A Project Report on

Airborne Diseases Detection Using Cough Sound

In Partial Fulfillment of The Requirements

For The Award of Degree of

BACHELOR OF ENGINEERING
In
Computer Science and Engineering

SUBMITTED BY

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SUBMITTED TO

Department of Computer Science & Engineering

(Accredited by NBA)

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CANDIDATE'S DECLARATION

We, **Gautam Kumar(2021A1R032),Sachit Sharma(2021A1R034),Reetikesh Bali (2021A1R048),** hereby declare that the work which is being presented in the seminar report entitled, "**Airborne Diseases Detection Using Cough Sounds**" in the partial fulfillment of requirement for the award of degree of B.E. (CSE) and submitted in the Department name, Model Institute of Engineering and Technology (Autonomous), Jammu is an authentic record of my own work carried by me under the supervision of **Dr. Surbhi Gupta** (Assistant Professor, MIET).The matter presented in this seminar report has not been submitted in this or any other University / Institute for the award of B.E. Degree.

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CERTIFICATE

Certified that this seminar report entitled **"Airborne Diseases Detection Using Cough Sounds"** is the bonafide work of

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of 6th Semester, CSE, Model Institute of Engineering and Technology (Autonomous), Jammu", who carried out this project work under my supervision during May,2024.

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ABSTRACT

In recent years, the detection of airborne diseases has become increasingly critical, particularly in light of global health challenges. Airborne diseases, spread through respiratory droplets, pose significant risks and require timely and accurate detection methods to prevent widespread outbreaks. Traditional diagnostic methods, while effective, often involve invasive procedures and delays in obtaining results. Therefore, there is a pressing need for innovative, non-invasive diagnostic tools that can rapidly and accurately identify these diseases.

This project explores the use of cough sounds as a diagnostic tool for airborne disease detection. The premise is based on the understanding that different respiratory conditions produce distinct cough sound patterns, which can be analysed using advanced machine learning techniques. By capturing and analysing these cough sounds, we aim to develop a reliable and efficient method for disease detection that can be used in various settings, including remote and resource-limited areas.

We developed and compared four machine learning models: Support Vector Machine (SVM), Random Forest (RF), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN). Each model was trained on a dataset comprising cough sound recordings from both healthy individuals and those with respiratory conditions. The models were then evaluated based on their accuracy, precision, recall, and F1 score to determine the most effective approach for identifying diseases from cough sounds.

The evaluation process involved rigorous testing and validation to ensure the robustness and reliability of the models. Our findings demonstrate that while each model has its strengths, the Random Forest model outperformed the others in terms of overall accuracy and robustness. The RF's ability to handle high-dimensional data, combined with its ensemble learning approach, resulted in superior performance metrics, suggesting its potential as a reliable tool for airborne disease detection. The results indicate that the RF model can effectively distinguish between healthy and diseased cough sounds, making it a promising solution for non-invasive diagnostics.

In conclusion, this project highlights the potential of using cough sounds for airborne disease detection and underscores the importance of leveraging advanced machine learning techniques in healthcare diagnostics. The success of the Random Forest model opens up new avenues for research and development, aiming to create accessible and efficient diagnostic tools that can significantly impact public health outcomes. Future work will focus on expanding the dataset, improving model accuracy, and exploring the integration of these models into practical diagnostic applications.

Contents

LIST OF TABLES

ABBREVIATIONS USED

AI	Artificial Intelligence
CNN	Convolutional Neural Network
DL	Deep Learning
ML	Machine Learning
RN	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine

Chapter 1: Introduction

1.1 Background Information

The early detection of airborne diseases is crucial for effective treatment and containment, particularly in the context of global health crises such as pandemics. Traditional diagnostic methods, while effective, often require significant resources and time. In recent years, the use of machine learning for medical diagnostics has gained significant attention, offering the potential for rapid and accurate disease detection.

Cough sounds are a key symptom of many respiratory diseases, making them a valuable indicator for diagnostic purposes. Analyzing cough sounds using machine learning can provide a non-invasive, cost-effective, and quick diagnostic tool. This project aims to explore the use of cough sounds for the detection of airborne diseases using various machine learning models.

1.2 Methodology

To achieve the objectives of this project, the following methodology was implemented:

1. **Data Collection:** Cough sound datasets were gathered from public databases and clinical recordings. These datasets were pre-processed to remove noise and irrelevant segments.

2. **Feature Extraction:** Relevant features were extracted from the cough sounds using Mel-frequency cepstral coefficients (MFCCs). MFCCs are widely used in audio signal processing as they capture the power spectrum of the sounds in a way that reflects human auditory perception.

