      (patch_embeddings): ASTPatchEmbeddings(
        (projection): Conv2d(1, 768, kernel_size=(16, 16), stride=(10, 10))
      )
      (dropout): Dropout(p=0.0, inplace=False)
    )
    (encoder): ASTEncoder(
      (layer): ModuleList(
        (0-11): 12 x ASTLayer(
          (attention): ASTAttention(
            (attention): ASTSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
            )
            (output): ASTSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.0, inplace=False)
            )
          )
          (intermediate): ASTIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): ASTOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (dropout): Dropout(p=0.0, inplace=False)
          )
          (layernorm_before): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (layernorm_after): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
        )
      )
    )
    (layernorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
  )
  (classifier): ASTMLPHead(
    (layernorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
    (dense): Linear(in_features=768, out_features=2, bias=True)
  )
)
```

Figure 5: AST model architecture summary as printed in PyTorch

The AST model follows a transformer-based structure tailored for audio classification tasks as shown in figures **??**, . Its components are described as follows:

- **Patch Embeddings:** The input spectrogram is divided into smaller patches using a 2D convolutional layer. These patches serve as tokens, similar to words in NLP transformers.
- **Transformer Encoder:** The core of the model contains 12 stacked transformer layers, each comprising:
  - Self-Attention: This mechanism allows the model to focus on the most relevant time-frequency regions of the audio signal.
