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Efficient DL Models for Voice Pathology Detection in Healthcare Applications using Sustained Vowels

مدل های یادگیری عمیق کارآمد برای تشخیص آسیب شناسی گفتار در پزشکی با استفاده از آوای واکه های پایدار

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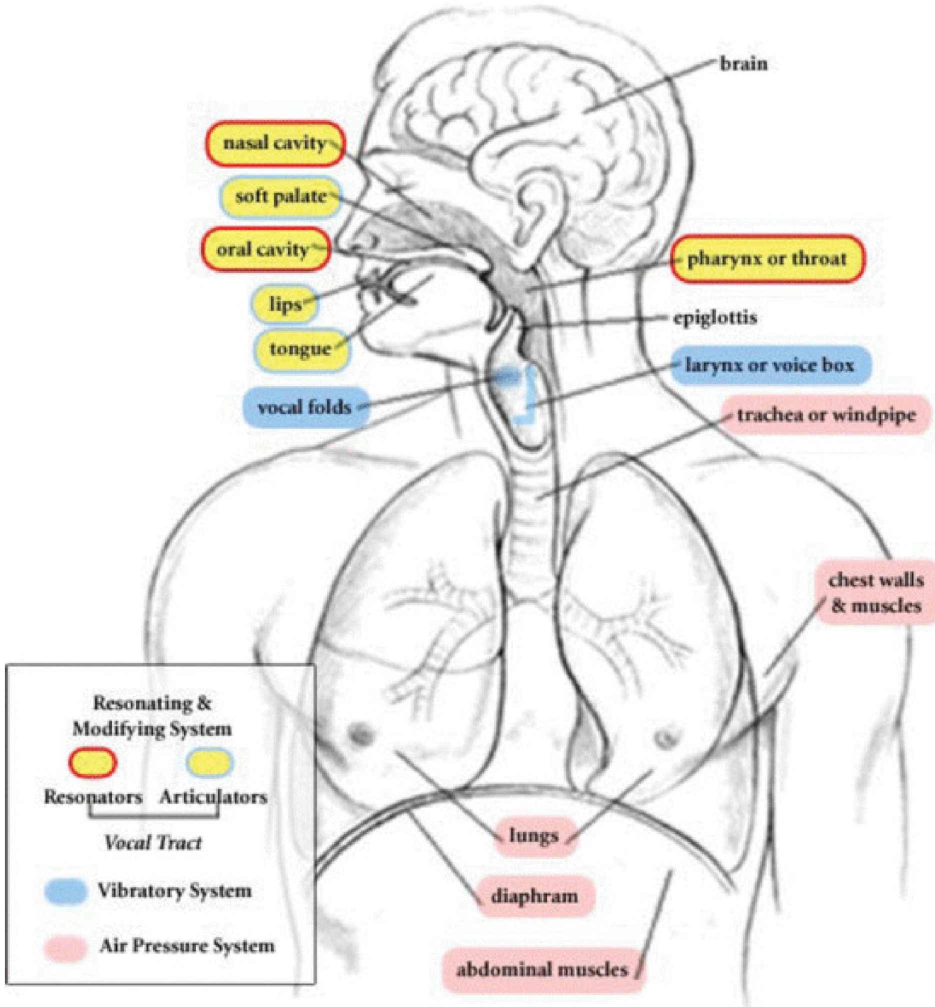
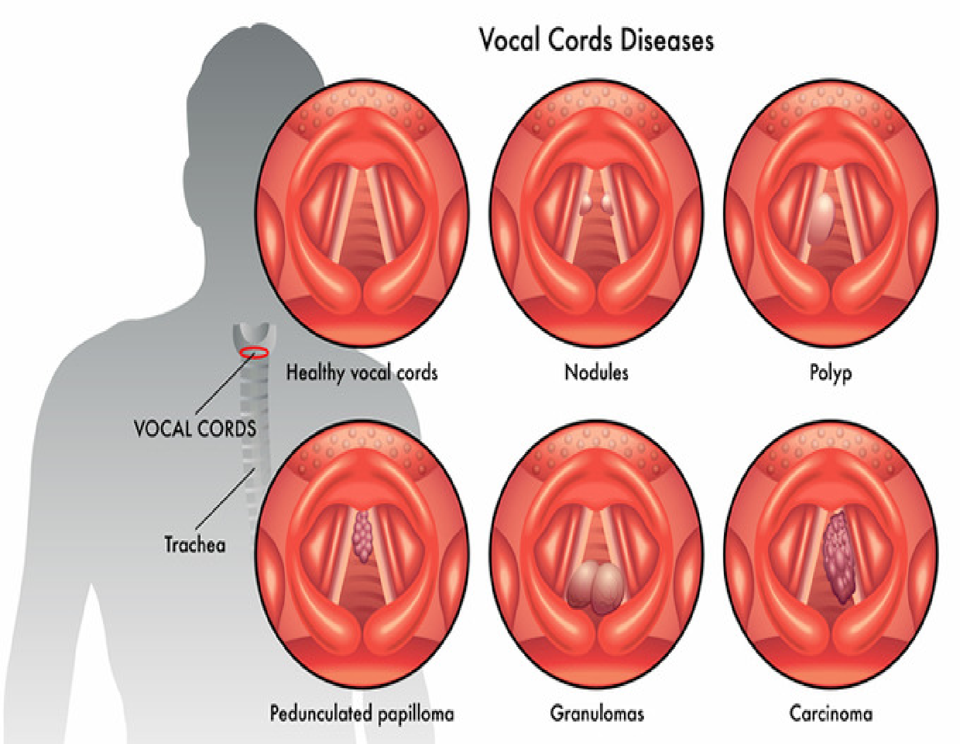
دانشگاه شهید بهشتی

