

MODEL DIAGNOSA PPOK MENGGUNAKAN DATA SUARA DENGAN CONVOLUTIONAL NEURAL NETWORK

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LATAR BELAKANG

Dalam beberapa tahun terakhir, **dampak penyakit pernapasan** secara bertahap **meningkat dan mengancam** kehidupan masyarakat. Fakta bahwa penyakit pernapasan seperti **PPOK** (Penyakit Paru Obstruktif Kronis) termasuk dalam **10 besar penyakit paling mematikan dunia** menunjukkan perlunya deteksi dini. Namun, penggunaan **metode tradisional**, masih memberikan banyak **keterbatasan** untuk sebagian besar orang.

Dengan munculnya penggunaan **pembelajaran mendalam** dalam sektor kesehatan, penerapan **klasifikasi suara** dapat menjadi solusi. Dengan menggunakan **data suara pernafasan**, pembelajaran mendalam dapat **membantu dokter mendiagnosis penyakit** tanpa dibatasi oleh keterbatasan metode tradisional.

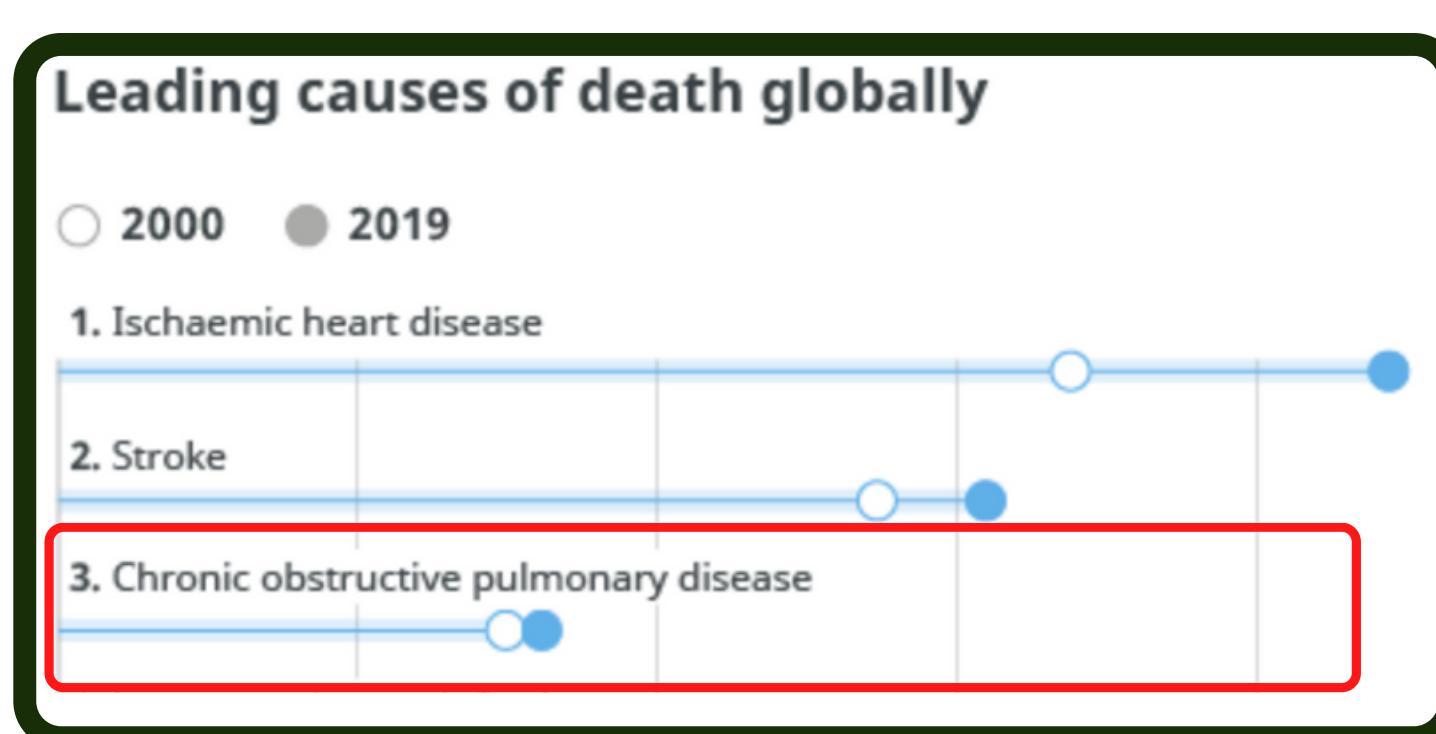
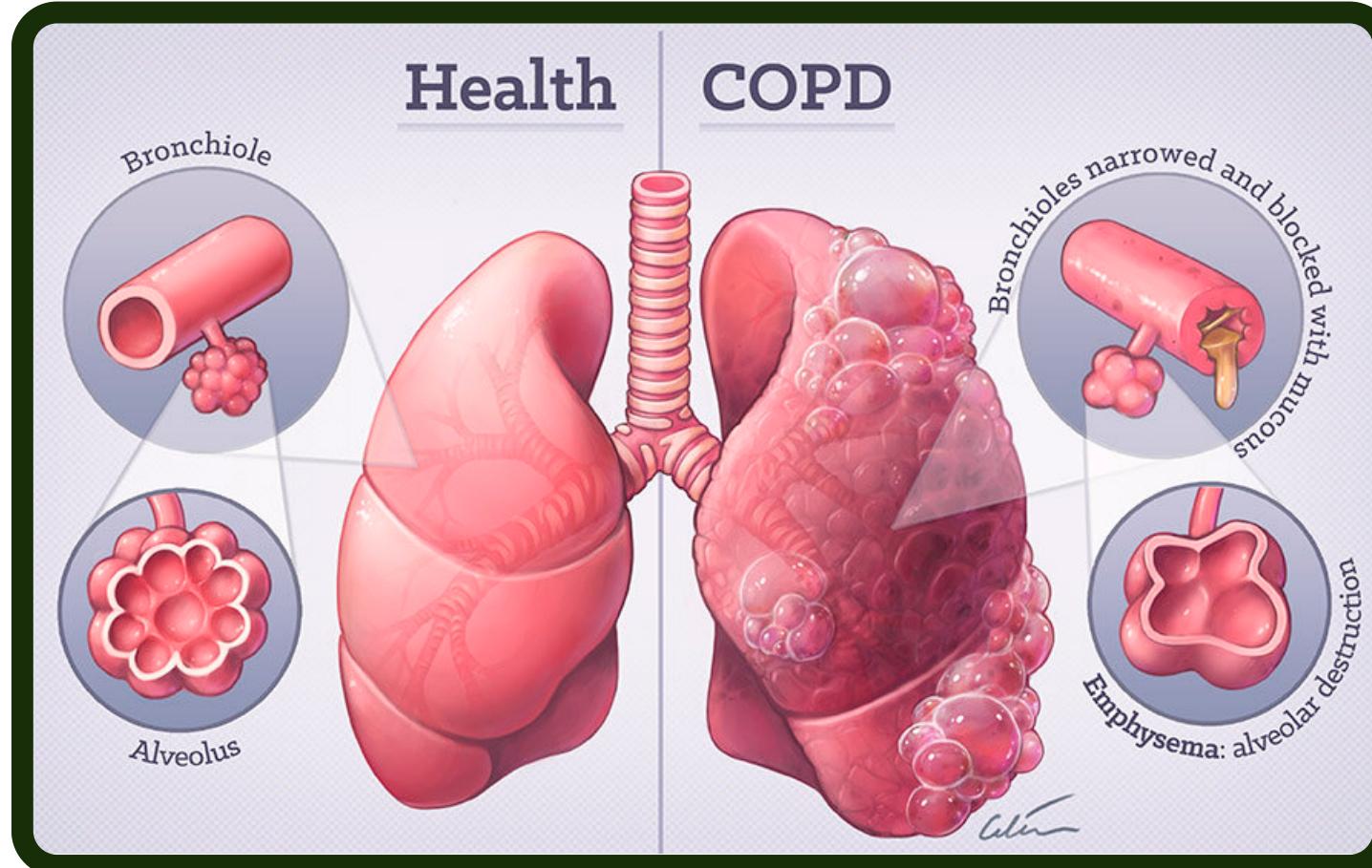
1. [HTTPS://WWW.NCBI.NLM.NIH.GOV/PMC/ARTICLES/PMC7959628/](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7959628/)

2. [HTTPS://WWW.WHO.INT/NEWS-ROOM/FACT-SHEETS/DETAIL/CHRONIC-OBSTRUCTIVE-PULMONARY-DISEASE-\(COPD\)-](https://www.who.int/news-room/detail/chronic-obstructive-pulmonary-disease-(copd)-)

3. [HTTPS://WWW.WHO.INT/NEWS-ROOM/FACT-SHEETS/DETAIL/THE-TOP-10-CAUSES-OF-DEATH](https://www.who.int/news-room/detail/the-top-10-causes-of-death)



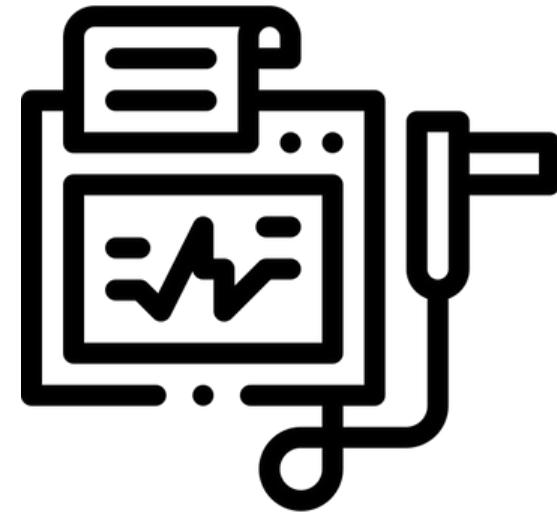
APA ITU PPOK?



- **PPOK** adalah jenis penyakit paru-paru yang ditandai dengan **kerusakan permanen** pada jaringan di paru-paru, sehingga **sulit bernapas**, seringkali disebut sebagai emfisema atau bronkitis kronik.¹
- Penybab :²
 - **paparan tembakau** dari perokok
 - paparan pekerjaan terhadap **debu, asap atau bahan kimia**;
 - **polusi udara** dalam ruangan
- WHO : PPOK termasuk kedalam **10 besar Penyakit paling mematikan dunia** yang menyebabkan jutaan kematian setiap tahunnya.³
- Penyakit paru obstruktif kronik (PPOK) merupakan **penybab kematian ketiga terbanyak di dunia**, menyebabkan **3,23 juta** kematian pada tahun **2019**.²

1. [HTTPS://WWW.CANCER.GOV/PUBLICATIONS/DICTIONARIES/CANCER-TERMS/DEF/CHRONIC-OBSTRUCTIVE-PULMONARY-DISEASE](https://www.cancer.gov/publications/dictionaries/cancer-terms/def/chronic-obstructive-pulmonary-disease)
2. [HTTPS://WWW.WHO.INT/NEWS-ROOM/FACT-SHEETS/DETAIL/CHRONIC-OBSTRUCTIVE-PULMONARY-DISEASE-\(COPD\)-](https://www.who.int/news-room/detail/chronic-obstructive-pulmonary-disease-(copd)-)
3. [HTTPS://WWW.WHO.INT/NEWS-ROOM/FACT-SHEETS/DETAIL/THE-TOP-10-CAUSES-OF-DEATH](https://www.who.int/news-room/detail/the-top-10-causes-of-death)

DIAGNOSA PPOK



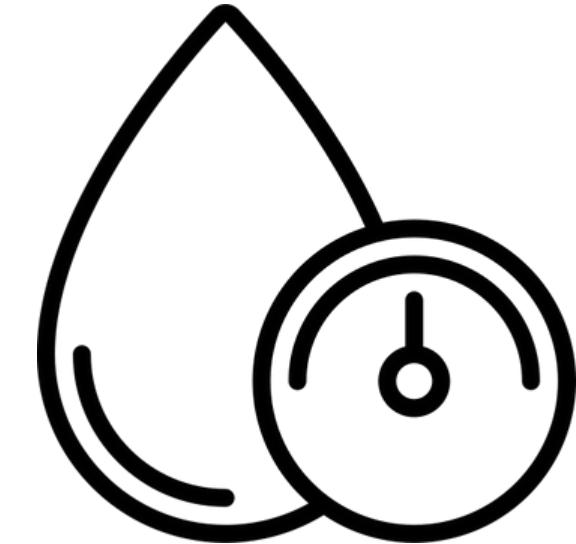
SPIROMETRI

Mengetahui kerja dari paru-paru



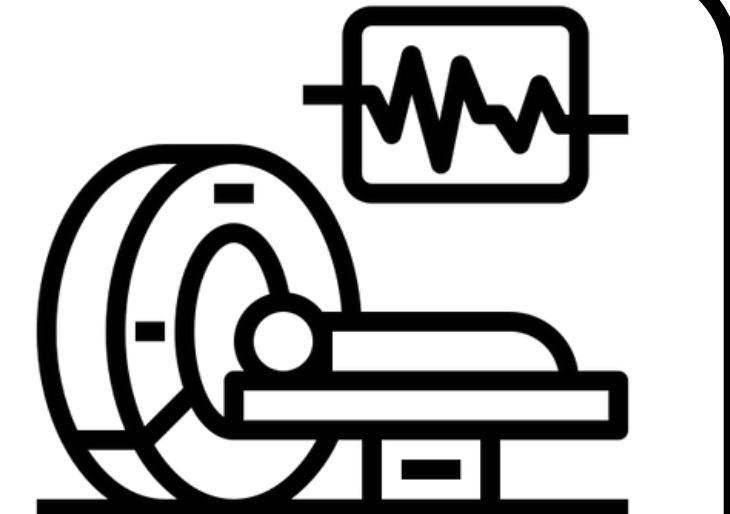
X-RAY

Gambar paru-paru untuk diagnosa dokter



TES GAS DARAH ARTERI

Mengetahui level oksigen dalam darah.



CT - SCAN

Gambar paru-paru yang lebih akurat untuk diagnosa dokter

RUMUSAN MASALAH

- 1.** Bagaimana cara mengklasifikasikan pasien pengidap PPOK dan non-PPOK berdasarkan data suara pernafasan pasien?
- 2.** Bagaimana cara mengukur kekokohan model CNN ?
- 3.** Bagaimana cara meningkatkan performa model CNN ?
- 4.** Bagaimana cara mengetahui kekokohan model CNN yang sudah ditingkatkan ?