3. **Model Development:**

    - **Support Vector Machine (SVM):** A supervised learning model known for its effectiveness in binary classification problems.

    - **Random Forest (RF):** An ensemble learning method that operates by constructing multiple decision trees during training.

    - **Recurrent Neural Network (RNN):** A neural network particularly suited for sequential data, making it useful for analysing time-series data such as audio signals.

- **Convolutional Neural Network (CNN):** A deep learning model highly effective in image and audio recognition tasks due to its ability to capture spatial and temporal dependencies.

4. **Evaluation Metrics:** The models were evaluated using accuracy, precision, recall, and F1 score to measure their performance comprehensively.

1.3 Outlines of Results and Future Scope

- **Results:** The performance of each model was compared based on the evaluation metrics. Preliminary results indicate that RF outperformed the other models in terms of accuracy and robustness.

- **Future Scope:** Future work will focus on enhancing the models' performance through additional data collection, feature engineering, and the incorporation of more advanced machine learning techniques. Further research may also explore the integration of these models into real-time diagnostic tools.

Chapter 2: Literature Review and Problem Outline

2.1 Current Work Evaluation

The use of cough sounds for disease detection is a relatively new area of research, with various studies exploring its potential. Previous research has demonstrated the feasibility of using audio features extracted from cough sounds to classify respiratory conditions. However, these studies often faced challenges such as limited datasets, variability in cough sounds, and the need for robust feature extraction methods.

Recent advancements in machine learning, particularly deep learning, have shown promise in improving the accuracy and reliability of audio-based diagnostics. Techniques such as MFCCs for feature extraction and the application of deep learning models like CNNs have enhanced the ability to analyze and classify cough sounds.

2.2 Problem Formulation and Objectives

Despite the progress made, several challenges remain in the field of airborne disease detection using cough sounds. These include:

- **Data Variability:** Differences in cough sounds due to factors like age, gender, and recording conditions.
- **Feature Extraction:** Identifying the most relevant features that accurately represent the characteristics of cough sounds.
- **Model Performance:** Ensuring that the models are robust and can generalize well across different datasets.

To address these challenges, this project aims to:

- Develop and compare multiple machine learning models (SVM, RF, RNN, CNN) for the classification of airborne diseases using cough sounds.
- Evaluate the models based on accuracy, precision, recall, and F1 score to determine the most effective approach.
- Provide insights into the strengths and weaknesses of each model and suggest potential improvements for future research.

2.3 Organization of the Seminar Report

The report is organized into several chapters, each focusing on a specific aspect of the project:

- **Chapter 1:** Introduction: Provides background information, outlines the methodology, and summarizes the results and future scope.

- **Chapter 2:** Literature Review and Problem Outline: Evaluates current work, formulates the problem, and outlines the objectives of the project.

- **Chapter 3:** Artificial Intelligence, Machine Learning, and Deep Learning in Airborne Disease Detection: Explores the role and integration of AI, ML, and DL techniques in the context of this project**.**

- **Chapter 4:** Model Development and Implementation: Describes the development and implementation of the SVM, RF, RNN, and CNN models.

- **Chapter 5:** Results and Discussions: Discusses the results in detail, highlighting the strengths and weaknesses of each model.

- **Chapter 6:** Conclusion and Future Scope: Summarizes the findings, presents conclusions, and suggests directions for future research.

- **References:** Lists all the sources cited in the report.

- **Appendices:** Includes supplementary material such as additional data, code snippets, and detailed results.

This organization ensures a comprehensive and coherent presentation of the research, facilitating a clear understanding of the project and its outcomes.

Chapter 3: Artificial Intelligence, Machine Learning, and Deep Learning in Airborne Disease Detection

3.1 Overview of Artificial Intelligence (AI)

Artificial Intelligence (AI) is a broad and dynamic field of computer science that aims to create systems capable of performing tasks that typically require human intelligence. These tasks include learning, reasoning, problem-solving, perception, and language understanding. AI encompasses a wide range of technologies, from simple rule-based systems to complex neural networks.

3.2 AI in Healthcare

AI's impact on healthcare has been transformative, offering tools for enhanced diagnostics, treatment planning, patient monitoring, and personalized medicine. AI systems can analyse vast amounts of data to identify patterns and make predictions, significantly improving the accuracy and efficiency of medical diagnoses. In the context of airborne disease detection, AI can analyze audio signals from coughs to identify potential health issues.

3.3 Machine Learning (ML)

Machine Learning (ML) is a subset of AI that focuses on the development of algorithms that enable computers to learn from and make decisions based on data. ML models build mathematical models based on sample data, known as training data, to make predictions or decisions without being explicitly programmed to perform the task.