Voice Production System:



- The power source for voice production is the airstream which originates in the lungs and is supported by a diaphragm. The voice production system shown in Figure begins at the vocal cords and terminates at the mouth. The vocal tract includes the larynx, pharynx above it, mouth, and the nasal cavity.

Voice Disorders:



- According to the American Speech-Language-Hearing Association, “Voice disorders occur when voice quality, pitch, and loudness differ or are inappropriate for an individual’s age, gender, cultural background, or geographic location.

- 110% rise in speech disorders among children (ages 0-12) post-pandemic.
- 1 in 5 Americans report voice disorders due to voice tech and occupational use.
- 18% of elderly (60+) suffer from voice-related disorders.

Why Automatic voice Pathology Detection?

AI-Powered Voice Pathology Detection: Key Benefits

□ Early & Accurate Detection

AI analyzes subtle acoustic features, improving diagnosis sensitivity & specificity.

💰 Non-Invasive & Cost-Effective

Eliminates the need for invasive tests; requires only a microphone & software.

⚡ Automation & Efficiency

Processes large voice data quickly, reducing workload for healthcare professionals.

Remote & Telemedicine Applications

Enables screening via smartphones, benefiting underserved regions.

📊 Continuous Monitoring & Personalized Treatment

Tracks voice changes over time for better therapy adjustments.