  - Intermediate Feedforward Layer: Applies a linear transformation followed by a GELU activation function to capture complex representations.
  - Layer Normalization and Residual Connections: These components ensure stable training and help retain learned information across layers.

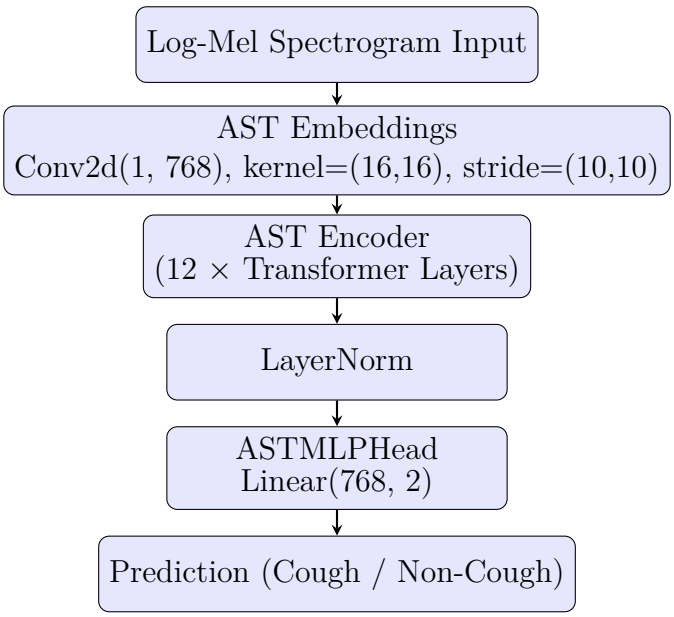


Figure 6: AST Model Architecture Flow

- **Classifier Head:** The output from the encoder is passed through a layer normalization layer and a fully connected linear layer. This maps the high-level features to class probabilities, such as distinguishing between cough and non-cough audio segments.

3.3.2 1D CNN

One dimensional Convolutional Neural Network is a type of convolutional neural network that is implemented for one dimensional data. This is normally used for sequential or temporal data like text, audio signal and time series. As the type of dataset used in this study is belongs to audio data, this model is well suited for training. Audio signals represents amplitude variations over time and they are naturally one dimensional [12].

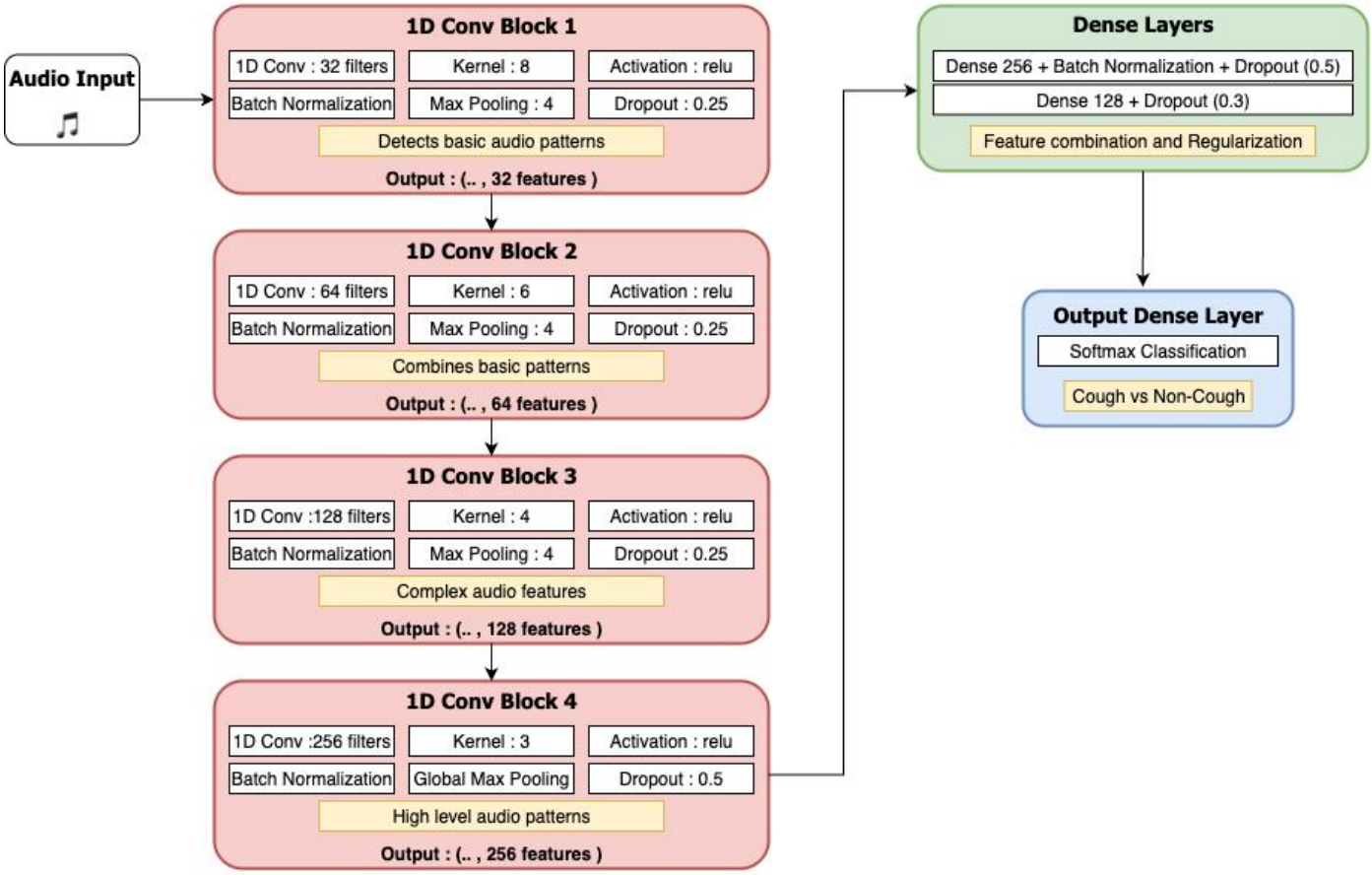


Figure 7: 1D CNN Architecture

In this study, zip folder of preprocessed datasets that contains train data, test data and validation data 8 was stored in Google drive and used Google Colab to implement 1D CNN architecture a binary classification to detect cough or non cough. The audio dataset is labeled as cough and non cough and by using librosa library it converts the audio files into NumPy arrays which is time domain waveform. Then the string labels ('cough','non cough') are converted into vectors using one hot encoding in order to reshape the waveform of data that is compatible with 1D CNN.