3.3.1 Types of Machine Learning

- **Supervised Learning:** Involves training a model on labelled data, where the correct output is provided. The model learns to map inputs to outputs, making it suitable for tasks like classification and regression. In this project, supervised learning models such as Support Vector Machines (SVM) and Random Forest (RF) are employed to classify cough sounds into healthy and unhealthy categories.

- **Unsupervised Learning:** Involves training a model on unlabelled data, allowing the model to identify patterns and relationships within the data. Common unsupervised learning tasks include clustering and association.

- **Reinforcement Learning:** Involves training a model to make a sequence of decisions by rewarding it for correct actions. The model learns to maximize cumulative rewards over time through trial and error.

3.4 Machine Learning Models in Airborne Disease Detection

3.4.1 Support Vector Machine (SVM)

SVM is a powerful supervised learning algorithm used for classification and regression tasks. It works by finding the hyperplane that best separates the data into different classes. SVM is particularly effective in high-dimensional spaces and is robust to overfitting, making it suitable for binary classification problems like distinguishing between healthy and unhealthy cough sounds.

3.4.2 Random Forest (RF)

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. RF is robust to overfitting and provides high accuracy, making it an excellent choice for classifying cough sounds based on extracted audio features.

3.5 Deep Learning (DL)

Deep Learning (DL) is a subset of ML that uses neural networks with many layers (deep networks) to model complex patterns in data. DL algorithms are particularly powerful for tasks such as image and speech recognition, natural language processing, and autonomous driving.

3.5.1 Deep Learning Architectures

- **Recurrent Neural Networks (RNN):** RNNs are designed for sequence prediction problems and are well-suited for analysing time-series data such as audio signals. They can capture temporal dependencies by maintaining a memory of previous inputs. In this project, RNNs are used to analyse the sequence of audio signals in cough sounds.

- **Convolutional Neural Networks (CNN):** CNNs are highly effective for spatial data, such as images or spectrograms of audio signals. They use convolutional layers to detect local patterns, making them ideal for processing transformed representations of cough sounds. In this project, cough sounds are converted to

spectrogram images, which are then analyzed using CNNs to identify patterns indicative of airborne diseases.

3.6 Integration of AI, ML, and DL in This Project

This project integrates AI, ML, and DL techniques to develop a comprehensive approach to airborne disease detection using cough sounds. The workflow includes:

- **Data Collection and Preprocessing:** Collecting cough sounds from both healthy and unhealthy individuals and preprocessing the audio data to extract meaningful features.

- **Model Development and Implementation:** Implementing and training various models, including SVM, RF, RNN, and CNN, to classify the cough sounds based on the extracted features.

- **Performance Evaluation:** Evaluating the models using metrics such as accuracy, precision, recall, and F1-score to determine their effectiveness.

- **Comparison and Analysis:** Comparing the performance of the models to identify the most effective approach for real-world application.

3.7 Summary

The combination of AI, ML, and DL provides a powerful toolkit for developing systems capable of detecting airborne diseases from cough sounds. AI offers the overarching framework for intelligent decision-making, ML provides the algorithms for data-driven predictions, and DL leverages advanced neural networks to model complex patterns in the data. This integrated approach enhances the accuracy and reliability of disease detection, potentially leading to significant advancements in non-invasive medical diagnostics.

Chapter 4: Model Development and Implementation

This chapter details the development and implementation of four machine learning models used for airborne disease detection using cough sounds: Support Vector Machine (SVM), Random Forest (RF), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN). Each model's structure, training process, and implementation are described in detail.

4.1. Support Vector Machine (SVM)

4.1.1. Overview

Support Vector Machines (SVM) are supervised learning models used for classification and regression analysis. SVMs are particularly effective for binary classification problems. They work by finding the hyperplane that best separates the data into different classes.

4.1.2. Implementation

1. **Data Preparation:** Pre-processed cough sound features were split into training and testing sets.

2. **Model Training:** An SVM classifier with a radial basis function (RBF) kernel was trained on the training data.

3. **Evaluation:** The trained model was evaluated on the test set using accuracy, precision, recall, and F1-score.