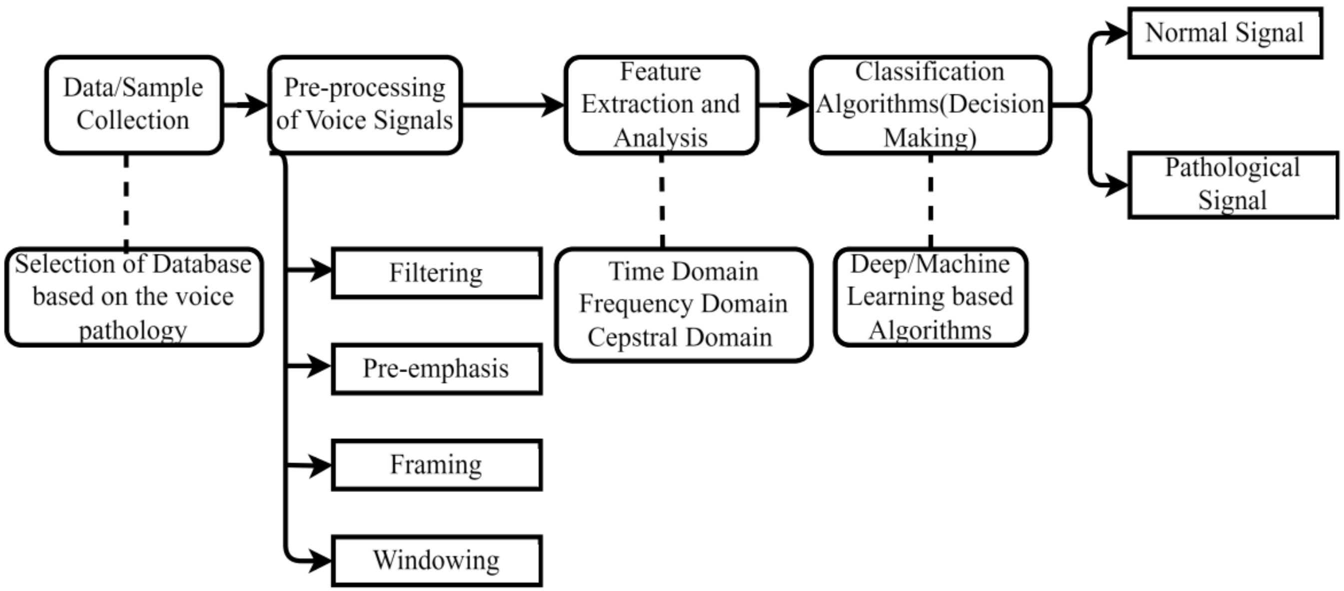
🔍 Detecting Subtle Patterns in Disorders

Identifies complex voice issues like vocal cord paralysis, Parkinson's, and ALS.

📡 Integration with Emerging Technologies

Works with IoT & wearables for real-time monitoring & speech therapy.

Automatic Voice Pathology Detection System:



Related Works:

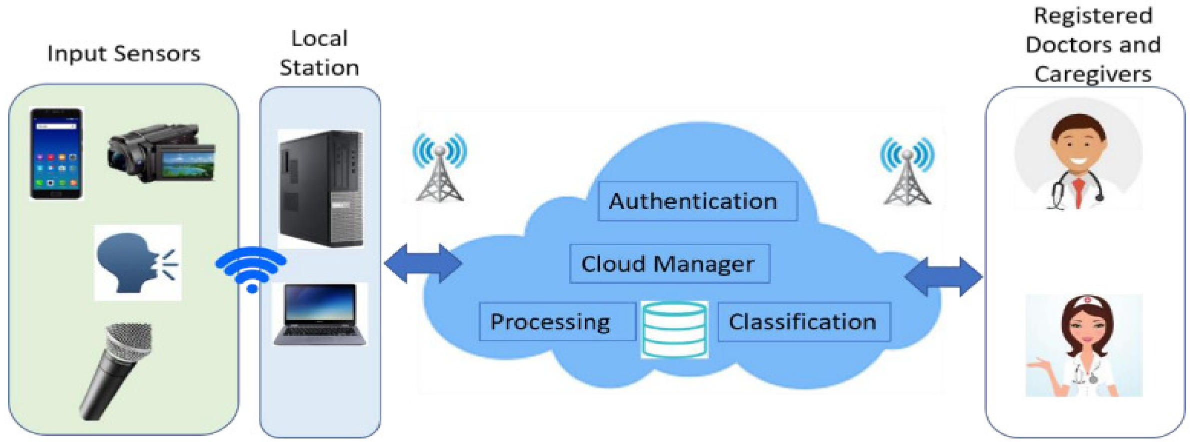
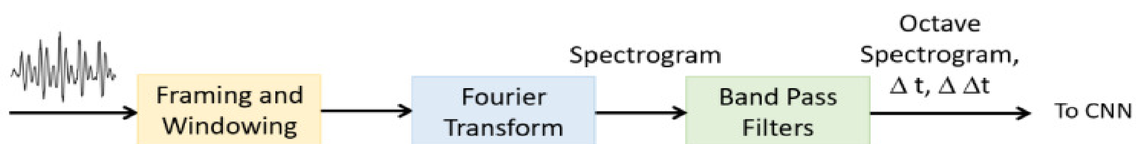


Figure 2. Mobile healthcare framework.