TUJUAN

- 1.** Membuat Model Deep Learning yang dapat mengklasifikasikan pasien pengidap PPOK dan non-PPOK berdasarkan data suara pernafasan pasien.
- 2.** Mengevaluasi Model CNN menggunakan metrik evaluasi model klasifikasi, untuk mengukur kekokohan model.
- 3.** Memperbanyak data class "non-ppok", menambah data suara, serta mengubah arsitektur model CNN untuk meningkatkan performa model.
- 4.** Mengevaluasi Model CNN dengan data tambahan, menggunakan metrik evaluasi model klasifikasi, untuk mengukur kekokohan model.

DATA

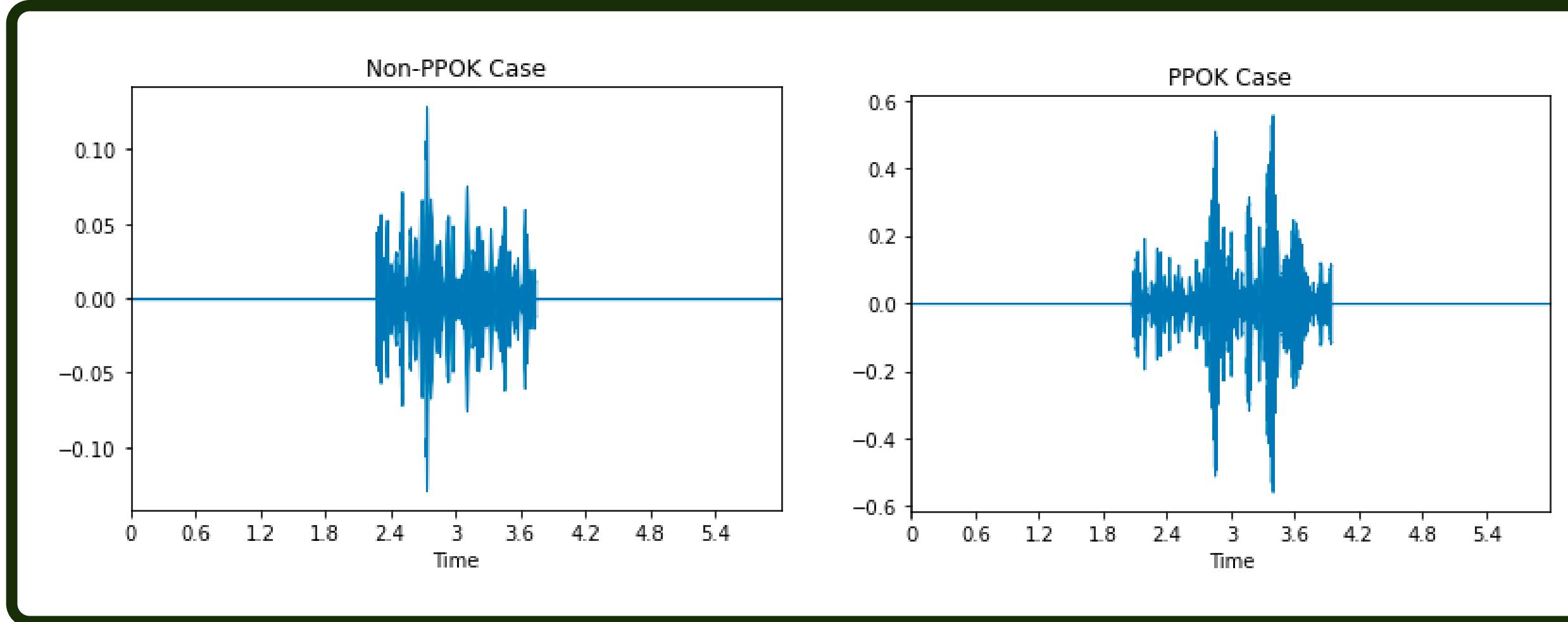
Terdiri dari : ¹

1.920 file audio (.wav) suara pernafasan pasien

2.920 text file (.txt) berisi rincian data suara

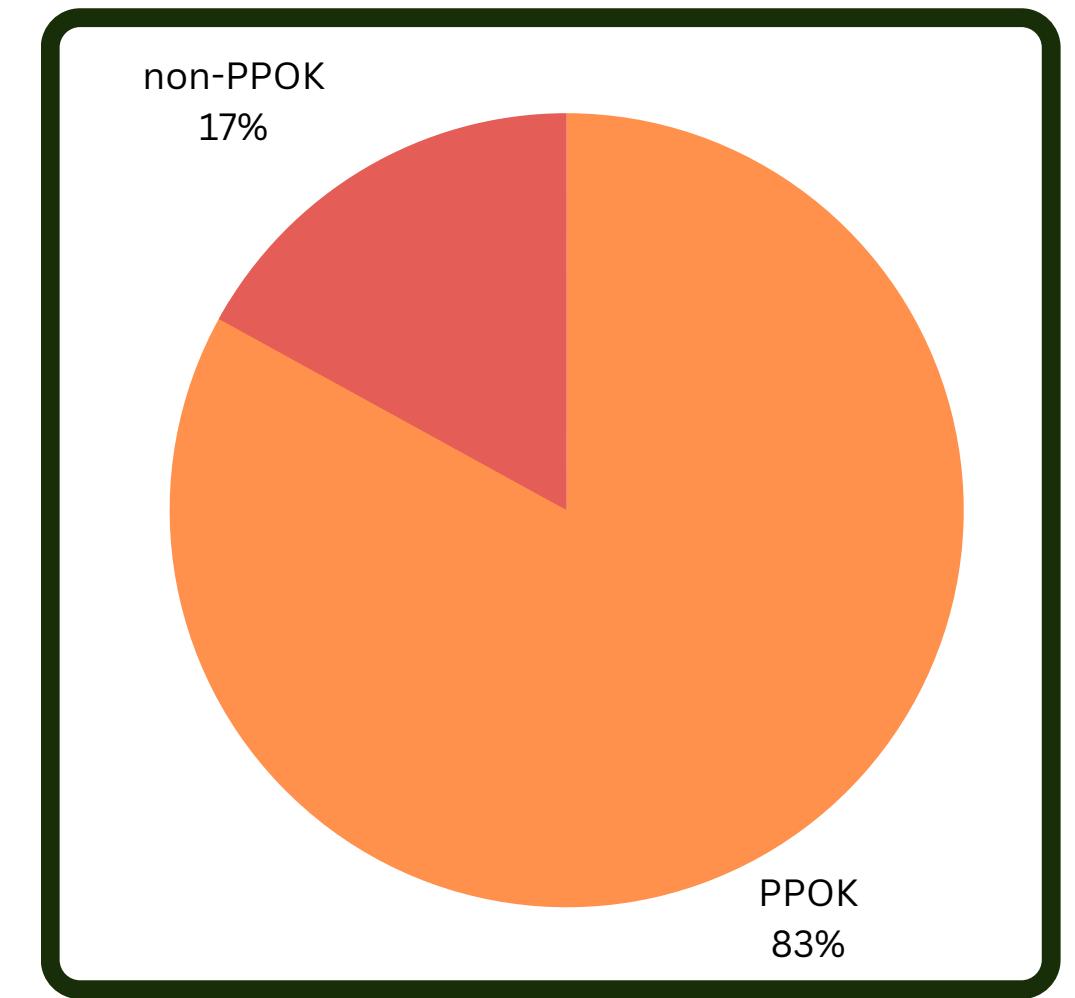
3.satu text file (.txt) berisi diagnosis setiap pasien (PPOK & non-PPOK)

4.satu text file (.txt) berisi penjelasan penamaan pada file audio

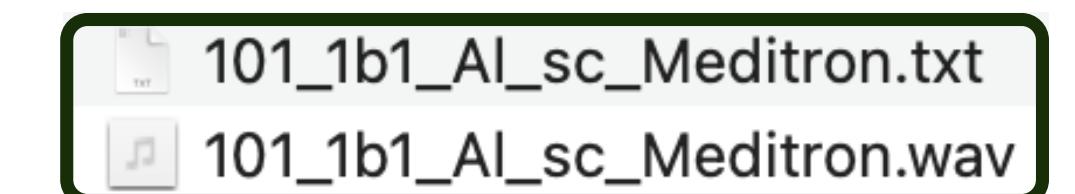


t_start	t_end	Crackles	Wheezes
9.279	11.15	0	0
11.15	13.036	0	0
13.036	14.721	0	0
14.721	16.707	0	0
16.707	18.507	0	0
18.507	19.964	0	0

2



3

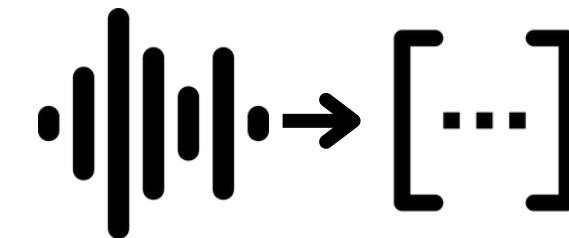


4

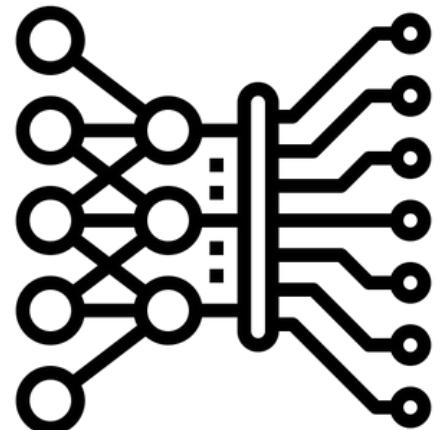
1 1. [HTTPS://BHICHALLENGE.MED.AUTH.GR/](https://bhichallenge.med.auth.gr/)