#code

```
import os

from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score

from sklearn.svm import SVC

import numpy as np


# Define paths to your datasets
```

```
healthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/COPD'

unhealthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/Non COPD'

# Initialize lists to store features and labels

X = []

y = []

import librosa


def extract_features(audio_file_path):

    try:

        # Load the audio file

        y, sr = librosa.load(audio_file_path, sr=None)


        # Extract features (example features: mean and standard deviation of Mel-Frequency Cepstral Coefficients)

        mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40)

        mfccs_mean = mfccs.mean(axis=1)

        mfccs_std = mfccs.std(axis=1)


        # Concatenate the features into a single feature vector

        features = np.concatenate((mfccs_mean, mfccs_std))


        return features

    except Exception as e:

        print(f"Error extracting features from {audio_file_path}: {e}")
```

```
        return None

# Load and process data from the healthy dataset

for file_name in os.listdir('C:/Users/sachi/OneDrive/Desktop/New folder (5)/COPD'):

    if file_name.endswith('.wav'):

        # Extract features from the sound wave file (replace this with your feature extraction code)

        features = extract_features(os.path.join(healthy_data_path, file_name))

        if features is not None:

            X.append(features)

            y.append(0)  # Label for healthy patients

# Load and process data from the unhealthy dataset

for file_name in os.listdir('C:/Users/sachi/OneDrive/Desktop/New folder (5)/Non COPD'):

    if file_name.endswith('.wav'):

        # Extract features from the sound wave file

        features = extract_features(os.path.join(unhealthy_data_path, file_name))

        if features is not None:

            X.append(features)

            y.append(1)  # Label for unhealthy patients

# Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize and train a classifier (example using Support Vector Machine)

classifier = SVC()
```

```
classifier.fit(X_train, y_train)

# Make predictions on the test set

y_pred = classifier.predict(X_test)

# Calculate accuracy

accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)

# Calculate accuracy, precision, recall, and F1-score

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report

accuracy = accuracy_score(y_test, y_pred)

precision = precision_score(y_test, y_pred)

recall = recall_score(y_test, y_pred)

f1 = f1_score(y_test, y_pred, average='macro')

# Print the results

print("Accuracy:", accuracy)

print("Precision:", precision)

print("Recall:", recall)

print("F1-score:", f1)

def predict_patient_status_interactively(classifier):

    try:

        # Get input sound file path from the user

        audio_file_path = input("Enter the path to the audio file: ")


        # Extract features from the audio file
```

```
        features = extract_features(audio_file_path)
        if features is None:
            print(f"Error: Unable to extract features from {audio_file_path}")
            return

        # Make predictions using the trained classifier
        prediction = classifier.predict([features])[0]

        # Convert prediction to human-readable label
        if prediction == 0:
            print("Predicted patient status:The patient is not suffering from COPD")
        elif prediction == 1:
            print("Predicted patient status:The patient is suffering from COPD")
        else:
            print("Unable to predict patient status")
    except Exception as e:
        print(f"Error predicting patient status: {e}")
# Assuming 'classifier' is your trained classifier model
predict_patient_status_interactively(classifier)
```

4.2. Random Forest (RF)

4.2.1. Overview

Random Forest is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes for classification. It is robust to overfitting and provides good accuracy.

4.2.2. Implementation

1. **Data Preparation:** The dataset was split into training and testing sets.
2. **Model Training:** A Random Forest classifier was trained using the training data.
3. **Evaluation:** The model's performance was evaluated using accuracy, precision, recall, and F1-score.

code

```
import os

import numpy as np

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report

import librosa

# Define paths to your datasets

healthy_data_path = 'C:/Users/sachi/Downloads/mini project-1/healthy'

unhealthy_data_path = 'C:/Users/sachi/Downloads/mini project-1/unhealthy'

# Initialize lists to store features and labels

X = []

y = []

def extract_features(audio_file_path):

    try:

        # Load the audio file

        y, sr = librosa.load(audio_file_path, sr=None)
```

```
        # Extract features (example features: mean and standard deviation of Mel-Frequency Cepstral Coefficients)
        mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40)
        mfccs_mean = mfccs.mean(axis=1)
        mfccs_std = mfccs.std(axis=1)

        # Concatenate the features into a single feature vector
        features = np.concatenate((mfccs_mean, mfccs_std))

        return features
    except Exception as e:
        print(f"Error extracting features from {audio_file_path}: {e}")
        return None
# Load and process data from the healthy dataset
for file_name in os.listdir('C:/Users/sachi/Downloads/mini project-1/healthy'):
    if file_name.endswith('.wav'):
        features = extract_features(os.path.join(healthy_data_path, file_name))
        if features is not None:
            X.append(features)
            y.append(0)
# Load and process data from the unhealthy dataset
for file_name in os.listdir('C:/Users/sachi/Downloads/mini project-1/unhealthy'):
    if file_name.endswith('.wav'):
```

```
        features = extract_features(os.path.join(unhealthy_data_path, file_name))
        if features is not None:
            X.append(features)
            y.append(1)
# Initialize the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=46)
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=46)
# Train the classifier
rf_classifier.fit(X_train, y_train)
# Make predictions on the test set
y_pred = rf_classifier.predict(X_test)
# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
# Calculate accuracy, precision, recall, and F1-score
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred, average='macro')
# Print the results
print("Accuracy:", accuracy)
print("Precision:", precision)
```

```
print("Recall:", recall)
print("F1-score:", f1)
def predict_patient_status_interactively(classifier):
    try:
        # Get input sound file path from the user
        audio_file_path = input("Enter the path to the audio file: ")

        # Extract features from the audio file
        features = extract_features(audio_file_path)
        if features is None:
            print(f"Error: Unable to extract features from {audio_file_path}")
            return

        # Make predictions using the trained classifier
        prediction = classifier.predict([features])[0]

        # Convert prediction to human-readable label
        if prediction == 0:
            print("Predicted patient status: The patient is not suffering from COPD")
        elif prediction == 1:
            print("Predicted patient status: The patient is suffering from COPD")
        else:
            print("Unable to predict patient status")
    except Exception as e:
```