```
Files extracted successfully!
📁 Output directory created/verified: /content/drive/MyDrive/ML_Project8/
Loading preprocessed data...
Found 3711 cough files in train
Found 4043 non_cough files in train
train set: 7754 samples
Found 494 cough files in val
Found 409 non_cough files in val
val set: 903 samples
Found 588 cough files in test
Found 471 non_cough files in test
test set: 1059 samples

Preparing data...
Classes: ['cough' 'non_cough']
train - X shape: (7754, 32000, 1), y shape: (7754, 2)
val - X shape: (903, 32000, 1), y shape: (903, 2)
test - X shape: (1059, 32000, 1), y shape: (1059, 2)
```

Figure 8: Files Extraction

In the implementation of 1D CNN, four blocks of convolutional layers **??** are used

initially. Each layer uses filters and detect the audio signal patterns. When defining the convolution block number of filters, kernal size and the activation function. Kernal size refers to number of consecutive samples which the filter uses at one time.

```
model = models.Sequential([
    # First Conv Block
    layers.Conv1D(32, kernel_size=8, activation='relu', input_shape=input_shape),
    layers.BatchNormalization(),
    layers.Conv1D(32, kernel_size=8, activation='relu'),
    layers.MaxPooling1D(pool_size=4),
    layers.Dropout(0.25),

    # Second Conv Block
    layers.Conv1D(64, kernel_size=6, activation='relu'),
    layers.BatchNormalization(),
    layers.Conv1D(64, kernel_size=6, activation='relu'),
    layers.MaxPooling1D(pool_size=4),
    layers.Dropout(0.25),

    # Third Conv Block
    layers.Conv1D(128, kernel_size=4, activation='relu'),
    layers.BatchNormalization(),
    layers.Conv1D(128, kernel_size=4, activation='relu'),
    layers.MaxPooling1D(pool_size=4),
    layers.Dropout(0.25),

    # Fourth Conv Block
    layers.Conv1D(256, kernel_size=3, activation='relu'),
    layers.BatchNormalization(),
    layers.GlobalMaxPooling1D(),
    layers.Dropout(0.5),
```

Figure 9: 4 blocks of 1D CNN

The first block uses 32 filters with kernal size of 8 and activation function named relu. This block tries to identify the basic pattern such as sudden increases in the amplitude which can be happened in the start of the cough. Then batch normalization is used to prevent the spread out and to make sure the activations are scaled and centered. As this technique reduces the changes of distribution of inputs to layers, it allows the training to get speed up. The output after processing batch normalization is inserted into next layer with same filter size, kernal size and activation function. This second layer is responsible for building the pattern learned from the previous layer. 1D MaxPooling is used to decrease size of the output by getting the maximum value from each four step window. This helps the model more resilient and faster to small time shifts by reducing the size of output by getting the maximum value from each 4 step window. Next dropout technique is used to randomly drop neurons by 25% to prevent overfitting.

The second block seems to be more similar to the first one but it goes more deeper as it uses 64 filters with kernel size of 6 and same relu activation function. At this stage, the network can capture features with more longer time. This includes features such as regular patterns of coughing or silences in between sound. Again batch normalization, max pooling and dropout methods are used with same values to continue the stable structure with same downsampling and regularization.

Third block of 1D CNN has doubled the size of filters(128) with same kernel size(4) of second block. Batch normalization, max pooling and dropout techniques are also same as the previous one. This assist the model to learn time patterns and frequency patterns with high precision. Bat This may include cough signal substructures such as rasps, mul-

tiple cough or breaths happen in between cough. At this stage, this model can recognize more complex sound features as the block has increased the depth and capacity.

In the fourth 1D CNN block, it has increased the number of filters into 256 and reduce the kernel size into 3 with same relu activation function which helps to capture high level features. Then batch normalization technique is used. Here, global max pooling technique is used instead of max pooling. Applying global max pooling in the last block is important because it identifies the strongest signal in the entire audio. Normally cough has one main peak and this method assists to know the strength of that peak part.

After the four blocks of 1D CNN, two dense layers 10 with relu activation function have used to help the final decision of classification. The fist dense layer uses 256 neurons to grab the pooled features and learn complex combinations. Then batch normalization and dropout technique with 0.5 value are used. The second dense layer uses 128 neurons and acts as a bottleneck layer that compresses learned patterns which gives more efficient input to the output layer. Dropout is done after second dense layer as well with 0.3 value to ensure the generalization during inference. Finally the output dense layer consists of number of classes which is two and the softmax activation function which turns the output into probability in both classes.

```
    # Dense layers
    layers.Dense(256, activation='relu'),
    layers.BatchNormalization(),
    layers.Dropout(0.5),

    layers.Dense(128, activation='relu'),
    layers.Dropout(0.3),

    # Output layer
    layers.Dense(num_classes, activation='softmax')
```

Figure 10: Dense layers

During the model compilation, Adam (Adaptive Moment Estimation) optimizer is used with a learning rate of 0.001. Adam optimizer is well suited for deep learning models as it helps to learn in the right direction and perform a good generalization. In this case, though the audio signals behave in a complex way with noise, Adam optimizer can capture different patterns in the signal properly. Categorical crossentropy is used as the loss function which is more suitable for classification and one hot encoded. This calculates the difference between the prediction and the correct label. The metrics that considered during training and validation is accuracy which is the percentage of correct predictions over time.

```
# Compile model
self.model.compile(
    optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

Figure 11: Compiling the model

3.4 Evaluation

Each experiment was evaluated using precision, recall, F1-score, accuracy, Training Loss, and Validation Loss metrics.

Accuracy: Accuracy measures the proportion of correctly predicted instances over the total number of predictions. It provides a general sense of model correctness.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision: Precision is the ratio of correctly predicted positive observations to the total predicted positives. It answers the question: "Of all instances labeled as positive, how many were actually positive?"

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall: Recall (also called Sensitivity or True Positive Rate) is the ratio of correctly predicted positive observations to all actual positives. It answers: "Of all actual positive instances, how many did the model capture?"

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1-Score: The F1-Score is the harmonic mean of Precision and Recall. It provides a single score that balances both concerns, especially useful in imbalanced datasets.