METODOLOGI

Pembersihan dan
Transformasi Data



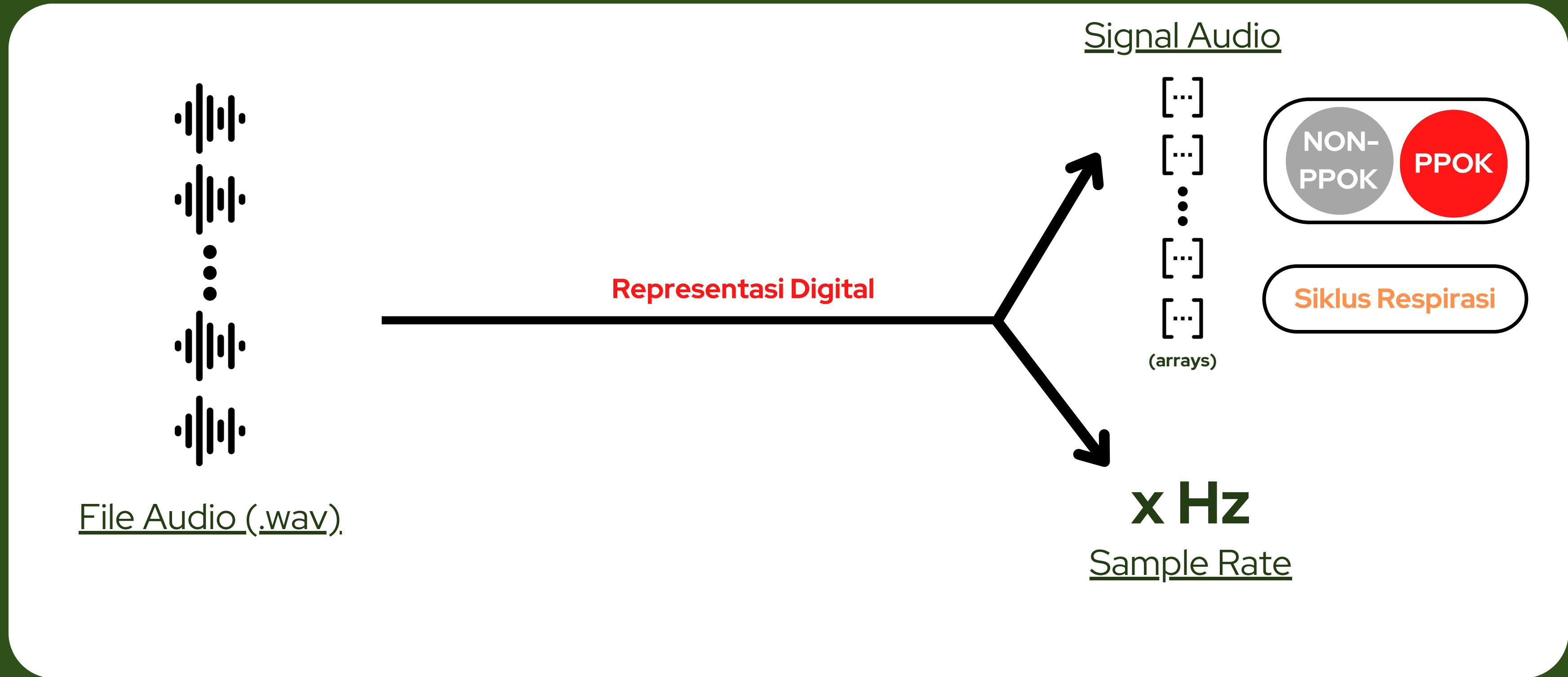
Pemodelan



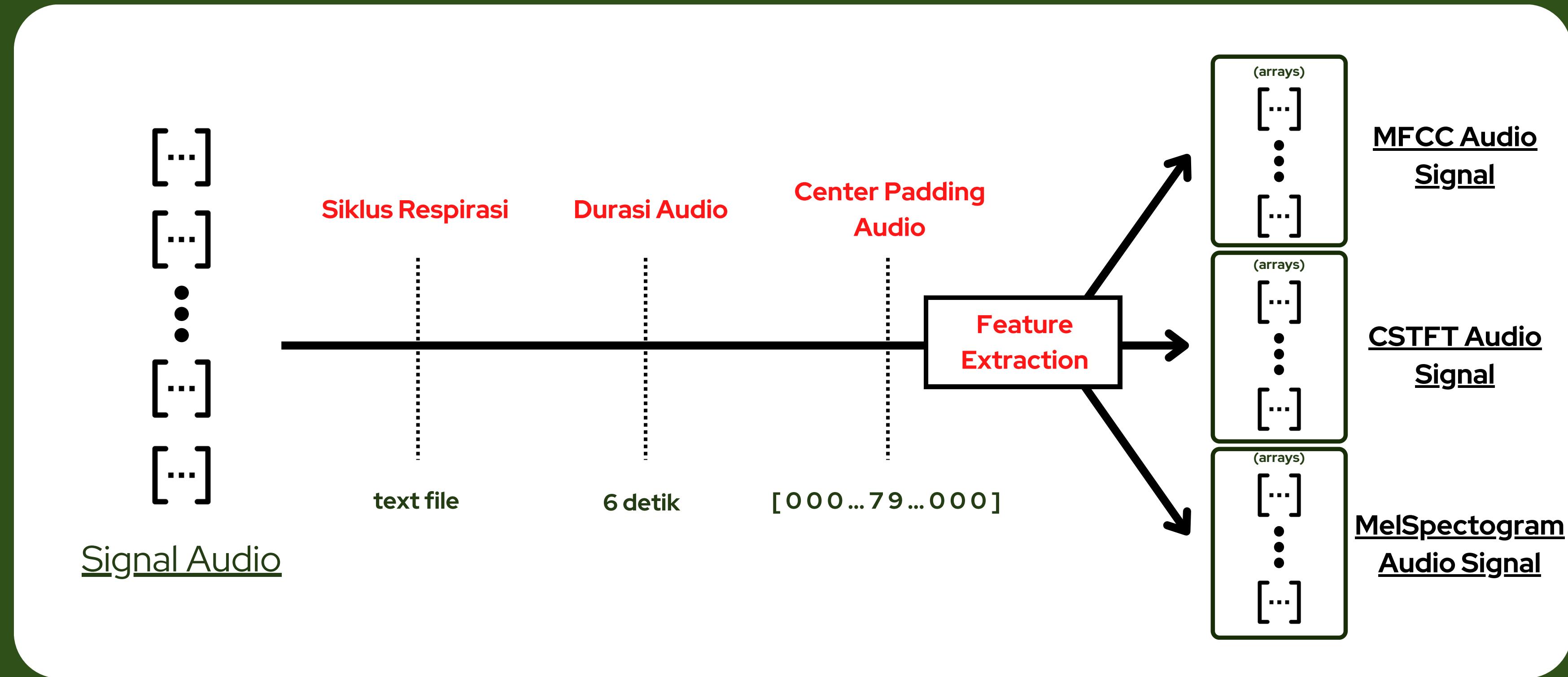
Evaluasi
Model



TRANSFORMASI & PEMBERSIHAN DATA



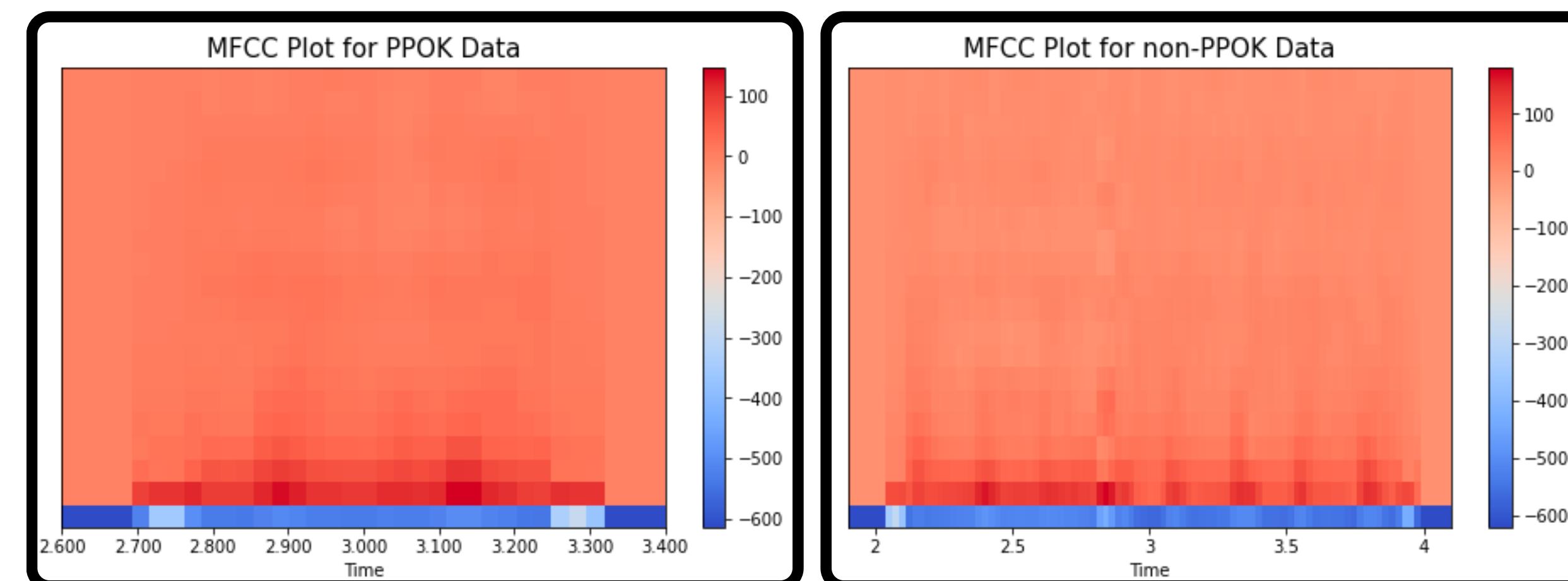
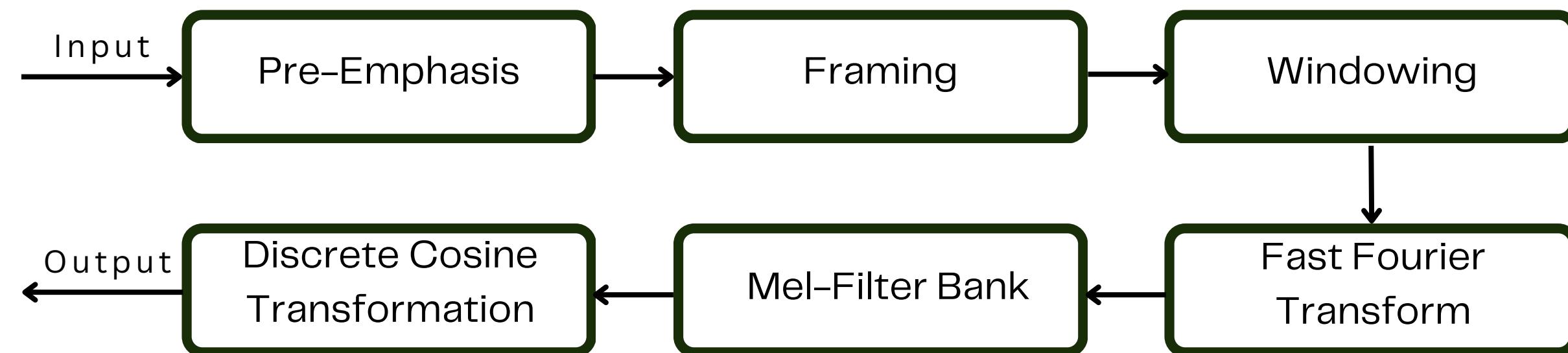
TRANSFORMASI & PEMBERSIHAN DATA



MFCC

FEATURE EXTRACTION PROCESS

MFCC memperhatikan persepsi pendengaran manusia yang tidak dapat merasakan frekuensi lebih dari 1Khz.



Pre-Emphasis

- Mengkompensasi bagian frekuensi tinggi.
- Memperkuat pentingnya proporsi frekuensi tinggi pada data suara.

$$Y[n] = X[n] - 0.95 X[n-1]$$

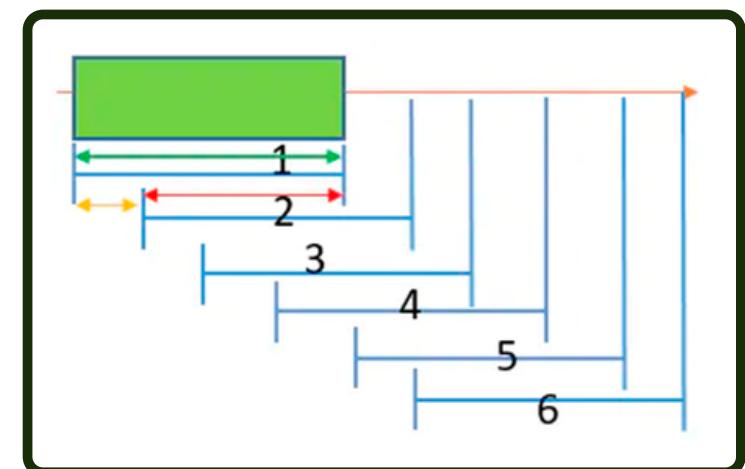
$Y[n]$: hasil pre-emphasis sinyal audio

$X[n]$: sinyal audio awal

n : suku ke- n dari sinyal audio

Framing

- Sinyal Audio di bingkai (*frame*).
- Sinyal suara dibagi menjadi beberapa frame dengan isinya berisi N sampel.
- notasikan banyaknya bingkai adalah F



Windowing

- Hamming Window digunakan sebagai jendela, dan mengaplikasikannya untuk setiap frame yang diapatkan pada proses sebelumnya.

$$Y(n) = X(n) \times W(n)$$

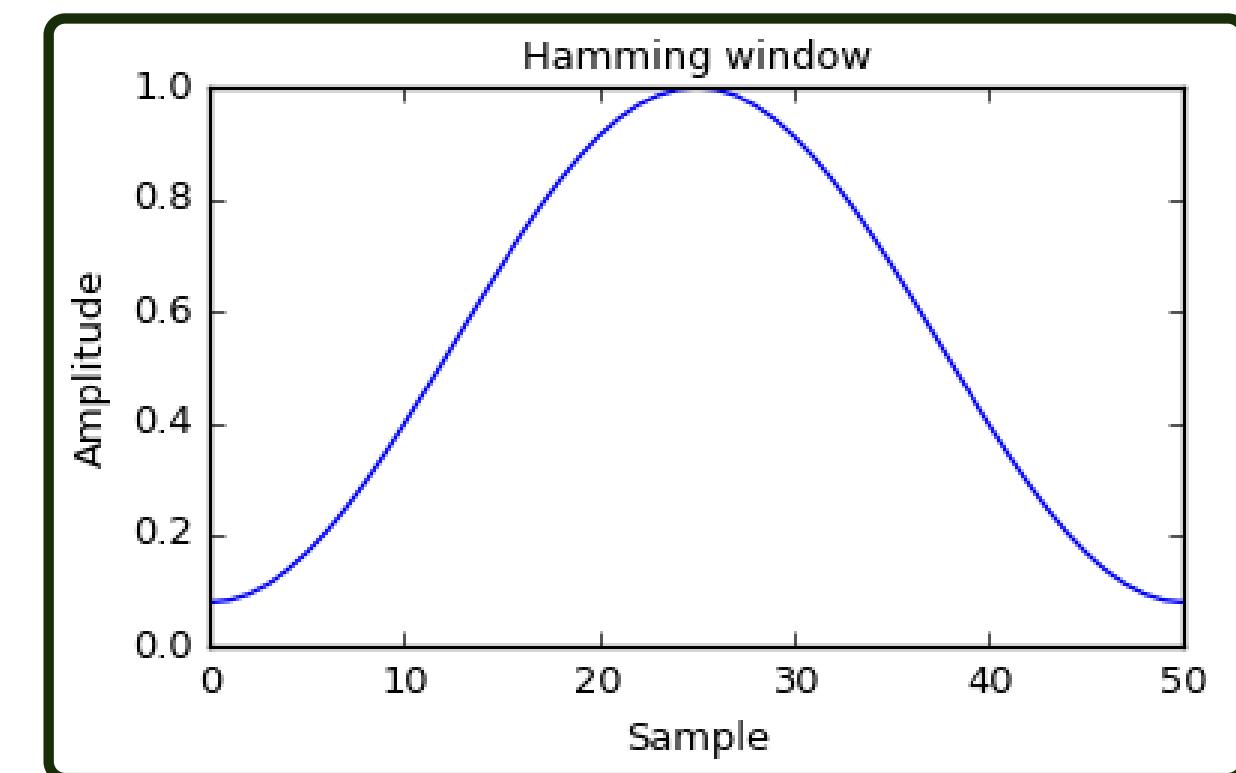
N = number of samples in each frame

$Y[n]$ = Output signal

$X(n)$ = input signal

$W(n)$ = Hamming window, then the result of windowing signal is shown below:

$$W(n) = 0.54 - 0.46 \cos \left(\frac{2\pi n}{N-1} \right) \quad 0 \leq n \leq N-1$$