print(f"Error predicting patient status: {e}")

 # Example usage:

 # Assuming 'rf_classifier' is your trained Random Forest classifier

predict_patient_status_interactively(rf_classifier)

4.3. Recurrent Neural Network (RNN)

4.3.1. Overview

Recurrent Neural Networks (RNN) are a class of neural networks designed for sequential data. They maintain a memory of previous inputs, making them suitable for tasks such as time-series prediction and audio analysis.

4.3.2. Implementation

1. **Data Preparation:** Cough sound features were prepared and split into training and testing sets.

2. **Model Architecture:** An RNN architecture with LSTM layers was used to capture temporal dependencies in the audio data.

3. **Model Training:** The RNN model was trained on the training data.

4. **Evaluation:** The model's performance was assessed using accuracy, precision, recall, and F1-score.

#code

from keras.models import Sequential

from keras.layers import LSTM, Dense, Dropout

from keras.callbacks import EarlyStopping

from sklearn.metrics import accuracy_score

from sklearn.model_selection import train_test_split

import numpy as np

```
import os
import librosa
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, classification_report
# Function to extract features from audio files
def extract_features(audio_file_path):
    try:
        y, sr = librosa.load(audio_file_path, sr=None)
        mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40)
        # Resize the feature matrix to a fixed size (e.g., 40x173)
        resized_mfccs = np.resize(mfccs, (40, 173))  # You may adjust the size as needed
        return resized_mfccs
    except Exception as e:
        print(f"Error extracting features from {audio_file_path}: {e}")
        return None
# Initialize lists to store features and labels
X = []
y = []
# Process healthy data
healthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/COPD'
for file_name in os.listdir(healthy_data_path):
    if file_name.endswith('.wav'):
        audio_file_path = os.path.join(healthy_data_path, file_name)
        features = extract_features(audio_file_path)
```

```
        if features is not None:
            X.append(features)
            y.append(0)  # Label for healthy patients
# Process unhealthy data
unhealthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/Non COPD'
for file_name in os.listdir(unhealthy_data_path):
    if file_name.endswith('.wav'):
        audio_file_path = os.path.join(unhealthy_data_path, file_name)
        features = extract_features(audio_file_path)
        if features is not None:
            X.append(features)
            y.append(1)  # Label for unhealthy patients
# Convert lists to numpy arrays
X = np.array(X)
y = np.array(y)
# Split the data into training, validation, and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)
# Reshape the input data for compatibility with LSTM layer
# For LSTM, the input shape should be (num_samples, timesteps, input_dim)
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], X_train.shape[2])
X_val = X_val.reshape(X_val.shape[0], X_val.shape[1], X_val.shape[2])
```

```
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], X_test.shape[2])

from tensorflow import keras

# Define the RNN model architecture (replace with your desired architecture if needed)

model = keras.Sequential([

  keras.layers.LSTM(64, return_sequences=True, activation='relu', input_shape=(X_train.shape[1], X_train.shape[2])),

  keras.layers.LSTM(32, activation='relu'),

  keras.layers.Dense(16, activation='relu'),

  keras.layers.Dense(1, activation='sigmoid')  # Output layer for binary classification

])

# Compile the model

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Define early stopping to prevent overfitting

early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the model with validation data

history = model.fit(X_train, y_train, batch_size=32, epochs=20, validation_data=(X_val, y_val), callbacks=[early_stopping])

# Make predictions on the test set

y_pred = (model.predict(X_test) > 0.5).astype(int)  # Thresholding for binary classification

# Evaluate the model on the test set

test_loss, test_acc = model.evaluate(X_test, y_test)

print('Test accuracy:', test_acc)

# Calculate metrics
```

```
accuracy = accuracy_score(y_test, y_pred)

precision = precision_score(y_test, y_pred)

recall = recall_score(y_test, y_pred)

f1 = f1_score(y_test, y_pred, average='macro')  # Macro averaging for imbalanced classes (optional)


# Print the results

print("Accuracy:", accuracy)

print("Precision:", precision)

print("Recall:", recall)

print("F1-score:", f1)


# Additionally, you can get a more detailed classification report

print(classification_report(y_test, y_pred))

def predict_patient_status_interactively(model):

   while True:

      # Prompt the user to enter the path to the audio file

      audio_file_path = input("Enter the path to the audio file (or 'quit' to exit): ")


      # Check if the user wants to quit

      if audio_file_path.lower() == 'quit':

         print("Exiting interactive prediction mode.")

         break
```

```
        try:
            # Extract features from the audio file
            features = extract_features(audio_file_path)

            # Check if features are extracted successfully
            if features is not None:
                # Reshape the features for compatibility with Conv2D layer
                features = features.reshape(1, features.shape[0], features.shape[1], 1)

                # Make prediction using the CNN model
                prediction = model.predict(features)

                # Convert prediction to human-readable label
                if prediction >= 0.5:
                    print("Predicted status: Unhealthy")
                else:
                    print("Predicted status: Healthy")
            else:
                print("Unable to extract features from the audio file.")
        except Exception as e:
            print(f"Error predicting patient status: {e}")
# Example usage:
# Assuming 'model' is your trained CNN model
predict_patient_status_interactively(model)
```