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2TP}{2TP + FP + FN} \tag{4}$$

Training Loss: Training loss represents the average error between predicted outputs and actual labels across the training data. It helps monitor how well the model is learning from the data.

$$\text{Training Loss} = \frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \mathcal{L}(y_i, \hat{y}_i) \tag{5}$$

Validation Loss: Validation loss measures the model's error on a separate validation set not seen during training. It is used to assess generalization performance and detect overfitting.

$$\text{Validation Loss} = \frac{1}{N_{\text{val}}} \sum_{i=1}^{N_{\text{val}}} \mathcal{L}(y_i, \hat{y}_i) \tag{6}$$

4. Results and Experiments

4.1 Results and Experiments on AST + Optimization

To evaluate the performance of the Hugging Fae Audio Spectrogram Transformer (AST) model on cough detection, we conducted three separate training experiments, each varying in batch size while keeping all other parameters constant. The experiments used a fine-tuned AST model from Hugging Face pretrained on AudioSet, and included early stopping, fixed learning rate, and identical data splits (80% training, 10% validation, 10% test).

The key variable across the experiments was the batch size:

- **Experiment 1:** Batch size = 8
- **Experiment 2:** Batch size = 16
- **Experiment 3:** Batch size = 32

All three experiments showed successful convergence within the 5-epoch limit, with early stopping triggered in some cases. As expected, increasing the batch size led to faster training per epoch, but potentially reduced generalization. Experiment 3 (batch size 32) provided the best trade-off between training time and model accuracy, achieving a balanced performance in terms of precision, recall, and F1-score.

We attempted to train the model with a batch size of 64; however, it resulted in a CUDA out-of-memory error, despite utilizing a 40GB GPU. This highlights that deep architectures like AST consume significantly more memory as the batch size increases, limiting scalability on resource-constrained hardware.The AST model needs a lot of memory because it looks at every part of the audio at once, which takes up space. When we use a bigger batch size, it tries to handle more data at the same time, so it quickly runs out of memory.

To further improve model robustness, an additional experiment was conducted using audio data augmentation. This included applying random time shifting, pitch shifting, and Gaussian noise to each sample, effectively doubling the dataset size. The AST model was then fine-tuned for 10 epochs using a batch size of 8. The augmented setup improved generalization, resulting in higher F1-scores and reduced confusion between cough and sneeze classes, as shown in the updated confusion matrix.

Below is a comparison summary of training settings and their respective implications:

Parameter	Value	Observation
Batch Size	8	Higher update frequency, potential overfitting
	16	Balanced performance and training speed
	32	Faster training, possible underfitting
Data Augmentation	Yes	Improved generalization and accuracy
Epochs	5 (Baseline), 10 (Augmented)	Fixed/extended training periods
Eval Strategy	steps / epoch	Used to monitor and save best model
Early Stopping	Enabled (baseline)	Prevents overfitting

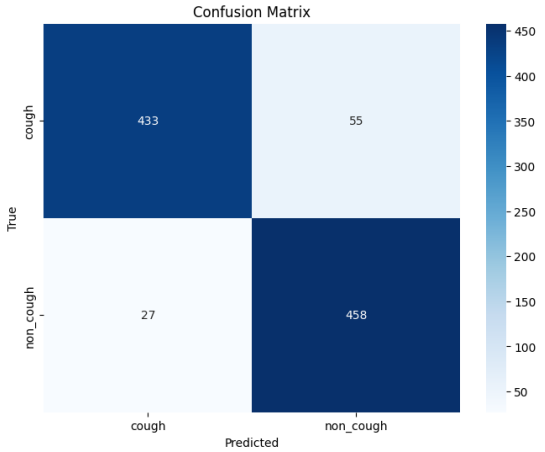
Table 3: Comparison of AST experiments with and without optimization

Table 4: Detailed Performance Comparison Across Batch Sizes and Augmentation

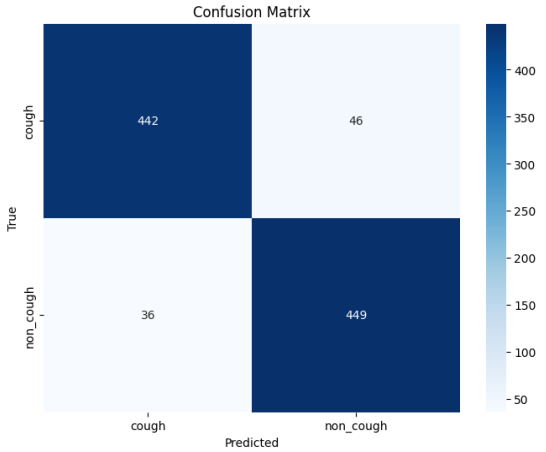
Experiment	Cough F1	Non-Cough F1	Macro Avg F1	Accuracy
Batch Size = 8	0.91	0.92	0.915	0.92
Batch Size = 16	0.92	0.92	0.92	0.92
Batch Size = 32	**0.93**	**0.93**	**0.93**	**0.93**
With Augmentation	0.896	0.896	0.896	0.90

Without data augmentation, the AST model achieved slightly higher accuracy and F1-score (approximately 93%) in fewer training steps, indicating faster convergence when trained on cleaner, unaltered data. However, such performance may not generalize effectively to real-world conditions where audio inputs are subject to noise, speaker variability, and different recording environments.