- ✓ A VPD system was developed within a mobile healthcare framework.
- ✓ Smart devices were utilized to capture and process voice signals, leveraging transfer learning with CNN models such as *VGG-16* and *CaffeNet*.
- ✓ Using the *Saarbrücken Voice Disorder* (SVD) database.
- ✓ The system achieved an accuracy of 97.5%, emphasizing the potential of mobile platforms in improving voice pathology diagnostics

- **Dataset:** AVFAD (University of Aveiro, Portugal).
- **Participants:** 709 total (346 with vocal pathologies, 363 healthy).
- **Recording Types:** Sustained vowels (/a/, /u/, /i/) – 3 repetitions each. Reading predefined text & six sentences. Spontaneous speech samples.
- **Sampling Rate:** 48 kHz for all recordings.

Waveform of a healthy and an unhealthy sample for vowel /a/:

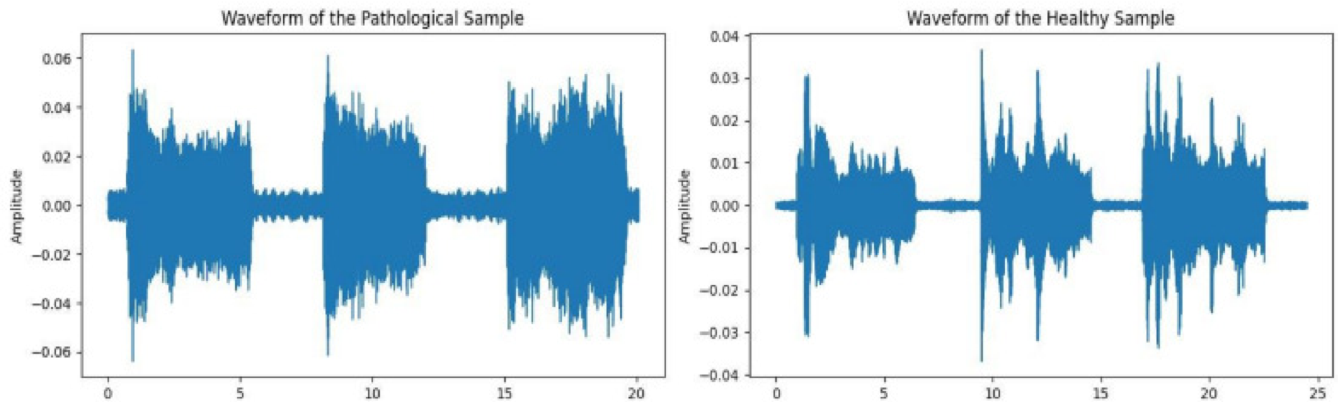


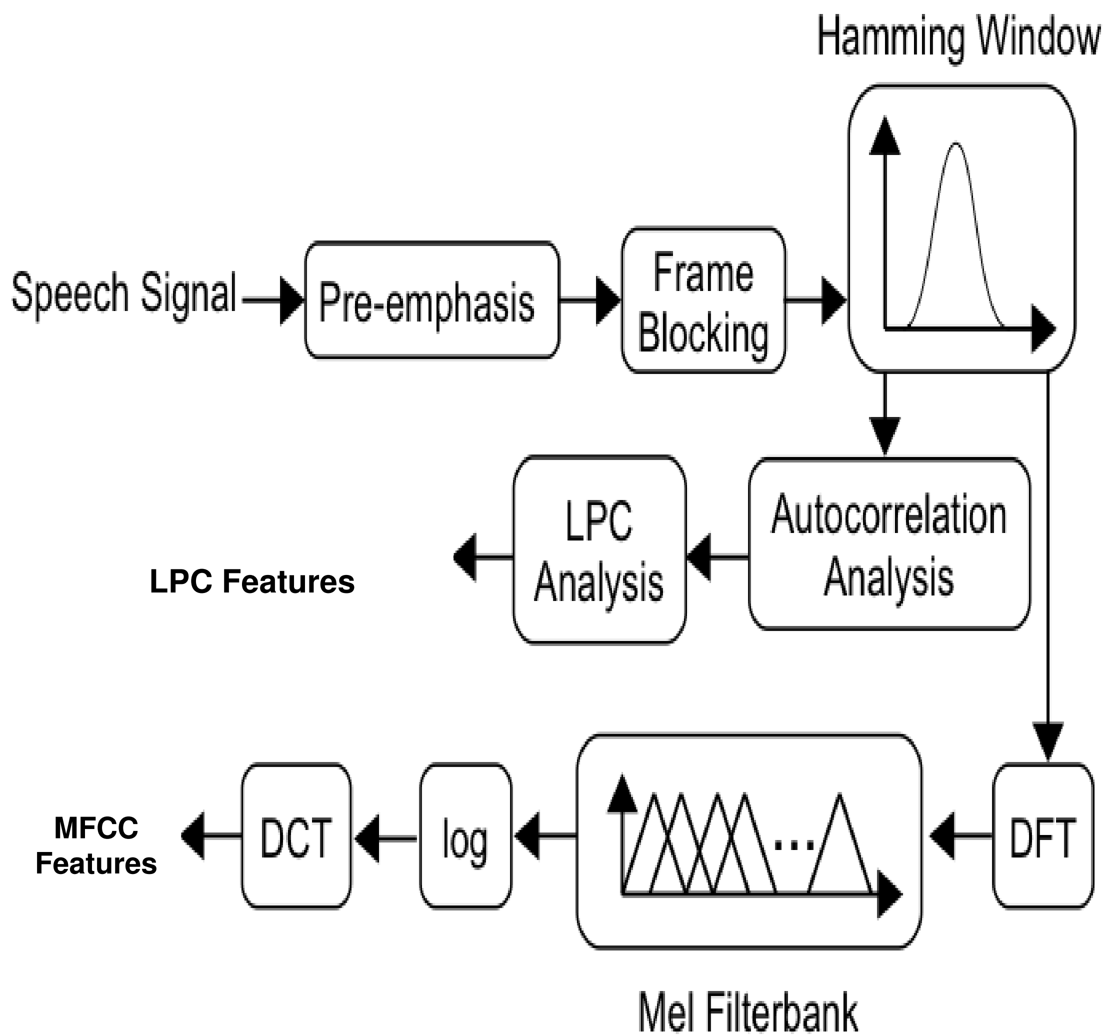
Table 1. Data Splitting Methodology in This Study for the AVFAD Dataset

Data	Train		Test		Validation	
Gender	***Male***	***Female***	***Male***	***Female***	***Male***	***Female***
Normal	73	162	22	50	18	37
Pathologic	64	161	20	49	13	37
Total (Gender)	137	323	42	99	31	74
Total (All)	460		141		105	

Table 2. Duration (sec) statistics for the vowels /a/, /i/, and /u/.

Vowels	Min	Max	Mean	Mean + STD
/a/	3.81	110.92	14.61	21.81
/i/	3.81	121.32	14.81	22.34
/u/	3.63	344.51	14.55	29.09

Feature extraction:



- **MFCC** mimics human auditory perception, effectively representing **timbre and spectral shape**. It is particularly useful in identifying **subtle frequency changes** caused by voice disorders.
- **LPC** models the vocal tract's resonant properties, making it excellent for capturing **speech production characteristics** and detecting **abnormal vocal cord vibrations**.