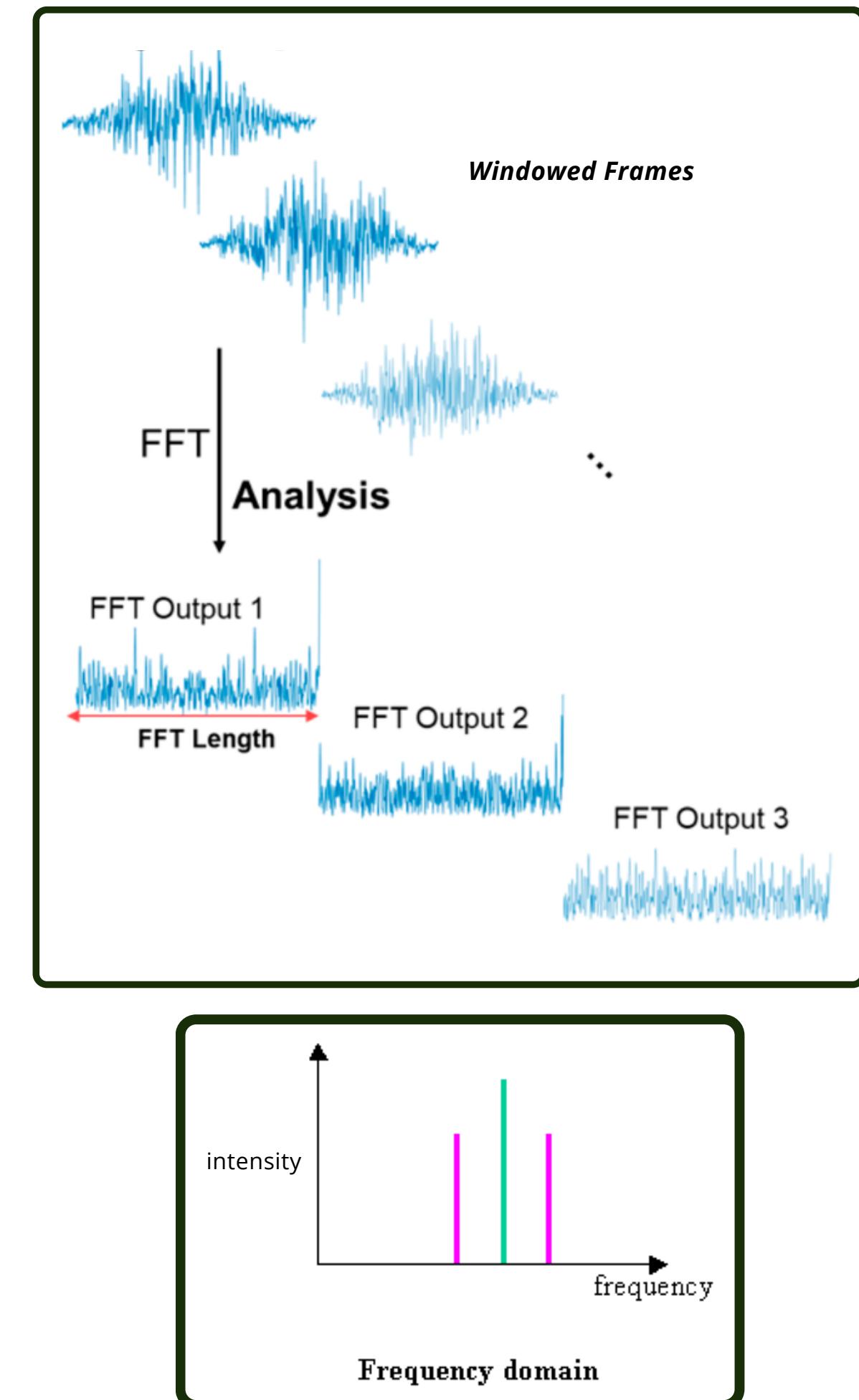
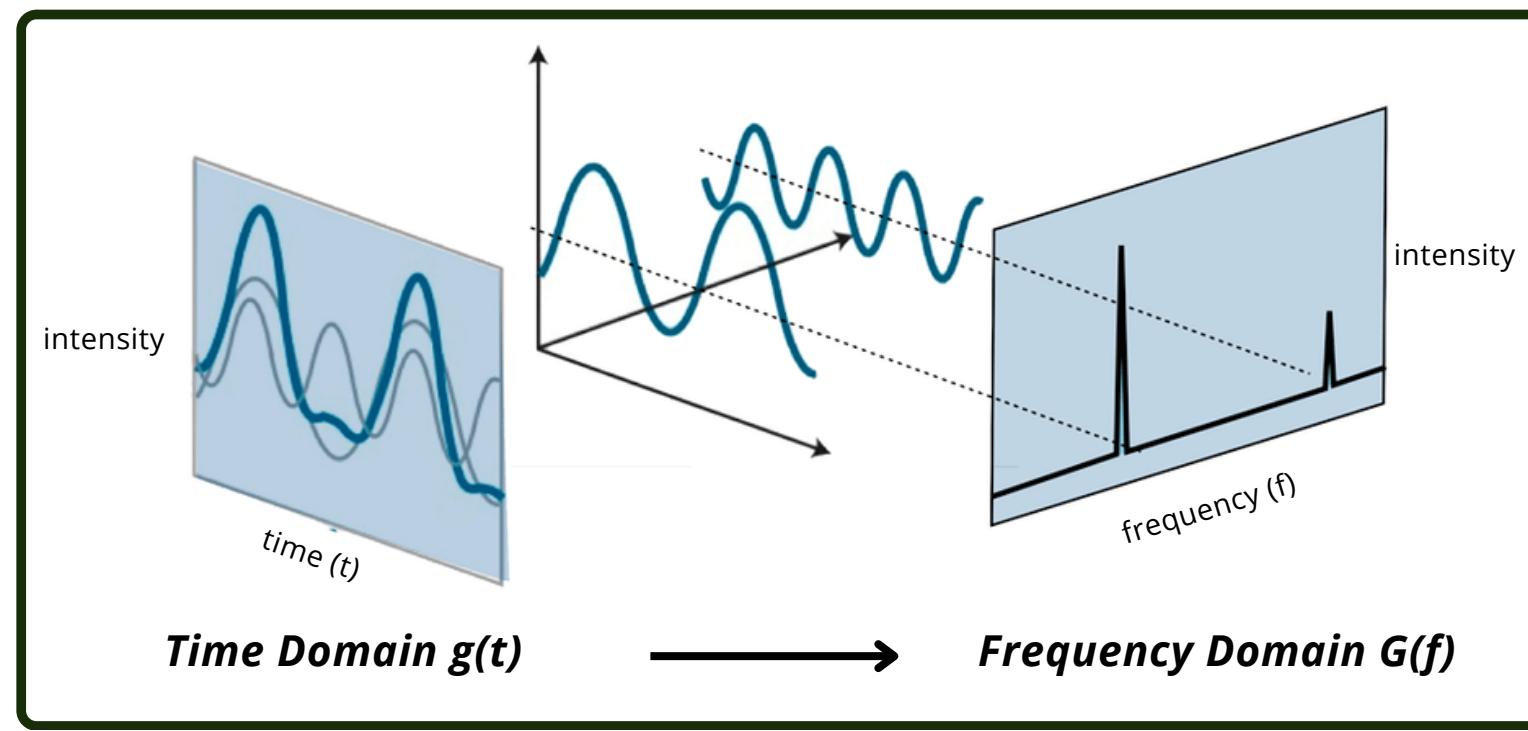


Fast Fourier Transform

- Algoritma yang efisien untuk menghitung DFT (Discrete Fourier Transform).
- Mengurangi kompleksitas DFT dari $O(n^2)$ menjadi $O(n \log n)$
- DFT :

$$X_k = \sum_{n=0}^{N-1} x_n \cdot e^{-i2\pi kn/N} = \sum_{n=0}^{N-1} x_n [\cos(2\pi kn/N) - i \cdot \sin(2\pi kn/N)]$$

- N = number of samples
- n = current sample
- k = current frequency, where $k \in [0, N - 1]$
- x_n = the sine value at sample n
- X_k = The DFT which include information of both amplitude and phase



Mel-Filter Bank

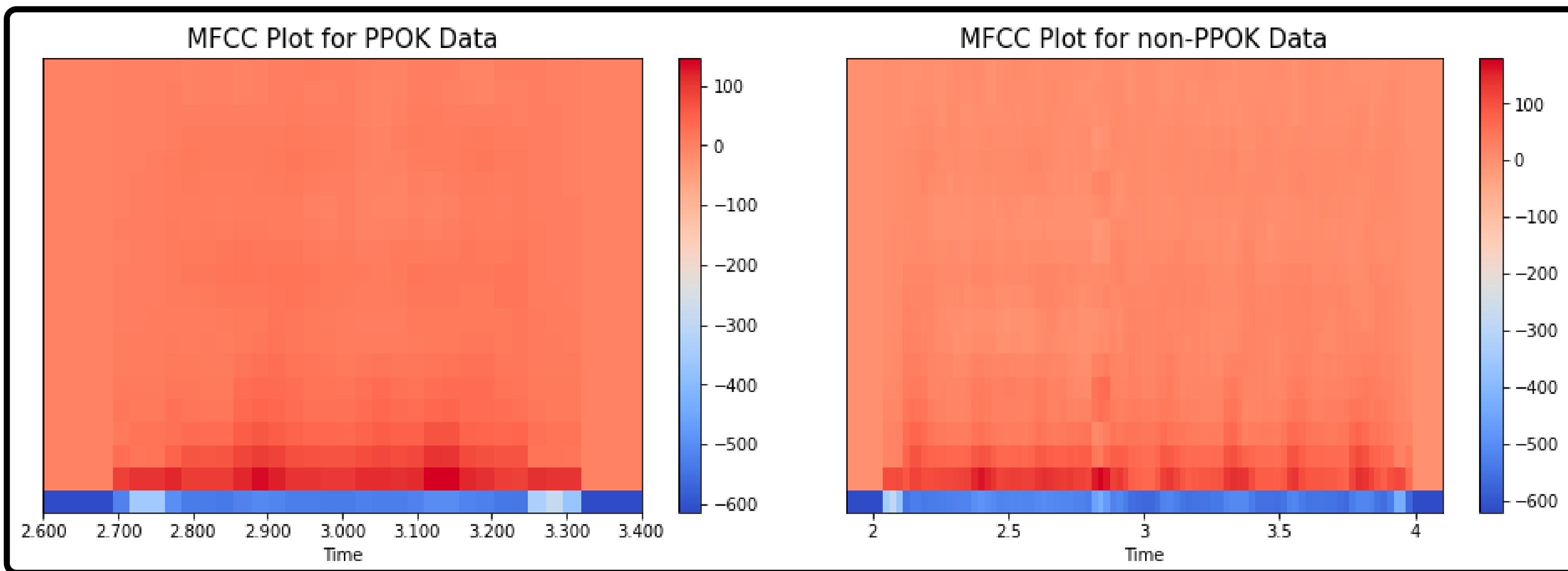
- Mel Filter Banks bekerja mirip dengan telinga manusia persepsi suara yang memberikan resolusi yang lebih baik pada frekuensi rendah dibandingkan pada frekuensi tinggi.
- Rumus menghitung Mel:

$$m = 2595 \log_{10} \left(1 + \frac{f}{700} \right)$$

$F(Mel)$: Mel
 f : frekuensi (Hz)

Discrete Cosine Transformation

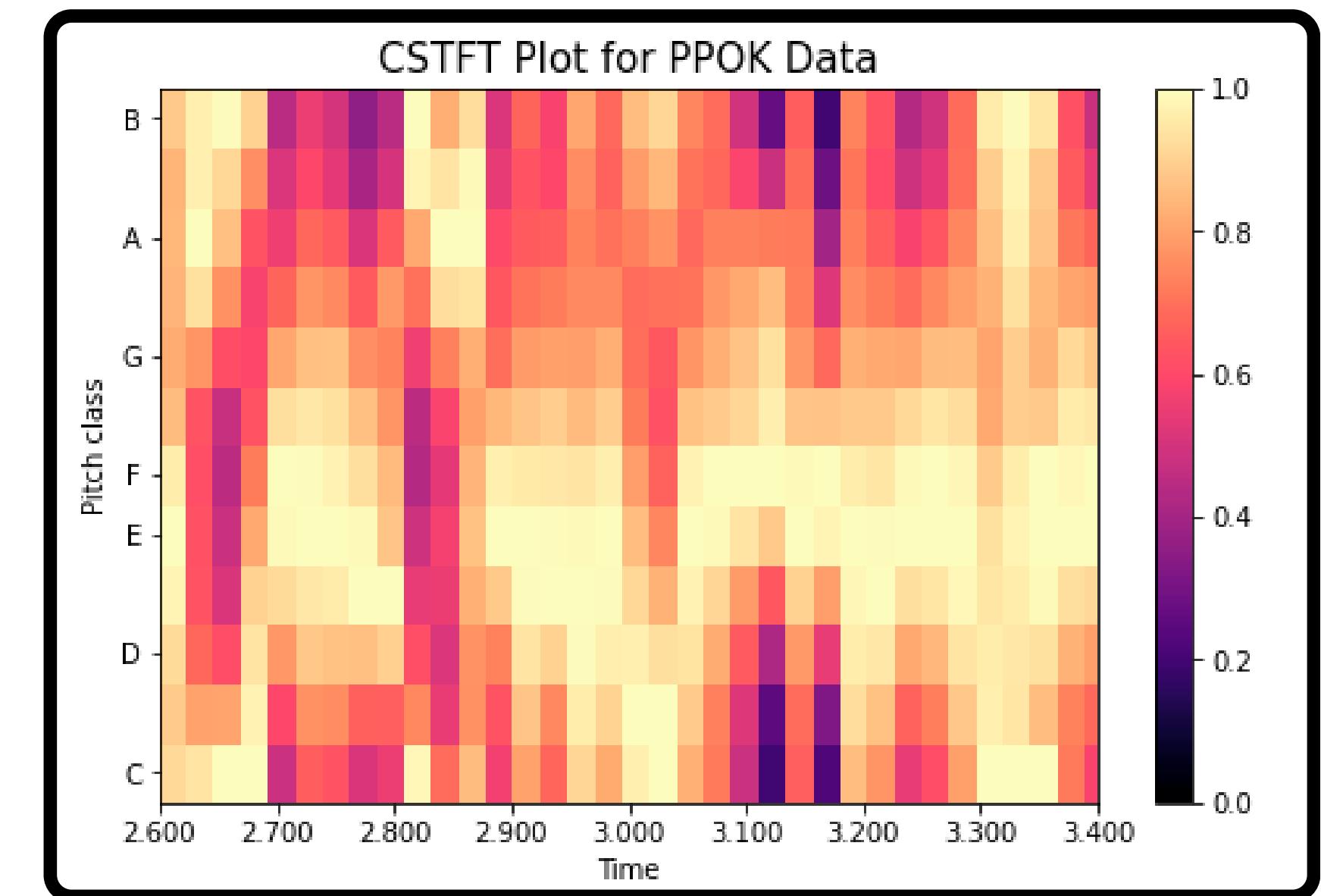
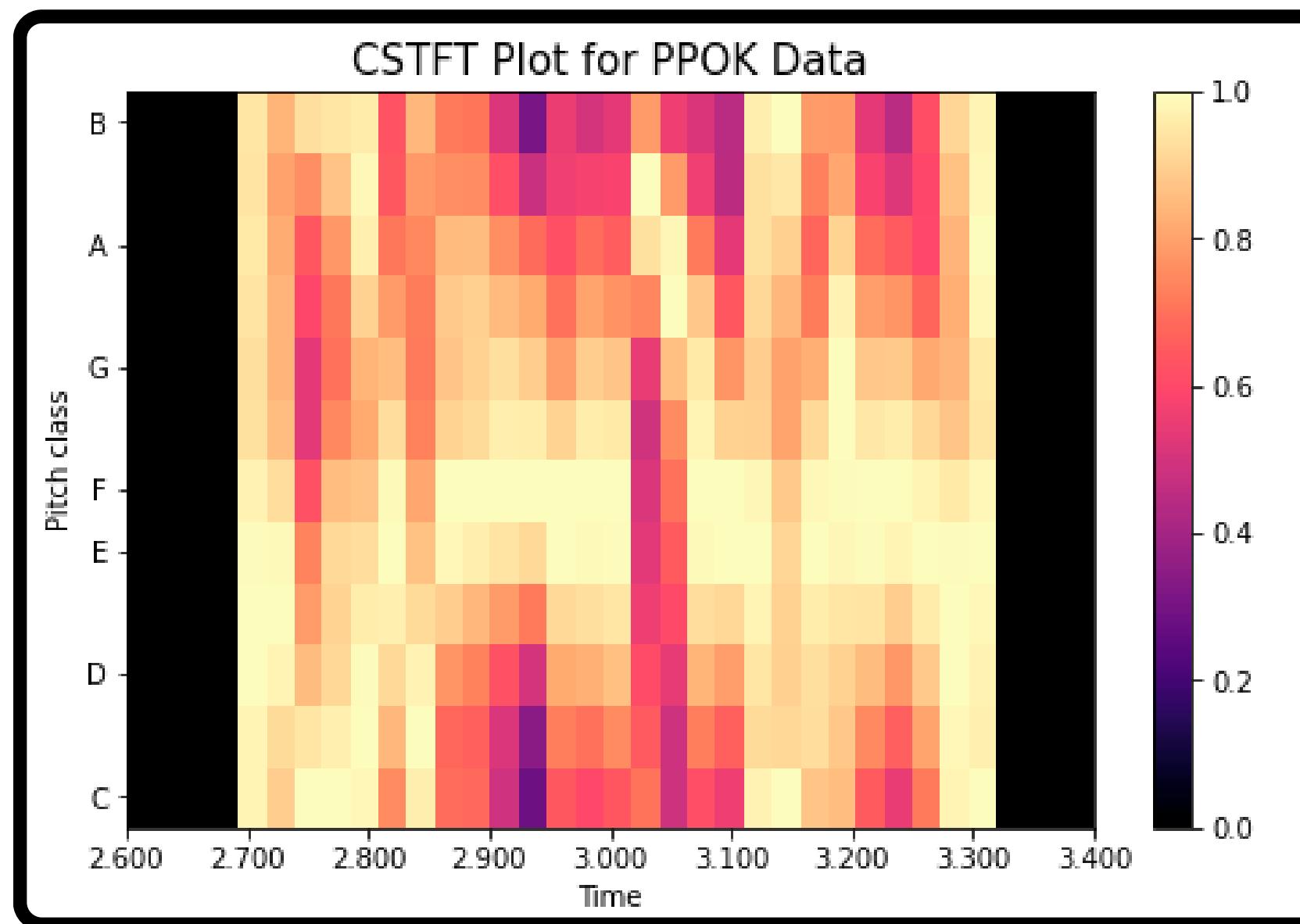
- Proses untuk konversi spektrum log Mel
- Hasil konversi tersebut dinamakan Mel Frequency Cepstrum Coefficient.