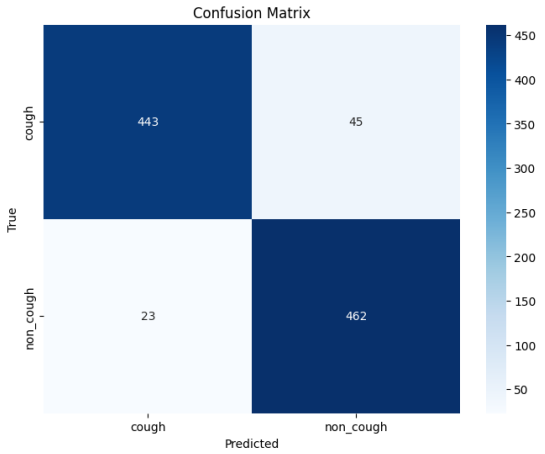
In contrast, the model trained with augmented data exhibited a slightly lower peak F1-score (approximately 89.6%) but demonstrated more stable learning across additional epochs. This training strategy reduces the risk of overfitting and enhances the model's robustness against pitch shifts, background noise, and diverse cough characteristics.



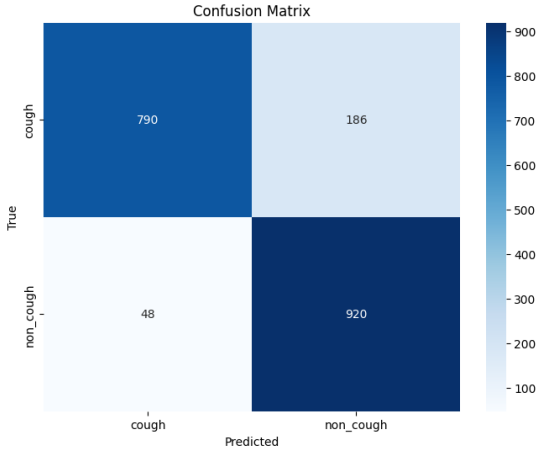
(a) Confusion Matrix (Batch Size = 8)



(b) Confusion Matrix (Batch Size = 16)



(c) Confusion Matrix (Batch Size = 32)



(d) Confusion Matrix (With Augmentation)

Figure 12: Confusion matrices for AST model under different training settings

4.2 Results and Experiments on 1D CNN

The initial model is trained for 100 epochs with the calculation of training accuracy, training loss, validation accuracy and validation loss in each epochs. Here, early stopping technique with a patience of 5 is used to prevent the overfitting of the model. In this case, as there is no improvement in the validation accuracy up to 5 epochs from 9th epoch, training is stopped at the 14th epoch. So the best model was obtained from 9th epoch with a test accuracy of 84.04% which is good performance. The classification report of the first attempt shows that the model is working somewhat better in identifying coughs with a precision of 90% and recall of 80%. For non-coughs audios, the precision is 78% and recall is 89%, that shows the model has successfully detected the non-cough audios as well. When considering F1 score for cough and non-cough, it is 0.85% and 0.83% respectively which depicts the balance of the model performance. As the macro and weighted averages are high and both values are close to each other, the model performs fairly for each class.

```
Test Loss: 0.4221
Test Accuracy: 0.8404

Classification Report:
              precision    recall  f1-score   support

       cough       0.90      0.80      0.85       588
   non_cough       0.78      0.89      0.83       471

    accuracy                           0.84      1059
   macro avg       0.84      0.85      0.84      1059
weighted avg       0.85      0.84      0.84      1059
```

Figure 13: Classification report - Base model

The performance of the model with respect to the test dataset is shown in the confusion matrix. The total number of actual cough samples was 588, and 471 were correctly predicted as cough(true positive) while 419 were detected as non-cough(true negative). There are 52 samples that are actually non-cough and miss classified as cough and there are 117 samples that are actually cough and miss classified as non cough. But the majority of the samples are correctly detected and the balance between the true positives and true negatives indicates the reliable classification of cough and non cough.