The Based CNN Model:

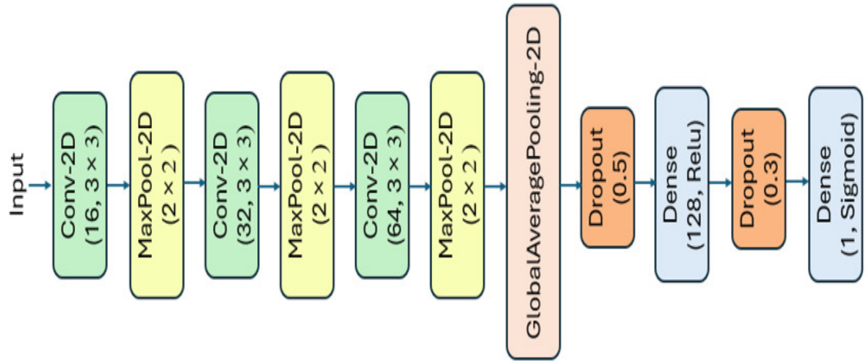


Table 3: The CNN model parameters and details.

Input Layer	Input Shape (Number of Frames, Feature Size, 1)
Convolutional Layer 1	Kernel Size: 3 x 3, Filters: 16, Activation: RELU, Padding: Same
Max pooling Layer 1	Pool Size: 2 x 2
Convolutional Layer 2	Kernel Size: 3 x 3, Filters: 32, Activation: RELU, Padding: Same
Max pooling Layer 2	Pool Size: 2 x 2
Convolutional Layer 3	Kernel Size: 3 x 3, Filters: 64, Activation: RELU, Padding: Same
Max pooling Layer 3	Pool Size: 2 x 2
Global Average Pooling	2 Dimensional
Dropout Layer 1	Rate: 0.5
Dense Layer 1	Units: 128, Activation: RELU
Dropout Layer 2	Rate: 0.3
Dense Layer 2	Units: 1, Activation: Sigmoid

Results:

Table 4: LPC-Based CNN Model - Validation & Test Accuracies for Different Vowels

Vowel type	Frames (Mean+STD) with silence	Frames (Mean+STD) without Silence	First 15 Seconds (with silence)
Vowel /i/	Valid:0.8952 **Test: 0.8591**	Valid:0.8571 **Test: 0.8098**	Valid:0.8857 Test: 0.8380
Vowel /a/	Valid:0.8666 Test: 0.8239	Valid:0.8476 Test: 0.7676	Valid:0.9142 **Test: 0.8450**
Vowel /u/	Valid:0.7619 Test: 0.8028	Valid:0.7333 Test: 0.7183	Valid:0.7809 Test: 0.7816

Table 5: MFCC-Based CNN Model - Validation & Test Accuracies for Different Vowels

Vowel type	Frames (Mean+STD) with silence	Frames (Mean+STD) Without Silence	First 15 Seconds (with silence)
Vowel /i/	Valid:0.8761 **Test:0.8661**	Valid:0.8476 **Test:0.8239**	Valid:0.8666 **Test:0.8521**
Vowel /a/	Valid:0.8857 Test:0.8309	Valid:0.8761 Test:0.7535	Valid:0.8761 Test:0.8380
Vowel /u/	Valid:0.9238 Test:0.8591	Valid:0.9047 Test:0.8098	Valid:0.9047 Test:0.8309

- **LPC-Based CNN Model**

•**Best Test Accuracy: 0.8591** (Vowel **/i/**, Frames with silence).

•**Best Test Accuracy without Silence: 0.8098** (Vowel **/i/**).

•**Best Test Accuracy for First 15 Seconds: 0.8450** (Vowel **/i/**).

- **MFCC-Based CNN Model**

•**Best Test Accuracy: 0.8661** (Vowel **/i/**, Frames with silence).

•**Best Test Accuracy without Silence: 0.8239** (Vowel **/i/**).

•**Best Test Accuracy for First 15 Seconds: 0.8521** (Vowel **/i/**).

- **Overall Best Accuracy**

•**MFCC-Based CNN Model performed best with vowel /i/** (Test Accuracy **0.8661**).