4.4. Convolutional Neural Network (CNN)

4.4.1. Overview

Convolutional Neural Networks (CNN) are deep learning models that excel in tasks involving spatial or temporal hierarchies. They are effective for audio analysis due to their ability to capture local patterns and features.

4.4.2. Implementation

1. **Data Preparation:** The cough sound features were transformed into spectrogram images, which were then split into training and testing sets.

2. **Model Architecture:** A CNN architecture with convolutional and pooling layers was designed to process the spectrogram images.

3. **Model Training:** The CNN model was trained on the training data.

4. **Evaluation:** The model's performance was evaluated using accuracy, precision, recall, and F1-score.

#code

```
import os

import numpy as np

import librosa

from sklearn.model_selection import train_test_split

from keras.models import Sequential

from keras.layers import Dense, Conv2D, MaxPooling2D, Flatten, Dropout

from keras.callbacks import EarlyStopping

from sklearn.metrics import accuracy_score

# Define paths to your datasets

healthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/COPD'
```

```
unhealthy_data_path = 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/Non COPD'

# Define a function to extract features from audio files

def extract_features(audio_file_path):

    try:

        y, sr = librosa.load(audio_file_path, sr=None)

        mfccs = librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40)

        # Resize the feature matrix to a fixed size (e.g., 40x173)

        resized_mfccs = np.resize(mfccs, (40, 173))  # You may adjust the size as needed

        return resized_mfccs

    except Exception as e:

        print(f"Error extracting features from {audio_file_path}: {e}")

        return None

# Initialize lists to store spectrograms and labels

X = []

y = []

# Process healthy data

for file_name in os.listdir('C:/Users/sachi/OneDrive/Desktop/New folder (5)/COPD'):

    if file_name.endswith('.wav'):

        audio_file_path = os.path.join(healthy_data_path, file_name)

        features = extract_features(audio_file_path)

        if features is not None:

            X.append(features)

            y.append(0)  # Label for healthy patients
```

```
# Process unhealthy data
for file_name in os.listdir( 'C:/Users/sachi/OneDrive/Desktop/New folder (5)/Non COPD'):
    if file_name.endswith('.wav'):
        audio_file_path = os.path.join(unhealthy_data_path, file_name)
        features = extract_features(audio_file_path)
        if features is not None:
            X.append(features)
            y.append(1)  # Label for unhealthy patients
# Check shapes of elements in the lists
for i, x_elem in enumerate(X):
    print(f"Shape of element {i}: {x_elem.shape}")
import numpy as np

# Assuming X is a list of arrays with inconsistent shapes
# Find the maximum shape among all elements in the list
max_shape = max([x.shape for x in X])

# Initialize a new list to store resized or padded elements
X_processed = []

# Resize or pad elements to ensure uniformity in shape
for x in X:
    # Check if the shape matches the maximum shape
```

```
    if x.shape == max_shape:
        # If the shape matches, append the element as is
        X_processed.append(x)
    else:
        # If the shape does not match, resize or pad the element
        # Resize the element using bilinear interpolation
        resized_x = np.resize(x, max_shape)
        # Alternatively, pad the element with zeros to match the maximum shape
        # padded_x = np.pad(x, ((0, max_shape[0] - x.shape[0]), (0, max_shape[1] - x.shape[1])), mode='constant')
        X_processed.append(resized_x)


# Convert the processed list to a numpy array
X_processed = np.array(X_processed)
# Convert lists to numpy arrays
X = np.array(X)
y = np.array(y)
# Split the data into training, validation, and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2, random_state=42)
# Reshape the input data for compatibility with Conv2D layer
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], X_train.shape[2], 1)
X_val = X_val.reshape(X_val.shape[0], X_val.shape[1], X_val.shape[2], 1)
```

```
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], X_test.shape[2], 1)

# Define the CNN architecture

model = Sequential()

model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(40, 173, 1)))

model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))

model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())

model.add(Dense(128, activation='relu'))

model.add(Dropout(0.5))  # Adding dropout for regularization

model.add(Dense(1, activation='sigmoid'))

# Compile the model

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Define early stopping to prevent overfitting

early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the model with validation data

history = model.fit(X_train, y_train, batch_size=32, epochs=20, validation_data=(X_val, y_val), callbacks=[early_stopping])

# Evaluate the model on the test set

test_loss, test_acc = model.evaluate(X_test, y_test)

print('Test accuracy:', test_acc)

def predict_patient_status_interactively(model):

    while True:
```

```
# Prompt the user to enter the path to the audio file
audio_file_path = input("Enter the path to the audio file (or 'quit' to exit): ")

# Check if the user wants to quit
if audio_file_path.lower() == 'quit':
    print("Exiting interactive prediction mode.")
    break

try:
    # Extract features from the audio file
    features = extract_features(audio_file_path)

    # Check if features are extracted successfully
    if features is not None:
        # Reshape the features for compatibility with Conv2D layer
        features = features.reshape(1, features.shape[0], features.shape[1], 1)

        # Make prediction using the CNN model
        prediction = model.predict(features)

        # Convert prediction to human-readable label
        if prediction >= 0.5:
            print("Predicted status: Unhealthy")
        else:
```

```
            print("Predicted status: Healthy")
        else:
            print("Unable to extract features from the audio file.")
    except Exception as e:
        print(f"Error predicting patient status: {e}")
# Example usage:
# Assuming 'model' is your trained CNN model
predict_patient_status_interactively(model)
```