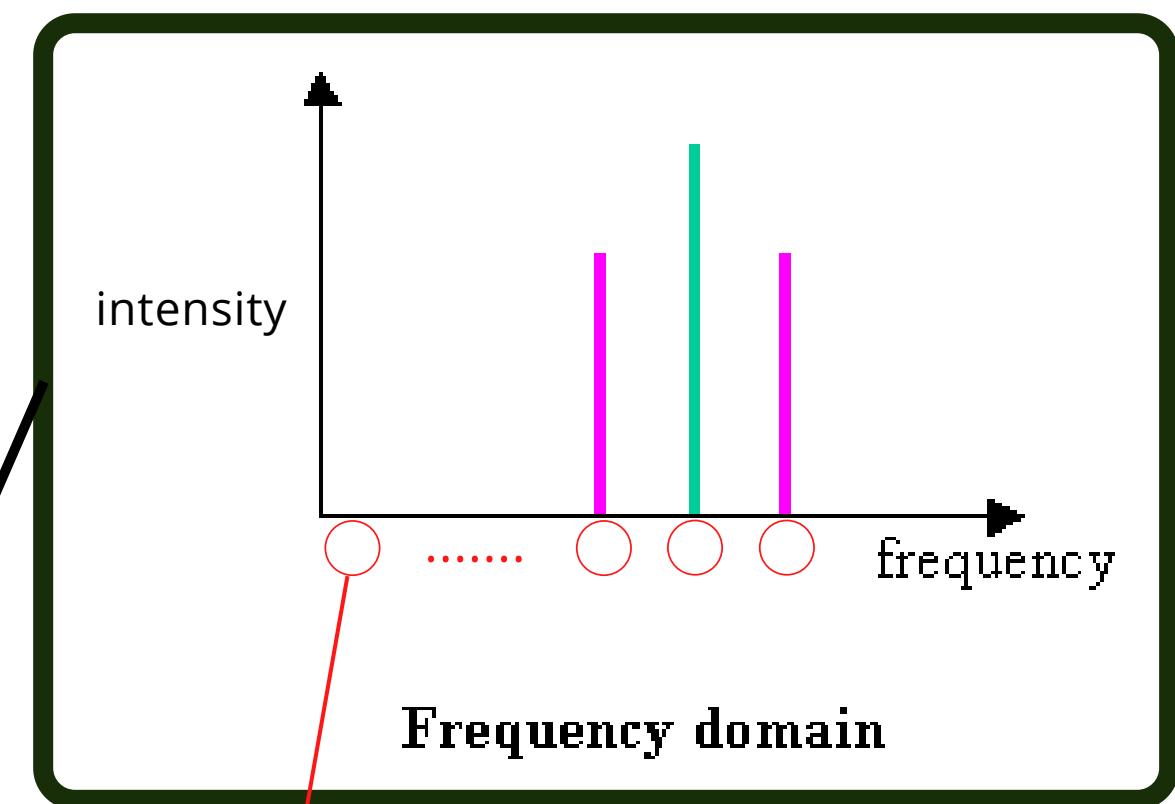
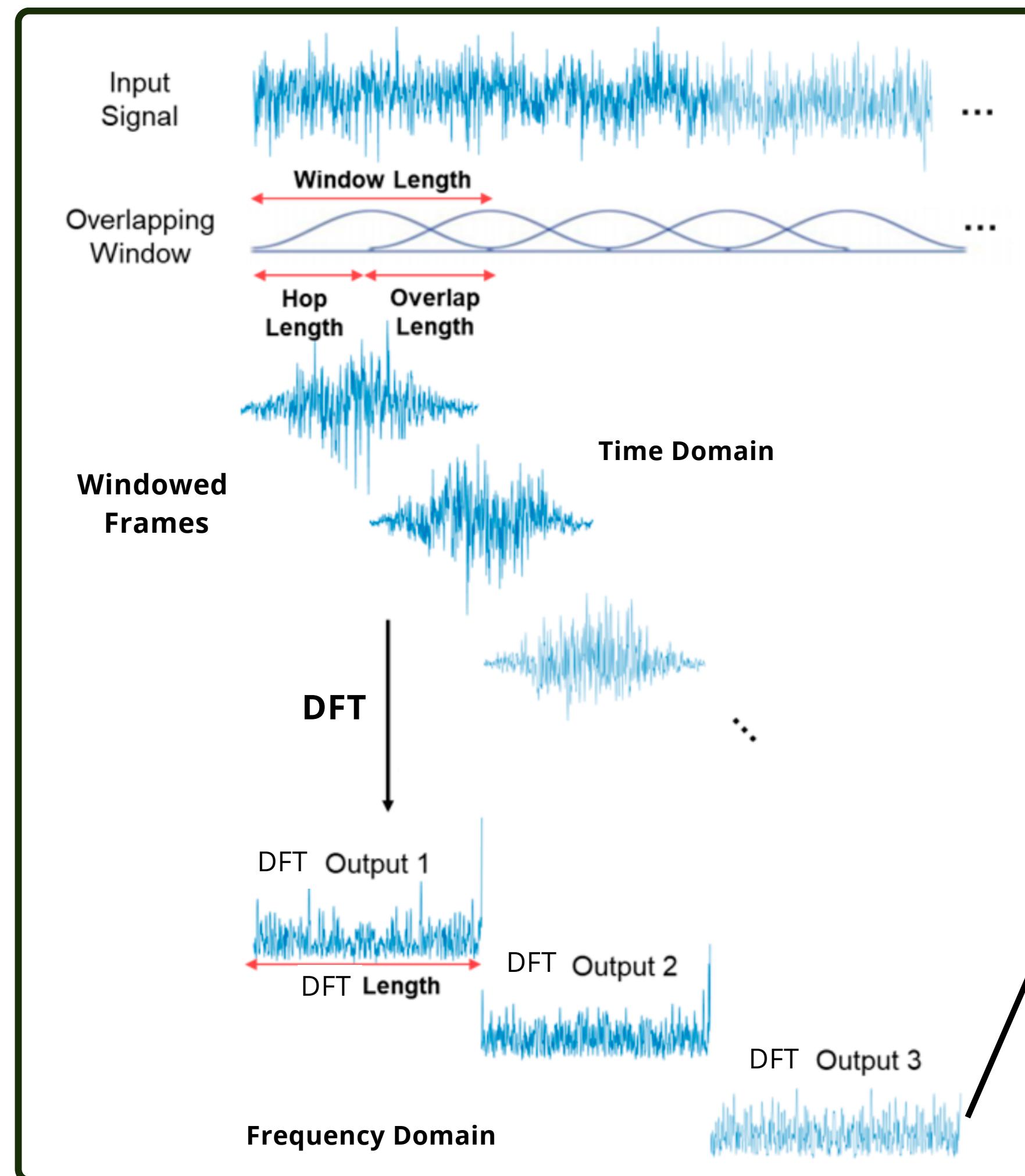


CSTFT

FEATURE EXTRACTION PROCESS

CSTFT memperhatikan persepsi manusia tentang nada bersifat periodik, artinya dua nada dianggap serupa dalam "warna" (harmoni yang serupa) jika berbeda satu atau beberapa oktaf (12 nada).





$$F_{\text{coef}}(k) := \frac{k \cdot F_s}{N}$$

F_s : Sample Rate Tetap (Hz)

m : frame ke- m dari seluruh frame ($0 \leq m \leq F$)

k : koefisien DFT ke- k ($0 \leq k \leq K$)

Octave	Note numbers												
	Do	Do#	Re	Re#	Mi	Fa	Fa#	Sol	Sol#	La	La#	Si	
	C	C#	D	D#	E	F	F#	G	G#	A	A#	B	
0	0	1	2	3	4	5	6	7	8	9	10	11	
1	12	13	14	15	16	17	18	19	20	21	22	23	
2	24	25	26	27	28	29	30	31	32	33	34	35	
3	36	37	38	39	40	41	42	43	44	45	46	47	
4	48	49	50	51	52	53	54	55	56	57	58	59	
5	60	61	62	63	64	65	66	67	68	69	70	71	
6	72	73	74	75	76	77	78	79	80	81	82	83	
7	84	85	86	87	88	89	90	91	92	93	94	95	
8	96	97	98	99	100	101	102	103	104	105	106	107	
9	108	109	110	111	112	113	114	115	116	117	118	119	
10	120	121	122	123	124	125	126	127					

- Dalam notasi MIDI (Musical Instrument Digital Interface), terdapat **128 nada**.

- 128 nada ini diberi nomor seri dimulai dengan 0 dan diakhiri dengan 127. ($p \in [0 : 127]$)

- Definisikan untuk setiap pitch $p \in [0 : 127]$, himpunan :
- $$P(p) := \{k \in [0 : K] : F_{\text{pitch}}(p - 0.5) \leq F_{\text{coef}}(k) < F_{\text{pitch}}(p + 0.5)\}.$$

$$F_{\text{pitch}}(p) = 2^{(p-69)/12} \cdot 440. \quad \text{Fpitch : Frequency Tengah}$$

$$F_{\text{coef}}(k) := \frac{k \cdot F_s}{N}$$

- Selanjutnya, untuk mendapatkan **log-frequency Spectrogram**, definisikan

$$\mathcal{Y}_{\text{LF}}(m, p) := \sum_{k \in P(p)} |\mathcal{X}(m, k)|^2.$$

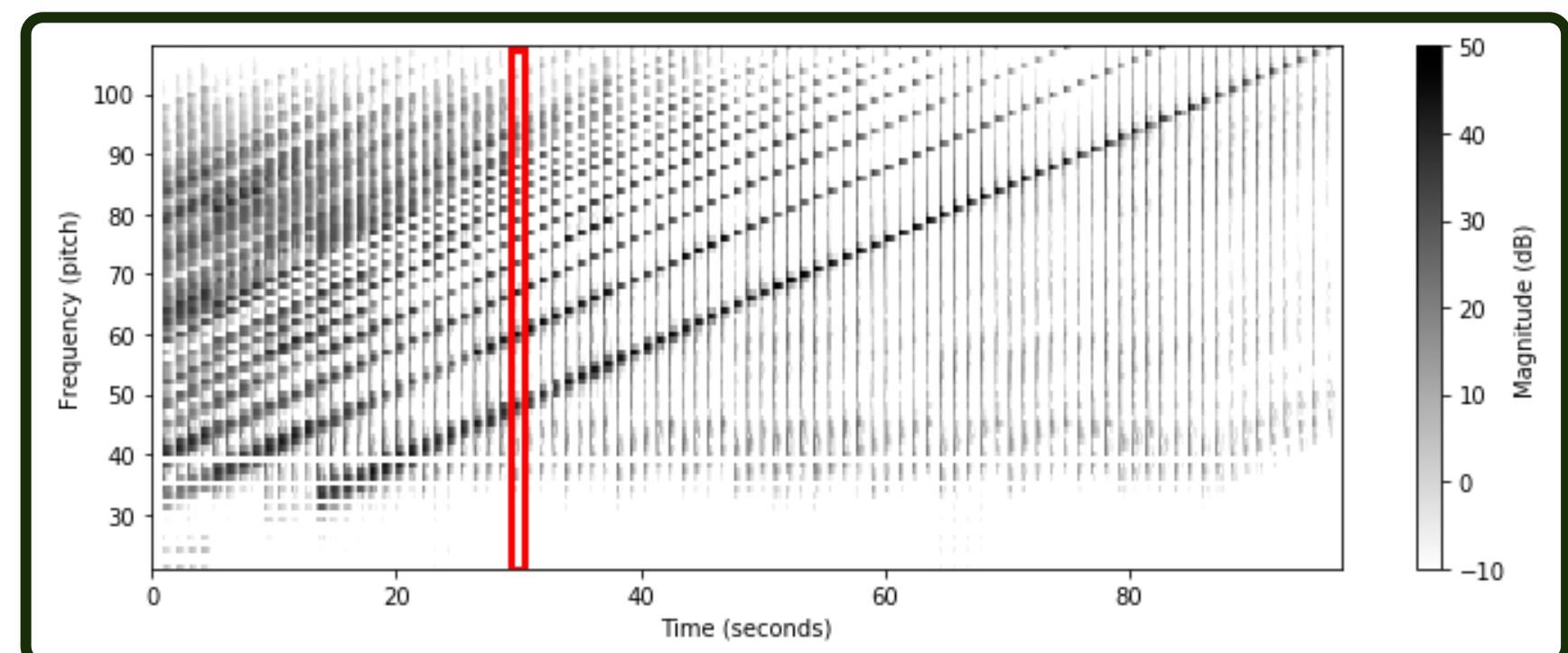
m : frame ke-m dari seluruh frame ($0 \leq m \leq F$)

k : koefisien Fourier ke-k ($0 \leq k \leq K$)

$\mathcal{X}(m, k)$: koefisien DFT ke-k dan pada frame ke-m

N : banyaknya sample dalam frame

H : parameter hop-size (ukuran pergeseran bingkai)



- Dalam notasi musik Barat, 12 atribut nada:
 - $\{C, C\#, D, D\#, E, F, F\#, G, G\#, A, A\#, B\}$.
- Notasikan himpunan $C = [0 : 11]$, $c \in C$
 - $c = 0$ merujuk ke kroma (nada) **C**
 - $c = 1$ ke kroma (nada) **C#**
- Kelas nada : Kumpulan semua nada yang memiliki **kroma yang sama**.
 - Chroma $c = 0$ (nada **C**) memiliki kelas nada :
 - $\{0, 12, 24, 36, 48, 60, 72, 84, 96, 108, 120\}$ (MIDI)
 - $\{C0, C1, C2, C3, \dots, C10\}$

- **Representasi chroma** : aggregasi semua *log-frequency spectogram* berdasarkan **pitch (p)** kedalam satu koefisien.