- **Base CNN Model 1**
  - **Architecture:** Three convolutional layers with 16, 32, and 64 filters, respectively, followed by max-pooling max-pooling layers.
  - **First Dense layer neurons:** 128.
  - **Parameters:** 31,745 (~124 KB)
  - **Validation Accuracy:** 0.8761
  - **Test Accuracy:** 0.8661

- **Small CNN Model 2**
  - **Architecture:** Two convolutional layers with 8 and 16 filters, followed by max-pooling layers. The third convolutional layer and its max-pooling layer were discarded.
  - **First Dense layer neurons:** 64.
  - **Parameters:** 1,721 (~6.72 KB)
  - **Validation Accuracy:** 0.8380
  - **Test Accuracy:** 0.7464

- **Small CNN Model 3**
  - **Architecture:** Two convolutional layers with 16 and 32 filters, followed by max-pooling layers. The third layers. The third convolutional layer and its max- and its max-pooling layer were discarded. discarded.
  - **First Dense layer neurons:** 64.
  - **Parameters:** 6,977 (~27.25 KB)
  - **Validation Accuracy:** 0.8571
  - **Test Accuracy:** 0.8309
- **Small CNN Model 4**
  - **Architecture:** Three convolutional layers with 8, 16, and 32 filters, each followed by max-pooling layers.
  - **First Dense layer neurons:** 64.
  - **Parameters:** 8,065 (~31.5 KB)
  - **Validation Accuracy:** 0.8666
  - **Test Accuracy:** 0.8521

Best Result:

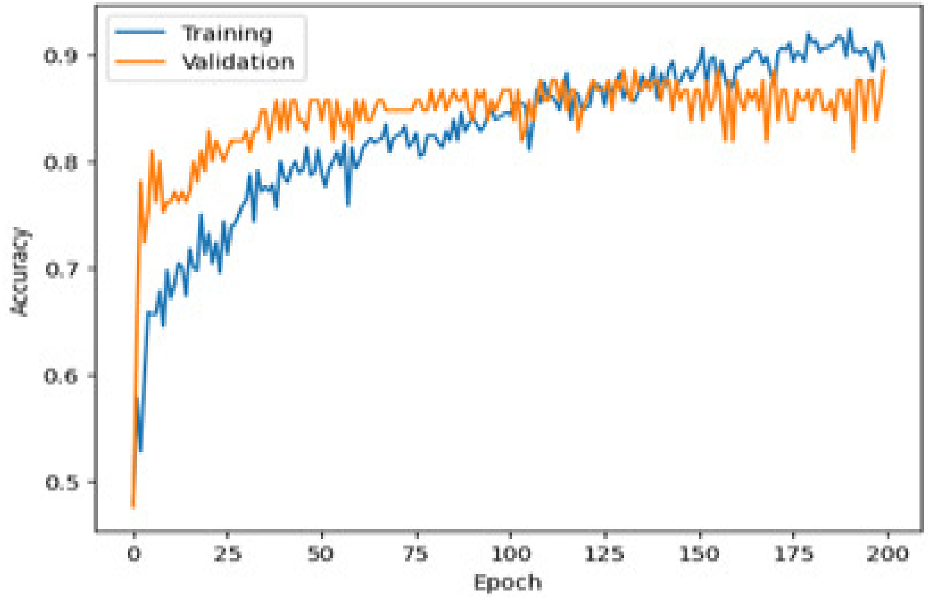


Figure 1: Validation Accuracy Curve for Optimal CNN Model on 20 MFCCs (Vowel /i/)

Table 6: Precision, Recall, and F1-Score for Healthy (0) and Unhealthy (1) Samples of 20 MFCCs for Vowel /i/ Using the Optimal CNN Model

Label	Precision	Recall	F1-Score
0	0.95	0.81	0.87
1	0.83	0.96	0.89

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Future Works:

- **Enhancing LPC Features:** Further exploration for deeper insights.
- **Optimizing Feature Extraction:** Varying coefficient numbers to improve classification.
- **Combining Vowel Sounds:** Using multiple vowels for better accuracy.
- **Leveraging Pre-Trained Models:** Enhancing efficiency in pathology detection.
- **CNN Model Improvements:** Exploring different **kernel sizes** for speech signals and testing **GELU activation** instead of ReLU.

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Thank you

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