NETAJI SUBHAS UNIVERSITY OF TECHNOLOGY

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Respiratory Health Analysis Using TinyML

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Abstract

The aim of this project is to predict respiratory health through audio analysis using TinyML. Healthcare is still widely inaccessible in various parts of the country and even in places where it isn't, symptoms are often ignored or underestimated. A lot of people avoid timely check ups either to save money or because of the overcrowded public health centers. Implementing Respiratory Health Analysis on TinyML aims to bridge the gap in healthcare, by enabling early self diagnosis of risk of Respiratory Diseases.

TinyML was implemented on a ESP32 board with the help of Arduino IDE. A model was trained on below mentioned machine learning models and was fed with *Respiratory Sounds Dataset.*[(1)]

An accuracy of 91.2% was achieved to predict possible respiratory health risks on the basis of respiratory sounds of a person.

Introduction

In the pursuit of advancing healthcare technologies, the integration of Machine Learning (ML) and Internet of Things (IoT) has paved the way for innovative solutions. In this project, our group explored and focused on the analysis of respiratory health and diagnosis using Tiny Machine Learning (TinyML) models deployed on microcontrollers, specifically the ESP32. Additionally, we envisioned the future applications of this localized setup.

Objective

- The objective is to predict the Respiratory Health of an individual through audio analysis.
- TinyML aims to bridge the gap of healthcare to the general public by reducing cost and setup complexity.
- This model aims to enable people to self diagnose a potential risk of a respiratory problem and facilitate better and focused resolution.

Methodology

Data Collection

Utilize publicly available respiratory health datasets, such as the Respiratory Sound Database.

Data Augmentation

It is a crucial aspect of training robust and effective machine learning models, especially when dealing with limited datasets. Techniques such as adding noise, masking time bands, time Stretching and pitch processing have been utilized.

Time Stretching

Apply time stretching by resampling the signal, changing its duration while preserving the underlying patterns. This helps the model become invariant to variations in the speed of input sequences.

Feature Extraction(MFCC)

It is a standard method for feature extraction in audio analytics. Steps involved in Mel-Frequency Cepstral Coefficients (MFCC) are Pre-emphasis, Framing, Windowing, FFT, Mel filter bank, computing DCT.

Model Development

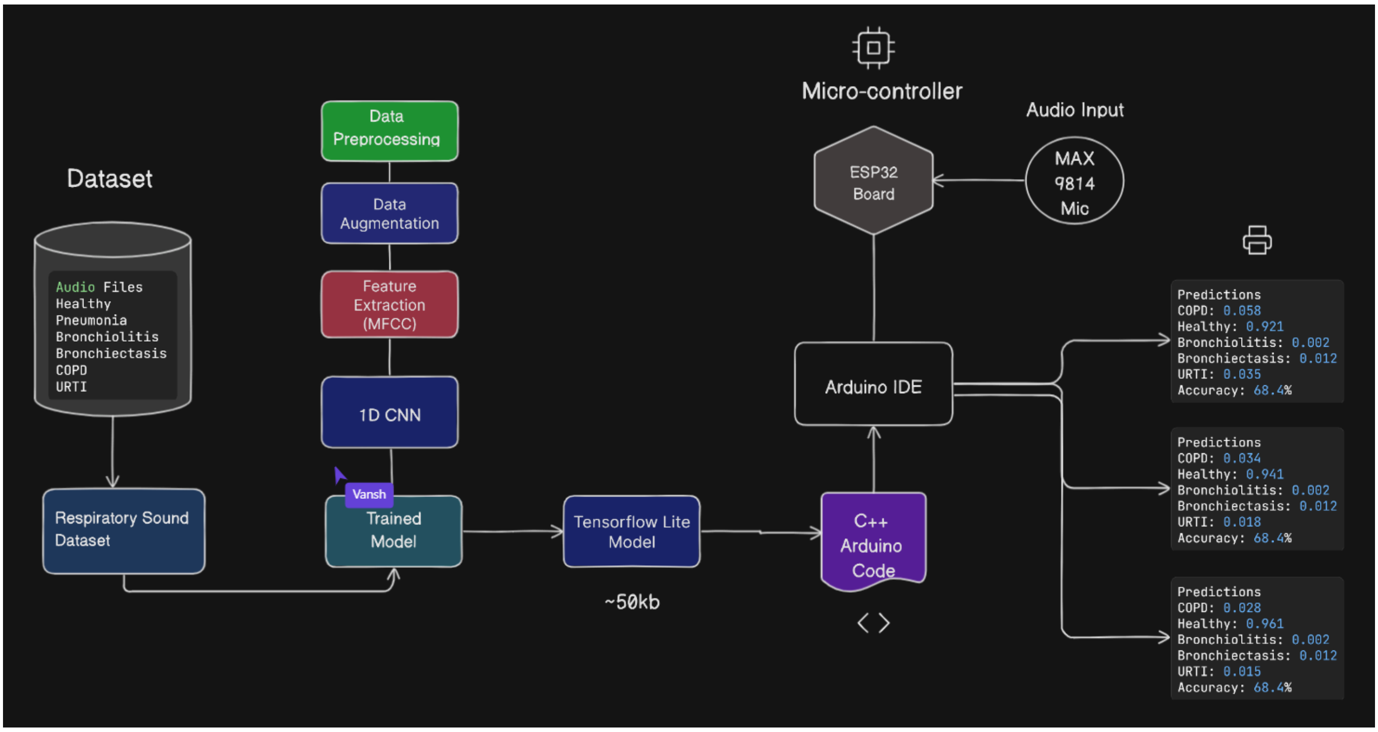
Develop deep learning models, including CNNs and hybrid architectures, for accurate respiratory disease classification and prediction. Use librosa library to extract data and sample rate from audios which finds its use in MFCC to further extract features to be used in model training.