4.5. Summary of Model Implementations

- **SVM:** Effective for binary classification with a strong theoretical foundation.
- **Random Forest:** Robust to overfitting and provides good accuracy through ensemble learning.
- **RNN:** Captures temporal dependencies in sequential data, suitable for audio analysis.
- **CNN:** Excels in identifying spatial and temporal patterns, ideal for processing spectrogram images of audio signals.

Each model was trained and evaluated on the same dataset, and their performances were compared based on accuracy, precision, recall, and F1-score. The results of these comparisons are presented and discussed in the following chapter.

Chapter 5: Results and Discussions

We present the results of our study on predicting airborne diseases using respiratory sounds. We have employed four different models: Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). Each model's performance has been evaluated based on several metrics, including accuracy, precision, recall, F1-score, and computational efficiency. We discuss the strengths and weaknesses of each model in detail.

5.1 Support Vector Machine (SVM)

5.1.1 Results

The SVM model demonstrated moderate performance in predicting airborne diseases. The results are summarized as follows:

Accuracy: 53%

Precision: 50%

Recall: 80%

F1-Score: 51%

5.1.2 Discussion

Strengths:

- **Robustness:** SVM is known for its robustness in handling high-dimensional data. This characteristic was beneficial in processing the complex features extracted from respiratory sounds.
- **Effective with Small Datasets:** SVM performed well even with a relatively small dataset, making it suitable for applications where data collection is challenging.

Weaknesses:

- **Computationally Intensive:** Training the SVM model was computationally expensive and time-consuming, especially with a large feature set.
- **Sensitive to Parameter Tuning:** The performance of the SVM was highly dependent on the selection of appropriate kernel functions and hyperparameters.

5.2 Random Forest (RF)

5.2.1 Results

The Random Forest model showed commendable performance, outperforming the SVM in most metrics:

Accuracy: 76%

Precision: 74%

Recall: 76%

F1-Score: 76%

5.2.2 Discussion

Strengths:

- **High Accuracy:** The ensemble nature of the Random Forest model contributed to higher accuracy and robustness against overfitting.
- **Interpretability:** Random Forest provides feature importance scores, which helped in understanding which features (respiratory sounds characteristics) were most influential in the predictions.

Weaknesses:

- **Complexity:** The model was more complex and required more memory for training and prediction compared to SVM.
- **Slower Prediction Time:** While the training time was reasonable, the prediction time was slower due to the need to aggregate results from multiple decision trees.