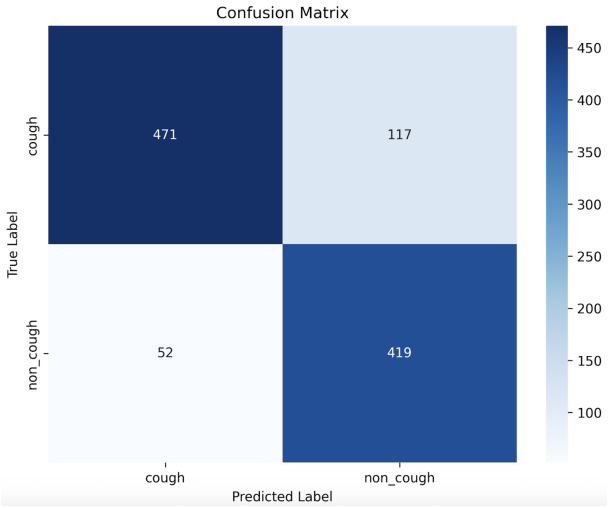


Figure 14: Confusion Matrix - Base model

The below graphs 15 shows the training and validation curves with respect to the accuracy and loss of the model. In the model accuracy graph, the training accuracy gradually increases over epochs and reached more than 85%. The validation accuracy shows a similar trends such that peaking in between 8th and 10th epochs in the same graph. The fluctuations showing after this can be a sign potential overfitting as the model continues to train. In the graph of model loss, the training loss decreases continuously, but the validation loss drops after initial few epochs and starts to going up after 10th epoch. This fluctuation also shows that the model starts to memorize the data. Due to early stopping technique, overfitting of model is controlled and gave the best model.

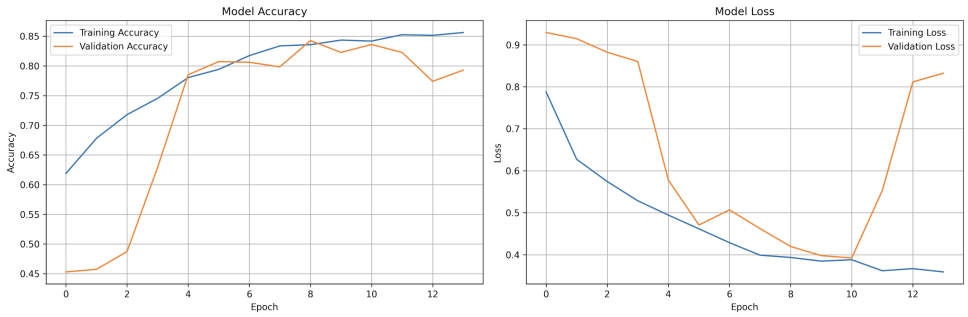


Figure 15: Model Accuracy and Loss - Base model

For the model optimization there are few changes done and observations are as below.

Experiment 1

In here, the early stopping was set to 5,batch size 32 and 100 epochs. There are three type of data augmentation methods to develop the performance of the model. Initially, time shift technique was given such that the audio data signal going forward and backward by random samples. Other method is pitch is shifting by using librosa library. In here it is increasing and decreasing pitch. Next change is adding Gaussian noise to data that assist the model to behave more tolerant to back ground.

Parameter	**Value**	**Observation**
Data Augmentation	Time shift Pitch shift Noise Addition	Improved generalization and accuracy = 86%

Table 5: 1D CNN model optimization with data augmentation

As per the observations, the test accuracy has increased into 86% with good generalization.

```
Test Loss: 0.3416
Test Accuracy: 0.8650

Classification Report:
              precision    recall  f1-score   support

       cough       0.92      0.83      0.87       588
   non_cough       0.81      0.90      0.86       471

    accuracy                           0.86      1059
   macro avg       0.86      0.87      0.86      1059
weighted avg       0.87      0.86      0.87      1059
```

Figure 16: Classification report - Data Augmentation

Experiment 2

In here, the early stopping was increased 5 to 10 epochs for the same batch size 32 and 100 epochs. The data augmentation part is removed in this phase.

Parameter	Value	Observation
Early Stopping	Patience = 10	Improved the accuracy = 87%

Table 6: 1D CNN model optimization by changing patience of early stopping

After increasing the patience in early stopping to 10, the test accuracy has increased into 87%.

```
Test Loss: 0.3178
Test Accuracy: 0.8744

Classification Report:
              precision    recall  f1-score   support

       cough       0.93      0.83      0.88       588
   non_cough       0.82      0.93      0.87       471

    accuracy                           0.87      1059
   macro avg       0.88      0.88      0.87      1059
weighted avg       0.88      0.87      0.87      1059
```

Figure 17: Classification report after changing early stopping

Experiment 3

In here, the early stopping was increased 5 to 15, with same batch batch size 32 and 100 epochs. No data augmentation part is done in this phase.