- output : 12 representasi chroma

- **Representasi chroma pada chromagram :**

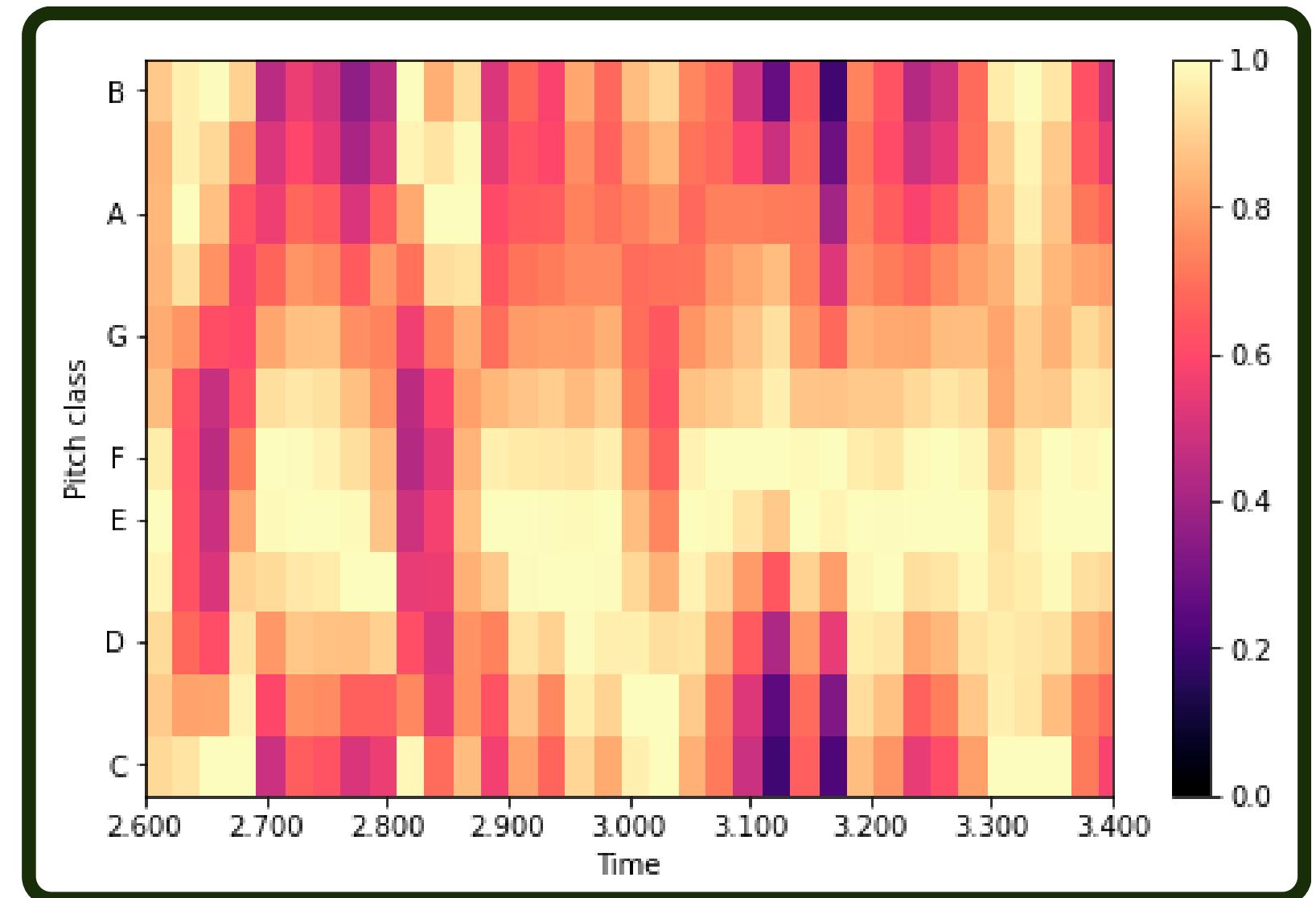
$$\mathcal{C}(m, c) := \sum_{\{p \in [0:127] \mid p \bmod 12 = c\}} \mathcal{Y}_{LF}(m, p) \quad \text{for } c \in [0 : 11].$$

m : frame ke- m dari seluruh frame ($0 \leq m \leq F$)

c : Chroma ke- c ($0 \leq c \leq 11$)

$\mathcal{Y}_{LF}(m, p)$: nilai *log-frequency* spectogram

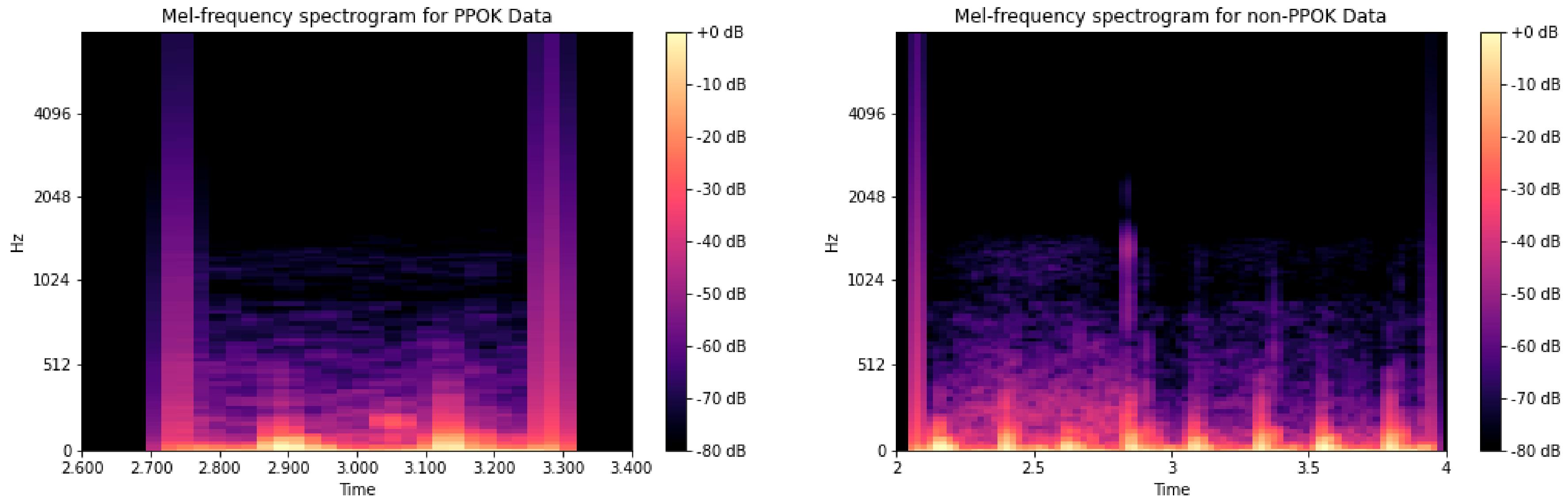
p : pitch ke- p



MEL SPECTROGRAM

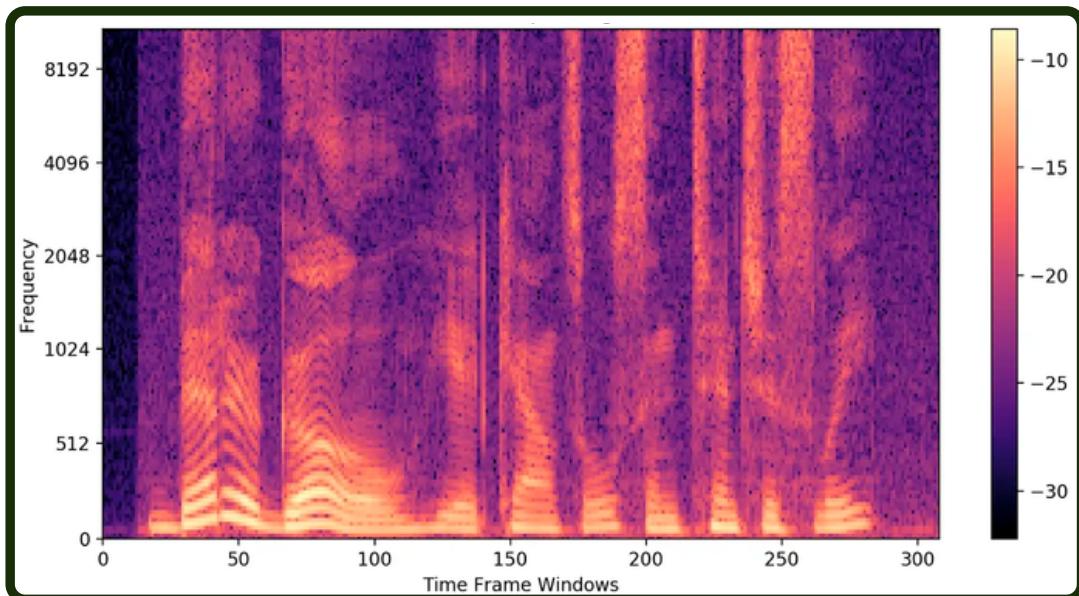
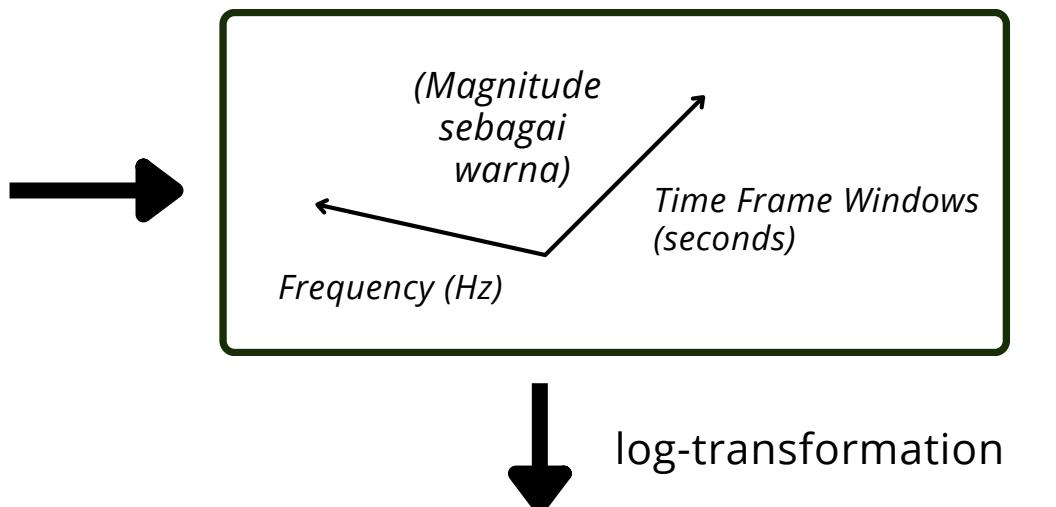
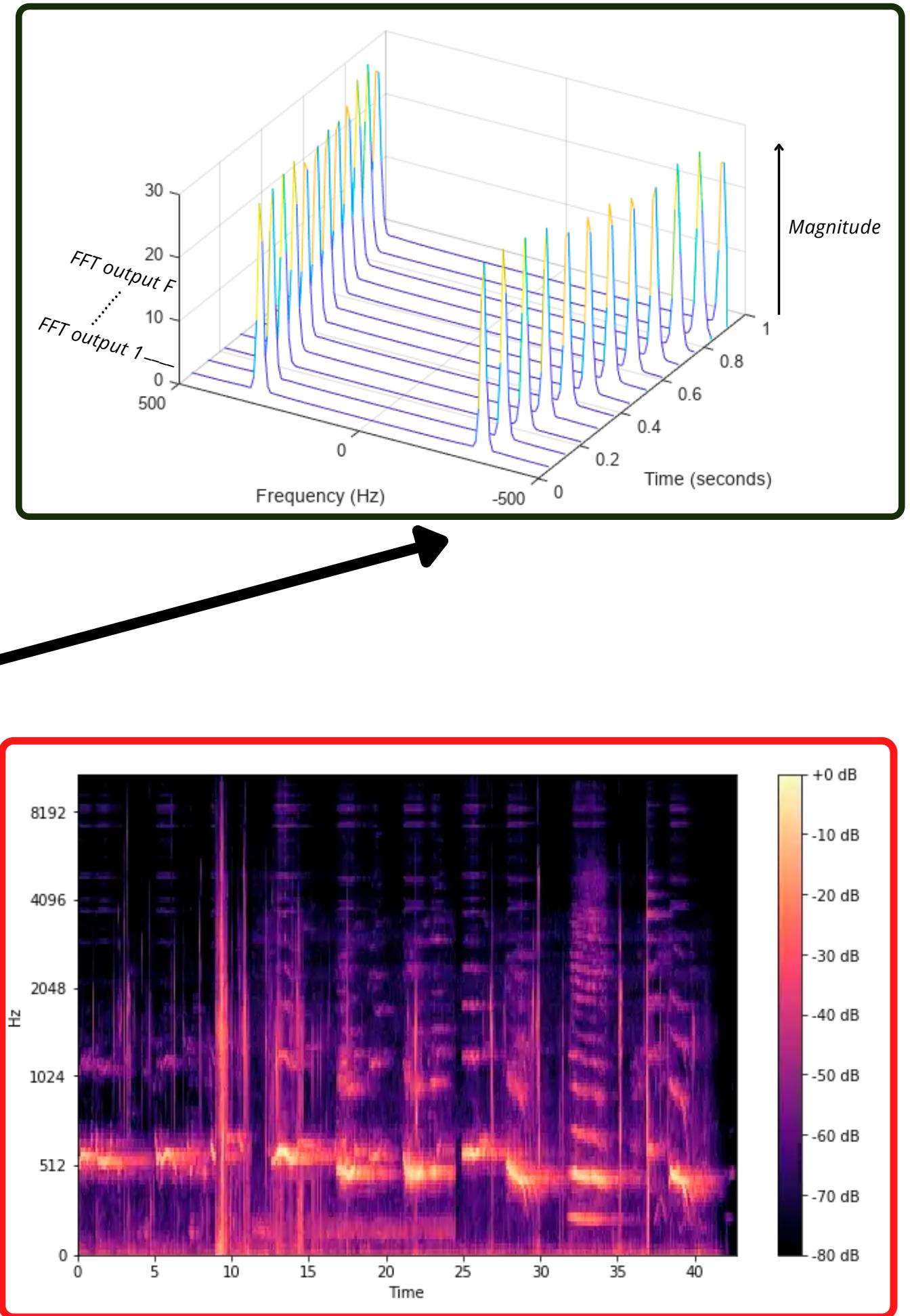
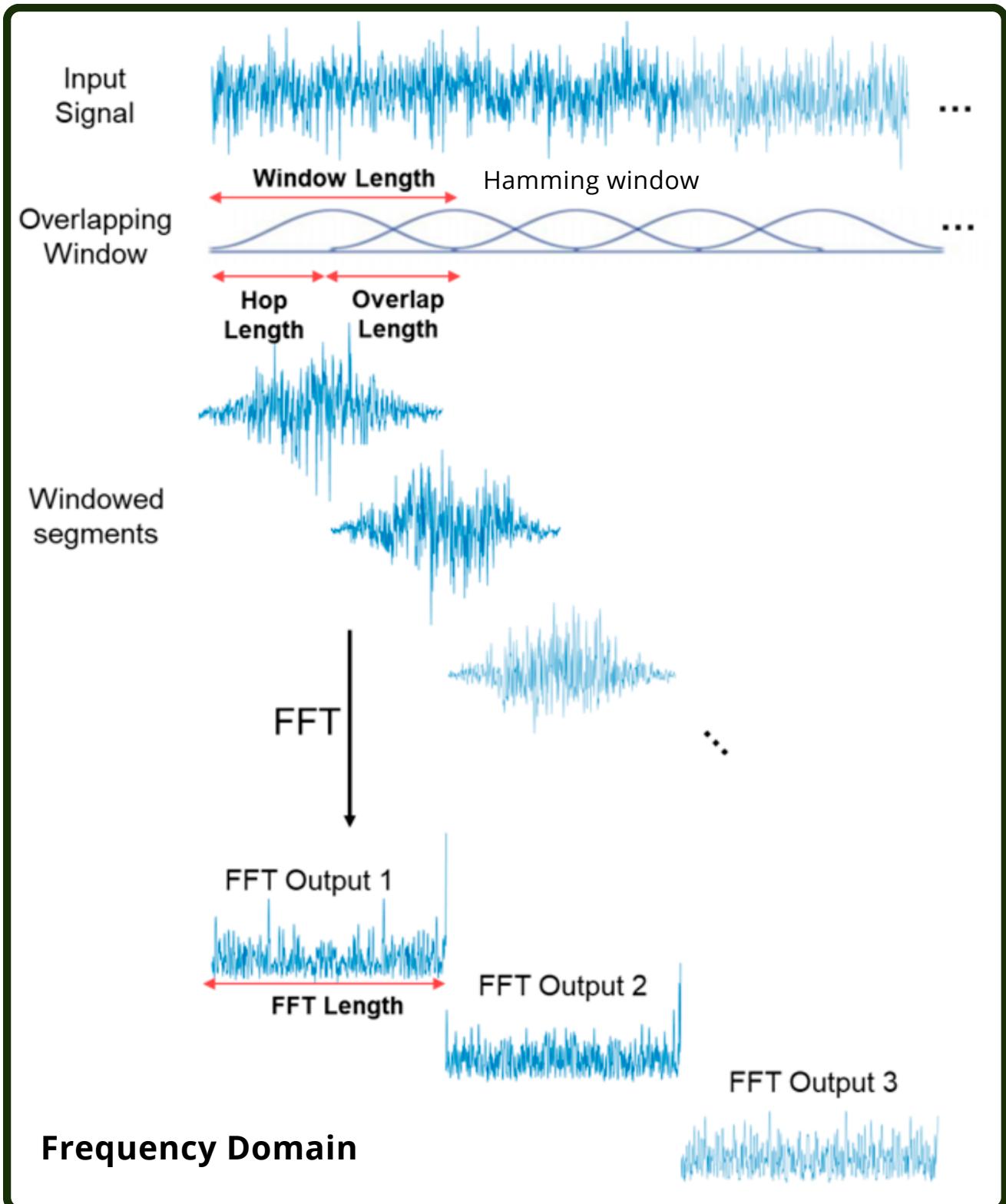
FEATURE EXTRACTION PROCESS