TensorFlow Lite

Use the TensorFlow Lite Converter to convert the trained model to the TensorFlow Lite format. Optimization techniques such as quantization applied to further reduce the model size or improve performance. Deploy the model on a target device, such as a mobile phone or edge device

Deployment with TinyML and Microcontrollers

Implement TinyML techniques to optimize deep learning models for deployment on resource-constrained devices. Utilize microcontrollers, such as ESP32S, to deploy the models for real-time diagnosis and monitoring in low-power environments.



Machine Learning Models

Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a class of deep neural networks. They excel at capturing hierarchical features through the use of convolutional layers. Key components of CNNs include convolutional layers, pooling layers, and fully connected layers.

1-D Convolution

1D convolutional layers are employed to capture patterns and features in one-dimensional sequences or time-series data. These layers use filters to slide over the input sequence, extracting local patterns and creating higher-level representations. 1D convolutional layers in CNNs are effective for tasks such as time-series analysis, speech recognition, and natural language processing.

Max Pooling

In the realm of deep learning for audio analysis, the utilization of pooling layers, particularly MaxPooling1D, plays a crucial role in feature extraction and dimensionality reduction. Pooling layers are typically inserted between convolutional layers in Convolutional Neural Networks (CNNs) to capture and highlight essential patterns in the input audio data.

Frontend Development

To provide a user-friendly interface for making predictions, we created a simple frontend using Arduino IDE. The frontend allowed users to input respiratory audio and receive predictions based on the trained machine learning models.

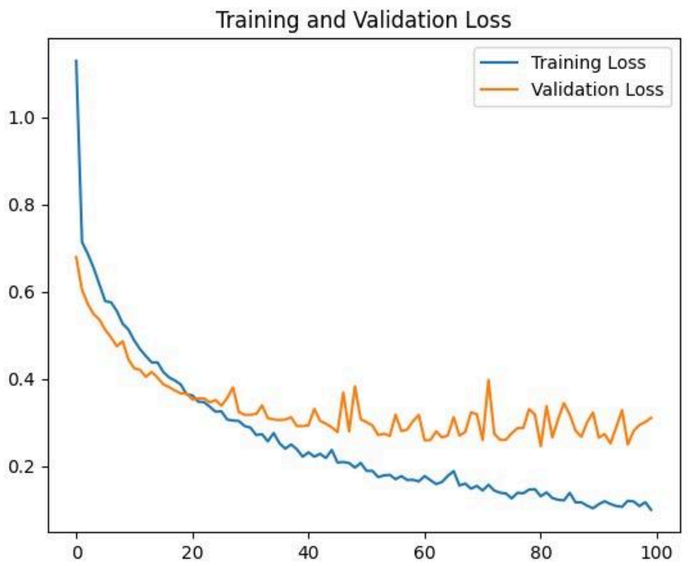
Key Challenges

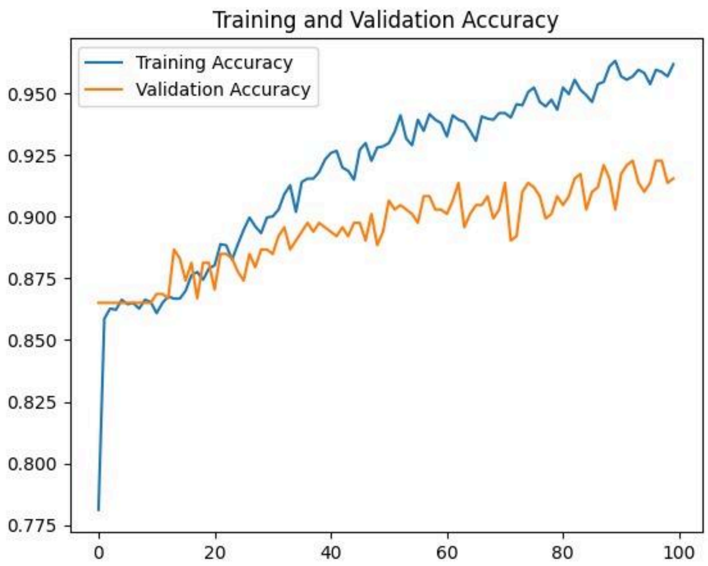
Predicting respiratory health through audio analysis of breath is a complicated process and has a lot of challenges. A stethoscope not only has higher precision that is not possible to mimic using a mic, but other challenges such as background noise, improper setup of the device are prominent difficulties.