Parameter	Value	Observation
Early Stopping	Patience = 15	Improved the accuracy = 89%

Table 7: 1D CNN model optimization by increasing patience of early stopping

After increasing the patience in early stopping up to 15, the test accuracy has increased into 89%.

```
Test Loss: 0.4089
Test Accuracy: 0.8867

Classification Report:
              precision    recall  f1-score   support

       cough       0.94      0.85      0.89       588
   non_cough       0.83      0.94      0.88       471

    accuracy                           0.89      1059
   macro avg       0.89      0.89      0.89      1059
weighted avg       0.89      0.89      0.89      1059
```

Figure 18: Classification report after increasing early stopping for the second time

Experiment 4

At this time, the type of optimizer changes without performing data augmentation. The batch batch size was 32 and 100 epochs was given. The existing one was the adam

optimizer with leraining rate of 0.001. So this was change to RMSprop with 0.0005 learning rate. No data augmentation part is done in this phase.

Parameter	**Value**	**Observation**
Optimizer	RMSprop learning rate= 0.0005	No improvement, accuracy = 88%

Table 8: 1D CNN model optimization by changing the optimizer

After changing the optimizer, the accuracy was given as 88%, showing no improvement in the model.

```
Test Loss: 0.2897
Test Accuracy: 0.8839

Classification Report:
              precision    recall  f1-score   support

       cough       0.95      0.84      0.89       588
   non_cough       0.82      0.94      0.88       471

    accuracy                           0.88      1059
   macro avg       0.89      0.89      0.88      1059
weighted avg       0.89      0.88      0.88      1059
```

Figure 19: Classification report- RMSprop optimizer

Experiment 5

Here, the batch size was chnaged. Initially it was 32 and it was giving 243 batches. Then batch size increased to 50 and it gave 156 batches per epoch. No data augmentation part is done in this phase. The optimizer used here is RMSprop with 0.0005

Parameter	**Value**	**Observation**
Batch size	Batch size= 50	No improvement , accuracy = 88%

Table 9: 1D CNN model optimization by increasing the batch size

After increasing the batch size up to 50, the test accuracy was shown as 88%.

```
Test Loss: 0.3121
Test Accuracy: 0.8763

Classification Report:
              precision    recall  f1-score   support

       cough       0.95      0.82      0.88       588
   non_cough       0.81      0.95      0.87       471

    accuracy                           0.88      1059
   macro avg       0.88      0.88      0.88      1059
weighted avg       0.89      0.88      0.88      1059
```

Figure 20: Classification report after increasing batch size

Experiment 6

In this case the batch size was brought back to 32 and early stopping was set to 15 for 100 epochs. No data augmentation part is done in this phase and the optimizer used here is adam optimizer with 0.001. Initially the 1D CNN layers were using small values of kernels inside the 4 1D CNN block as 8,6,4,3. At this time the values are increase up to 15,11,7,5.

Parameter	Value	Observation
Kernels	15,11,7,5	Improved the accuracy = 90%

Table 10: 1D CNN model optimization by increasing the batch size

After increasing the values of kernels, the accuracy was increased up to 90 and this is an good improvement in the model%.

```
Test Loss: 0.2420
Test Accuracy: 0.8980

Classification Report:
              precision    recall  f1-score   support

       cough       0.95      0.86      0.90       588
   non_cough       0.85      0.94      0.89       471

    accuracy                           0.90      1059
   macro avg       0.90      0.90      0.90      1059
weighted avg       0.90      0.90      0.90      1059
```

Figure 21: Classification report after increasing kernel sizes

Experiment 7

In this case another 1D CNN block was added with 512 filters. No data augmentation part is done and adam optimizer is usded with 0.001. The batch size was 32 and early stopping was set to 15 for 100 epochs. The values of kernels were 15,11,7,5.

```
# Fifth Conv Block (NEW)
layers.Conv1D(512, kernel_size=3, activation='relu'),
layers.BatchNormalization(),
layers.GlobalMaxPooling1D(),
layers.Dropout(0.5),
```

Figure 22: 5th 1D CNN block

Parameter	Value	Observation
5th 1D CNN block	512 filters Kernel size = 5 Dropout = 0.5	No improvement and accuracy = 89%

Table 11: 1D CNN model optimization by increasing another 1D CNN block

After adding another block of 1D CNN, there was no much progress in the model. The accuracy was reduced from the previous attempt to 89%.

```
Test Loss: 0.3513
Test Accuracy: 0.8867

Classification Report:
              precision    recall  f1-score   support

       cough       0.92      0.87      0.90       588
   non_cough       0.85      0.91      0.88       471

    accuracy                           0.89      1059
   macro avg       0.88      0.89      0.89      1059
weighted avg       0.89      0.89      0.89      1059
```

Figure 23: Classification report after adding 1D CNN block

Best Model

The highest accuracy was given in the experiment 6 by changing the kernel sizes. The classification report 21 of this experiment proves that this model is well balanced and there is no major bias. The confusion matrix of this experiment shows that there are 507 cough samples and 444 non cough samples correctly classified. Only 81 cough samples and 27 non cough samples were miss classified. This shows that the false negatives are bit higher number and still it is in the acceptable limits.