Spektogram mel adalah spektrogram yang frekuensinya diubah menjadi skala mel.



MEL SPECTROGRAM

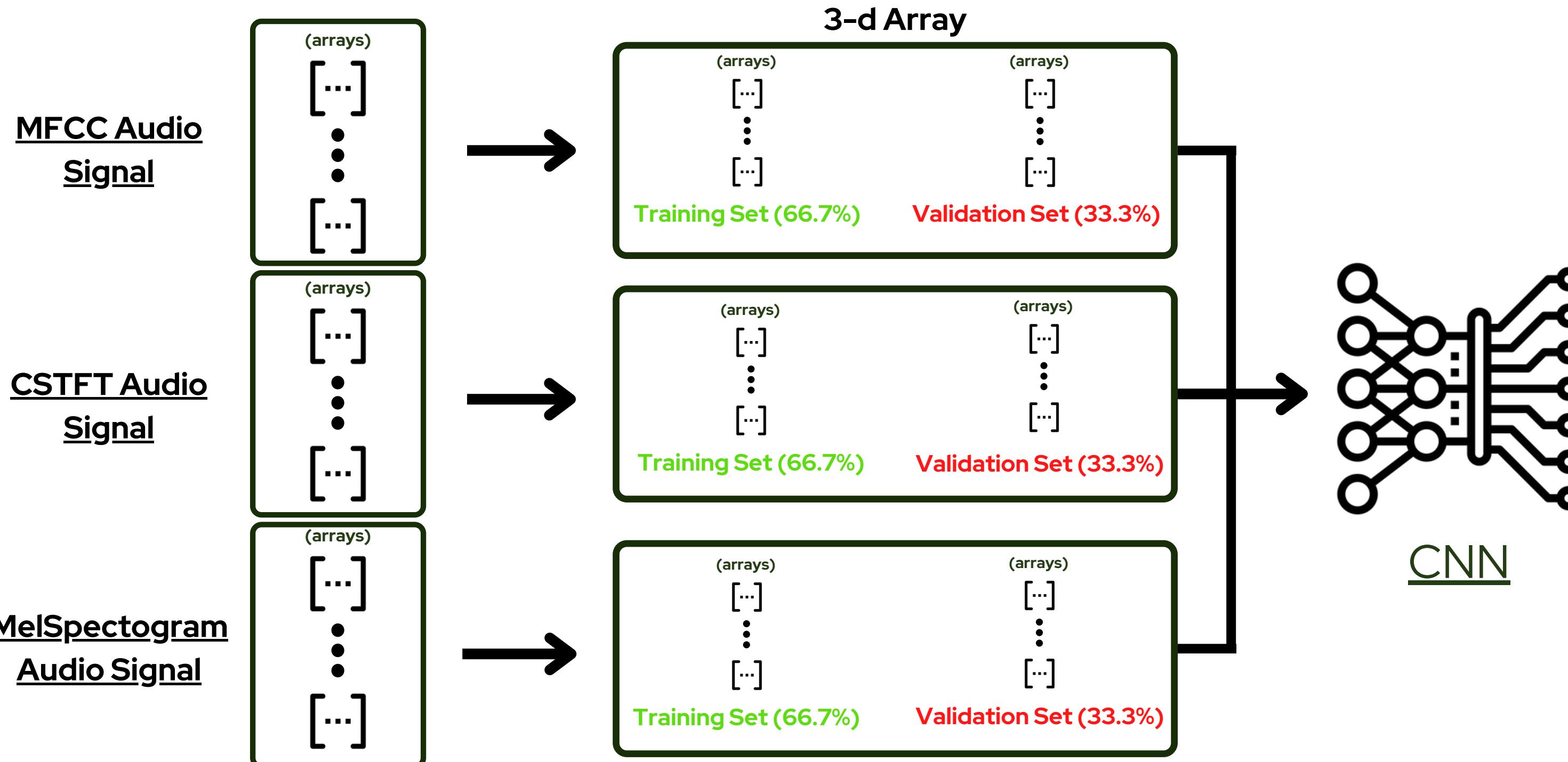
FEATURE EXTRACTION
PROCESS



Mel- Scaled Transformation

$$m = 2595 \log_{10} \left(1 + \frac{f}{700} \right)$$

PEMODELAN

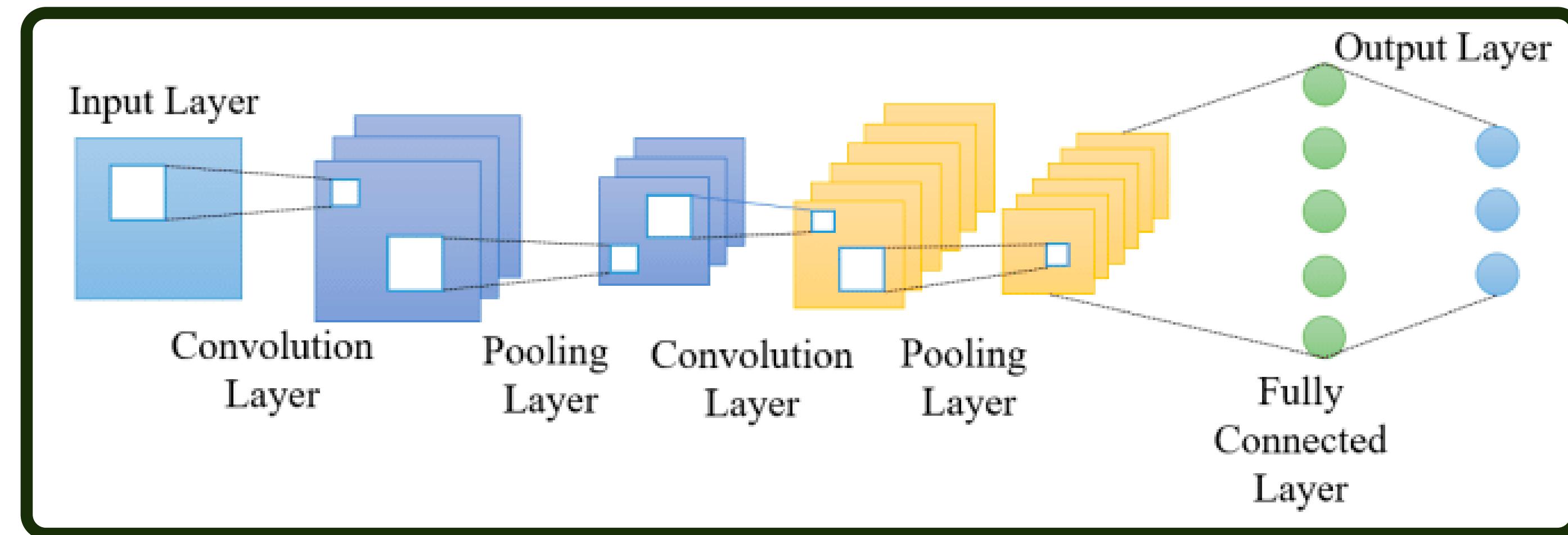


CNN

CONVOLUTIONAL NEURAL NETWORK

Salah satu dari berbagai jenis jaringan ***artificial neural network*** yang digunakan untuk berbagai aplikasi dan tipe data, paling umum diterapkan untuk **menganalisis gambar dan suara**.

Array 3 dimensi:
panjang, lebar,
kedalaman
(channel)
 $p \times l \times d$



Array 2 dimensi :
 $p \times l$

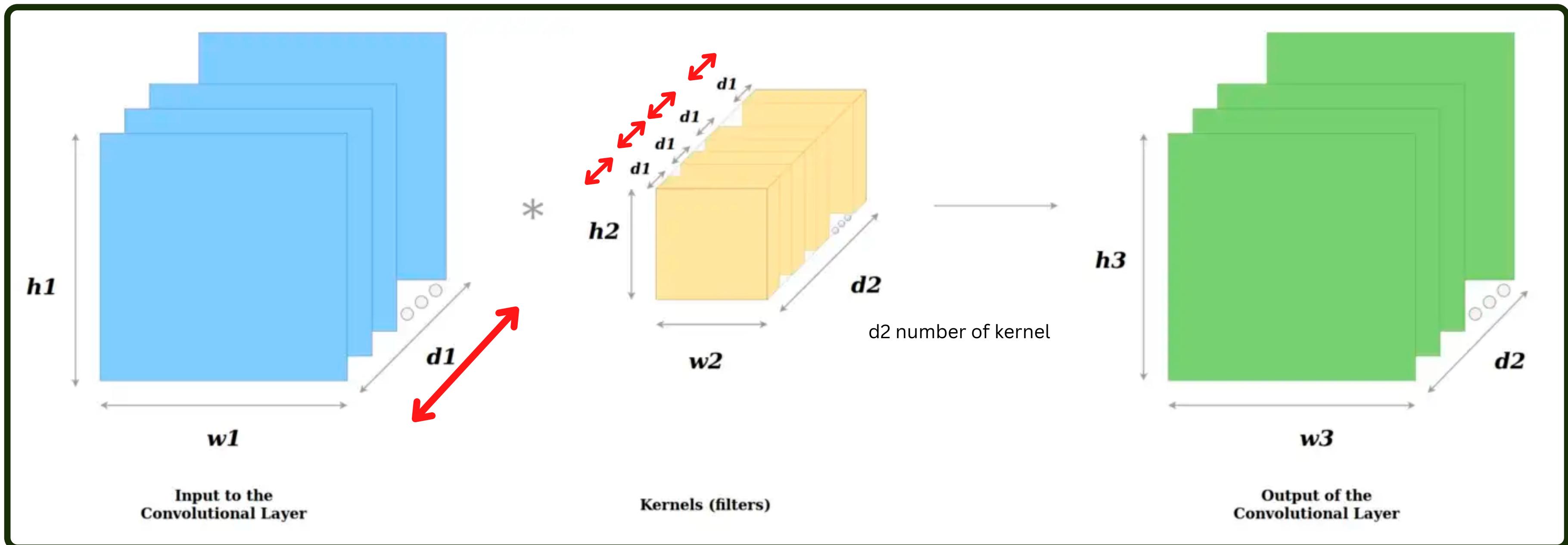
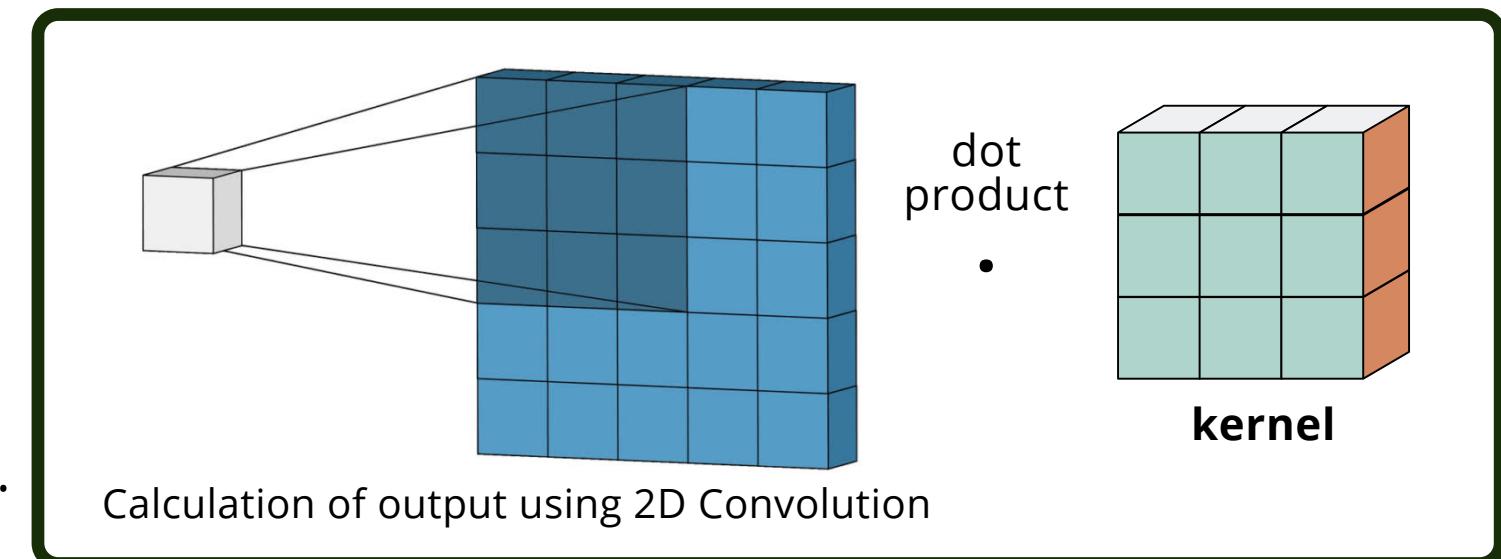
Convolutional Layer