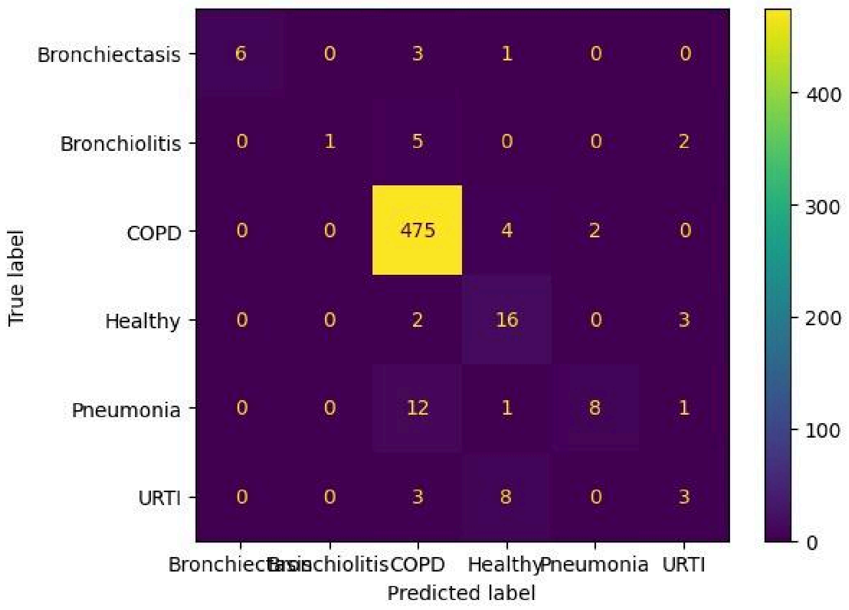
- **Limited Processing Power**: TinyML boards such as ESP32 have limited processing power and cannot run complex models.
- **Lack of Standardization**: Respiratory factors are not uniform and involve a lot of uncertainty and random patterns.
- **Lack of Respiratory Data**: Available datasets on respiratory health are limited and imbalanced. It is a challenge to acquire new data due to the sensitivity of health information.
- **Sample Collection & Hardware Challenges** : Audio data is difficult to process. Noise and other irregularities can often lead to erroneous output.

Results and Findings

- An accuracy of 91.2% was achieved for prediction of various respiratory health risks.
- The project demonstrates the effectiveness of Machine Learning and Deep Learning in enhancing respiratory health diagnosis.
- The use of TinyML and microcontrollers expands the applicability of deep learning models, making them accessible in resource-limited healthcare settings.
- Further research and development in this direction hold the potential to revolutionize respiratory health monitoring and diagnostics globally.







Future implications

This project can be extended in various domains and achieve a more accurate and wider range of predictions.

- **Collaboration and Data Sharing:** The future of respiratory health analysis involves collaborative efforts and data sharing among healthcare professionals, researchers, and technology developers. Establishing secure and privacy-preserving frameworks for data exchange will accelerate the pace of innovation. By fostering collaboration, the project aims towards a deeper understanding of respiratory diseases and their management.

- **Remote Patient Monitoring:** The future vision extends beyond individual health tracking to encompass remote patient monitoring. Patients with chronic respiratory conditions can benefit from wearable devices equipped with TinyML models on ESP32 microcontrollers. Healthcare providers will have real-time access to patient data, allowing for timely interventions and personalized treatment plans. This not only improves patient outcomes but also reduces the burden on healthcare facilities.

Conclusion

The integration of TinyML on ESP32 microcontrollers for respiratory health analysis holds immense potential for revolutionizing healthcare. The future vision encompasses personalized health insights, remote patient monitoring, accessibility, affordability, collaboration, and ethical considerations. As this project progresses, it contributes to the realization of a future where respiratory health management is proactive, personalized, and globally accessible.

References

Research Papers

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Dataset

Respiratory Sound Dataset- https://www.kaggle.com/datasets/vbookshelf/respiratory-sound-database