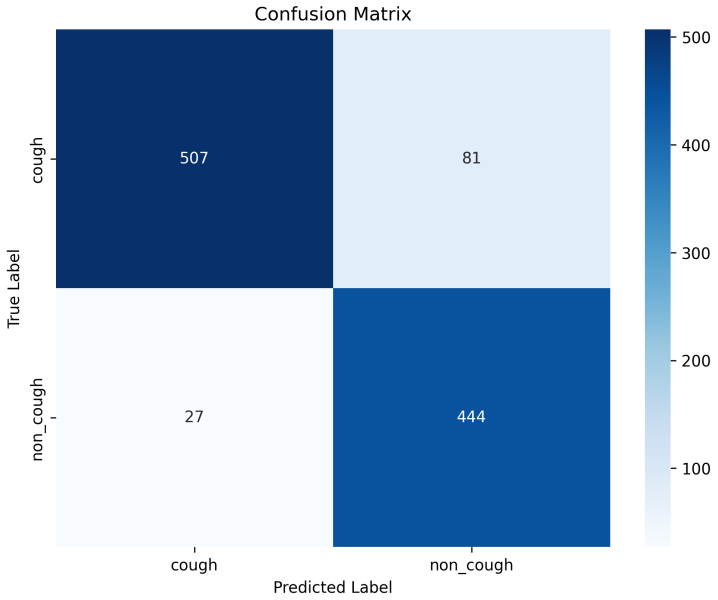


Figure 24: Confusion matrix of Experiment 6

The training history of this experiment shows the graph of model accuracy and model loss. Training accuracy and validation accuracy gradually increase and converge around the value of 90% without diverging and this is a good sign of generalization of the model. Although there are some fluctuations in the Validation loss line, this can be considered as normal. As the lines of both graphs keep going closer to each other, there is no

signs of overfitting. This model can be considered as a well balanced model with good performance.

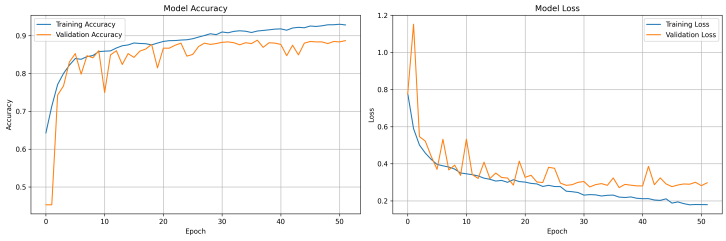


Figure 25: Training history Experiment 6

4.3 Comparison between AST and ID CNN

The Audio Spectrogram Transformer (AST) and 1D Convolutional Neural Network (1D CNN) are two distinct deep learning architectures employed in this project for classifying cough and non-cough sounds. AST, based on the transformer framework, processes log-Mel spectrograms using self-attention mechanisms, enabling it to capture long-range dependencies and complex patterns in time-frequency representations. In contrast, the 1D CNN model directly processes raw or preprocessed audio waveforms using hierarchical convolutional layers to extract local features.

In terms of performance, the AST model demonstrated slightly better generalization capabilities due to its attention-based architecture, especially when trained with augmentation. However, the 1D CNN model was significantly lighter and required less GPU memory, making it more suitable for deployment on edge devices. The AST model also showed higher memory consumption, making larger batch sizes infeasible even on high-end GPUs.

Metric	**AST**	**1D CNN**
Accuracy	0.93	0.90
Precision	0.93	0.90
Recall	0.93	0.90
F1-score	0.93	0.90

Table 12: Performance Comparison Between AST and 1D CNN Models

5. Conclusions

This report explored and compared two deep learning models,AST and 1D CNN,for classifying cough versus non-cough audio events. The AST model, with its transformer-based design, effectively captured complex patterns in spectrograms, achieving high accuracy, particularly with larger batch sizes and data augmentation. However, it demanded more computational resources.

On the other hand, the 1D CNN model provided a lightweight yet effective alternative, offering competitive performance while being more memory-efficient. Data preprocessing

steps, such as resampling, mono conversion, and segmentation into uniform clips, played a critical role in model performance and generalization.

Overall, both models demonstrated their applicability in health sound classification, with trade-offs between accuracy and computational efficiency. Future work could explore hybrid models, further augmentation techniques, or real-time deployment strategies for edge environments

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