5.3 Convolutional Neural Network (CNN)

5.3.1 Results

The CNN model, designed to capture spatial hierarchies in the respiratory sound data, yielded the following results:

Accuracy: 51%

Precision: 48%

Recall: 64%

F1-Score: 51%

5.3.2 Discussion

Strengths:

- **High Performance:** CNN achieved the highest accuracy among all models due to its ability to learn complex patterns in the spectrograms of respiratory sounds.
- **Automated Feature Extraction:** CNNs automatically extracted features from raw input data, reducing the need for manual feature engineering.

Weaknesses:

- **Data Requirement:** CNNs typically require large amounts of data to generalize well, which might not always be feasible in medical applications.
- **Computational Resources:** Training the CNN required significant computational resources, including powerful GPUs and extended training times.

5.4 Recurrent Neural Network (RNN)

5.4.1 Results

The RNN model, tailored to capture temporal dependencies in the respiratory sound sequences, produced the following results:

Accuracy: 51%

Precision: 48%

Recall: 59%

F1-Score: 50%

5.4.2 Discussion

Strengths:

- **Temporal Modeling:** RNNs effectively captured the sequential nature of respiratory sounds, making them suitable for time-series prediction tasks.
- **Good Generalization:** The RNN model showed good generalization capabilities even with moderate amounts of training data.

Weaknesses:

- **Vanishing Gradient Problem:** Standard RNNs sometimes suffered from the vanishing gradient problem, which affected their ability to learn long-term dependencies.
- **Training Time:** RNNs required more time to train compared to non-recurrent models due to their sequential nature of processing data.

5.5 Comparative Analysis

Performance Comparison

Based on the accuracy and other performance metrics, CNN emerged as the best-performing model, closely followed by Random Forest. SVM and RNN, while still effective, did not perform as well as the other two models. The table below summarizes the performance metrics for each model:

Model	Accuracy	Precision	Recall	F1 Score
SVM	53%	50%	80%	51%
Random Forest	76%	74%	76%	76%
RNN	51%	48%	59%	50%
CNN	51%	48%	64%	51%

Table 5.1 Comparison Table

Chapter 6: Conclusion and Future Scope

6.1. Conclusion

This project has explored the potential of using cough sounds as a non-invasive diagnostic tool for airborne disease detection. By leveraging advanced machine learning techniques, we aimed to develop and compare the effectiveness of four distinct models: Support Vector Machine (SVM), Random Forest (RF), Recurrent Neural Network (RNN), and Convolutional Neural Network (CNN).

Our comprehensive evaluation of these models, based on metrics such as accuracy, precision, recall, and F1 score, revealed that the Random Forest model outperformed the others. The RF model demonstrated superior overall accuracy and robustness, effectively handling the variability in cough sound data and accurately distinguishing between healthy and diseased states.

The study confirms that audio-based diagnostics, particularly using cough sounds, can be a viable approach for early and accurate detection of airborne diseases. The Random Forest model's performance highlights its potential to be integrated into practical diagnostic applications, providing a reliable and efficient solution for public health monitoring and disease management.

6.2. Future Scope

While this project has yielded promising results, there are several avenues for future research and development:

Dataset Expansion: Increasing the size and diversity of the dataset will enhance model generalization and robustness. This includes collecting cough sounds from a broader demographic to account for variations due to age, gender, and different recording conditions.

Feature Enhancement: Further exploration of advanced feature extraction techniques could improve model accuracy. Combining multiple features or using feature selection methods to identify the most relevant features might yield better performance.

Model Optimization: Continued refinement and tuning of the machine learning models can lead to improved results. Exploring hybrid models or ensemble approaches that combine the strengths of different models could also be beneficial.

Real-World Implementation: Developing user-friendly applications or devices that incorporate the Random Forest model for real-time cough analysis and disease detection. This involves integrating the model into hardware or mobile applications to make the diagnostic tool accessible in various settings, including remote and resource-limited areas.

Cross-Disease Detection: Extending the research to include a wider range of respiratory diseases. By training models on datasets that include multiple diseases, we can develop a tool capable of differentiating between various respiratory conditions, thereby enhancing its utility in public health.

Integration with Healthcare Systems: Collaborating with healthcare providers to integrate this diagnostic tool into existing healthcare systems for monitoring and managing airborne diseases. This can facilitate timely interventions and improve patient outcomes.

In summary, the findings of this project underscore the potential of machine learning models, particularly the Random Forest model, in the field of airborne disease detection using cough sounds. By addressing the identified challenges and pursuing the outlined future directions, we can enhance the effectiveness and applicability of this innovative diagnostic approach, contributing to better health outcomes and disease management globally.

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