Pooling Layer

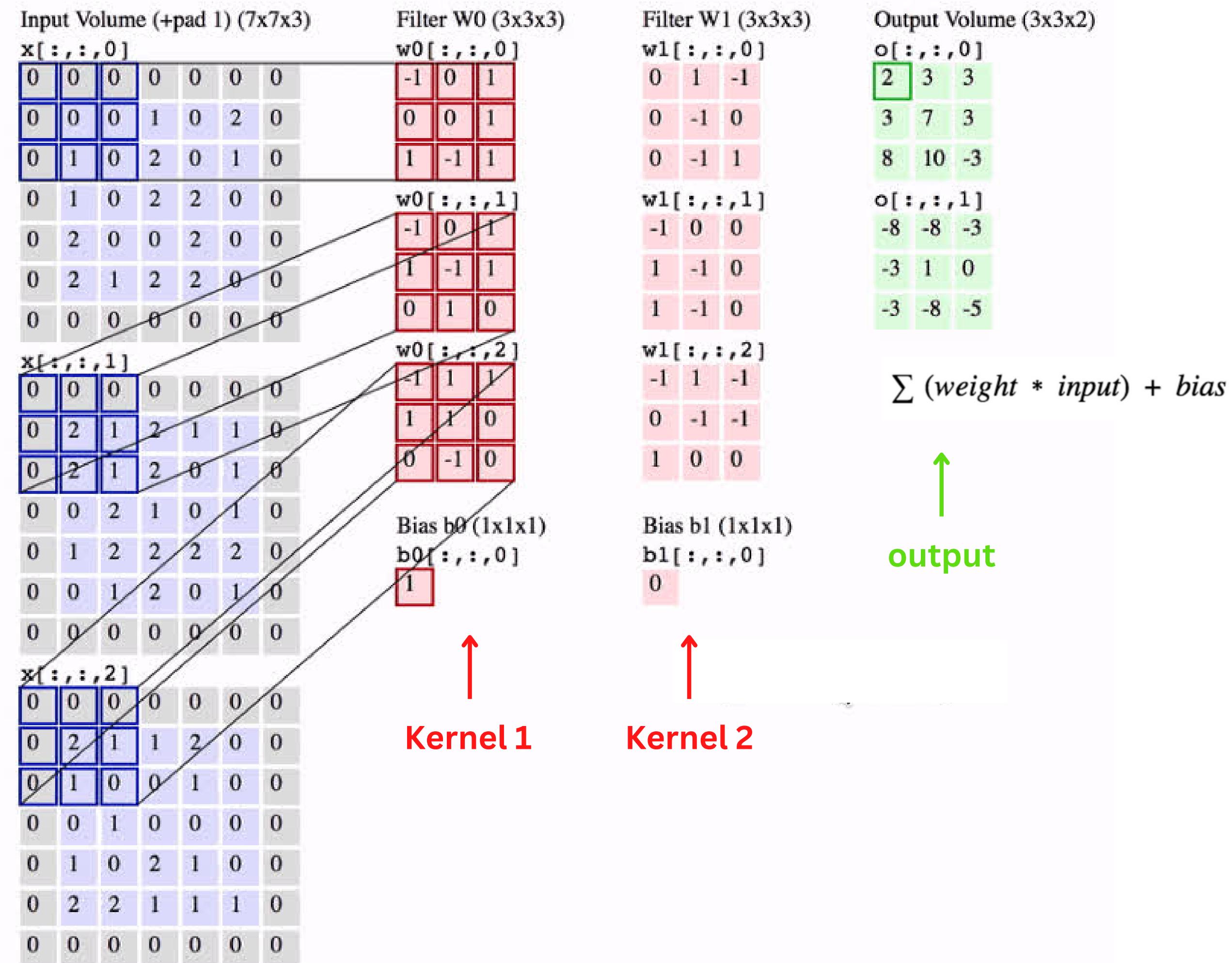
Fully Connected Layer

CONVOLUTIONAL LAYER

- Komponen paling **signifikan**
- Terdiri dari **koleksi kernel (filter) konvolusi** dan terjadi **dot product**.
- **Kernel : filter** yang digunakan dalam operasi konvolusi untuk **mengekstrak fitur**.



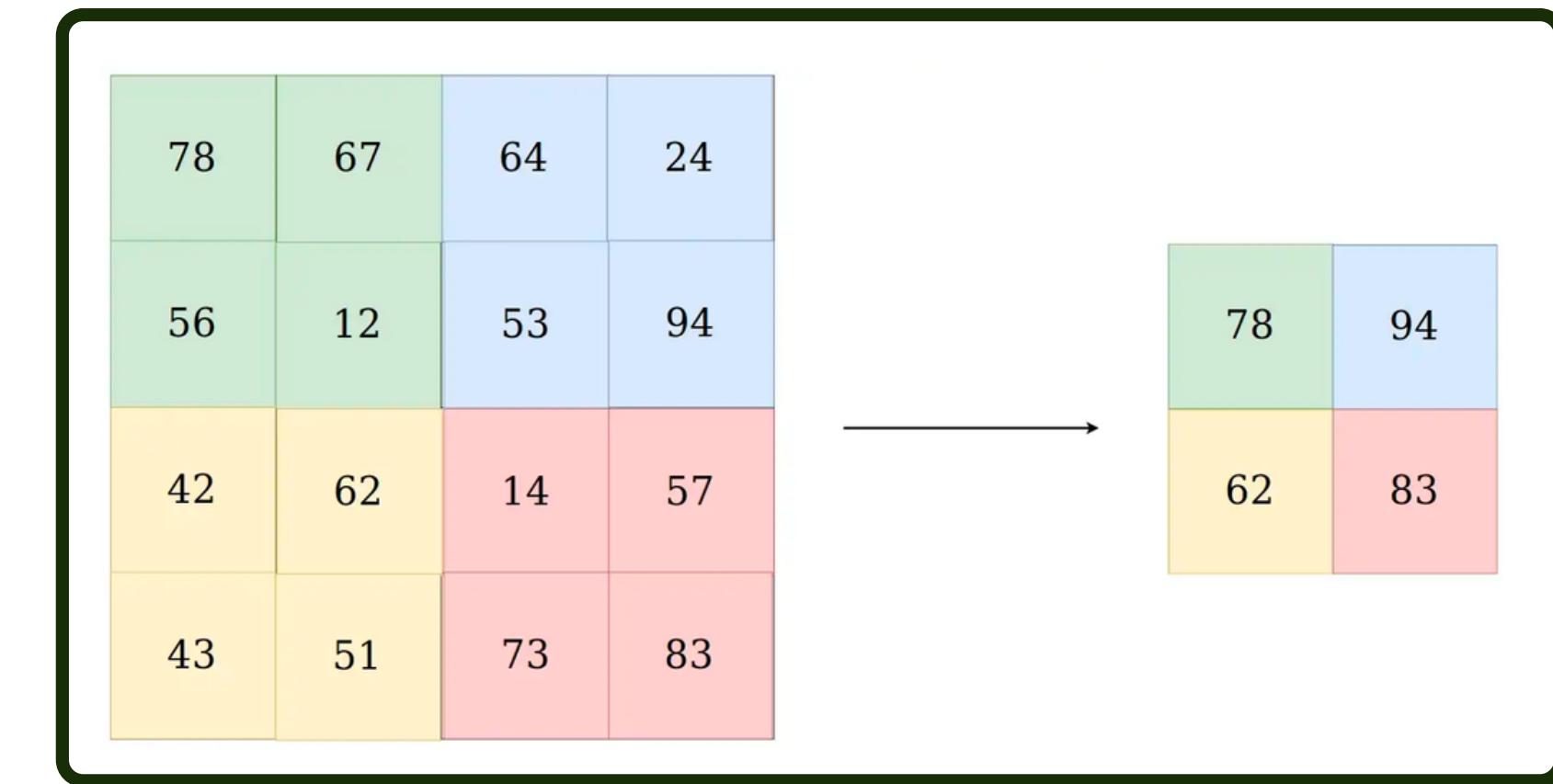
CONVOLUTIONAL LAYER - CNN



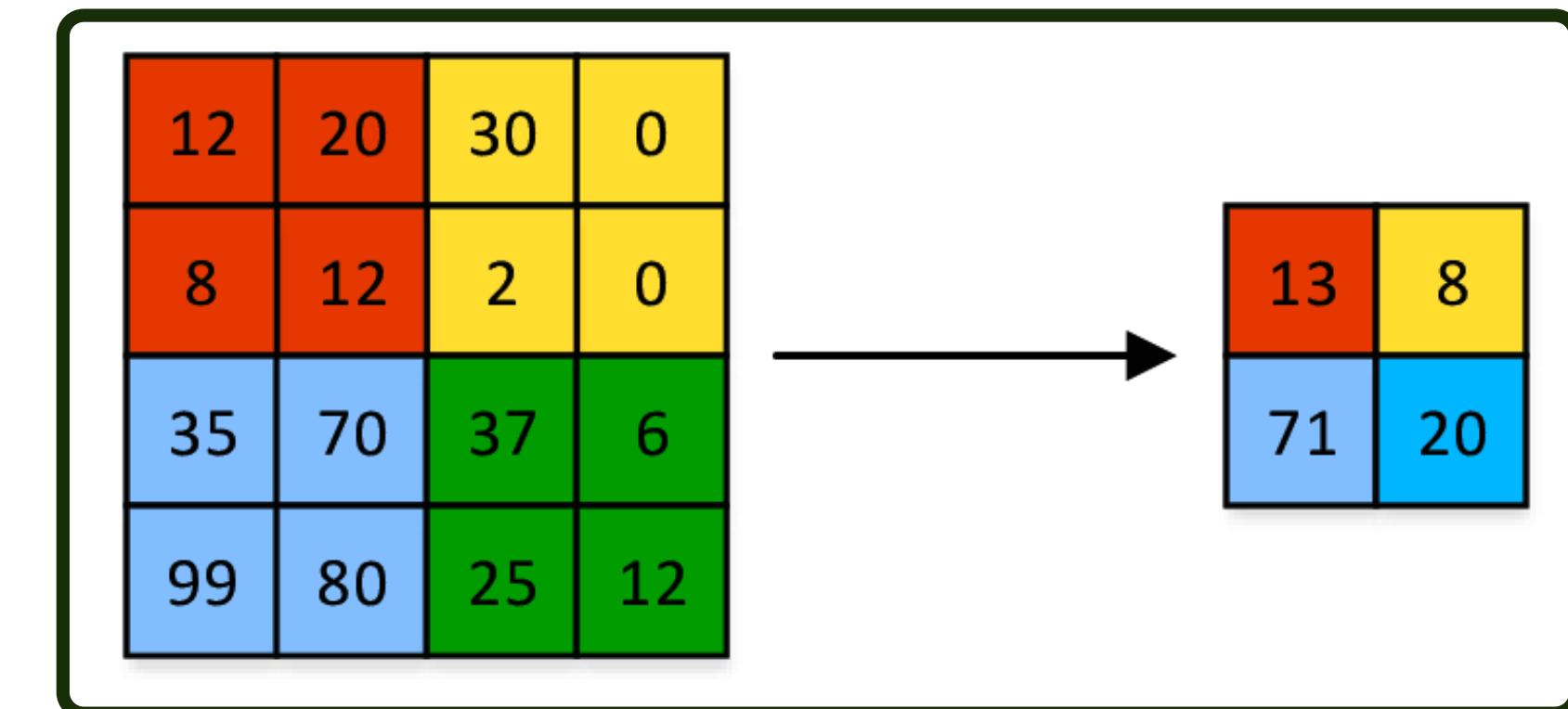
- **Stride : Pergerakan filter**
(atas-bawah, kanan-kiri)
- **Padding : Memberi *border* ujung-ujung array.**

POOLING LAYER

- Memiliki konsep yang **mirip dengan convolutional layer** saat **menggeser kernel**.
- **Mengurangi parameter dari input :**
 - Kekurangan :
 - **Hilangnya informasi** dari input
 - Kelebihan :
 - Meningkatkan **efisiensi**
 - Mengurangi **kompleksitas**
 - Mengurangi **dimensi dari peta fitur**
- Tipe :
 - **Max-Pooling**
 - **Average-Pooling**



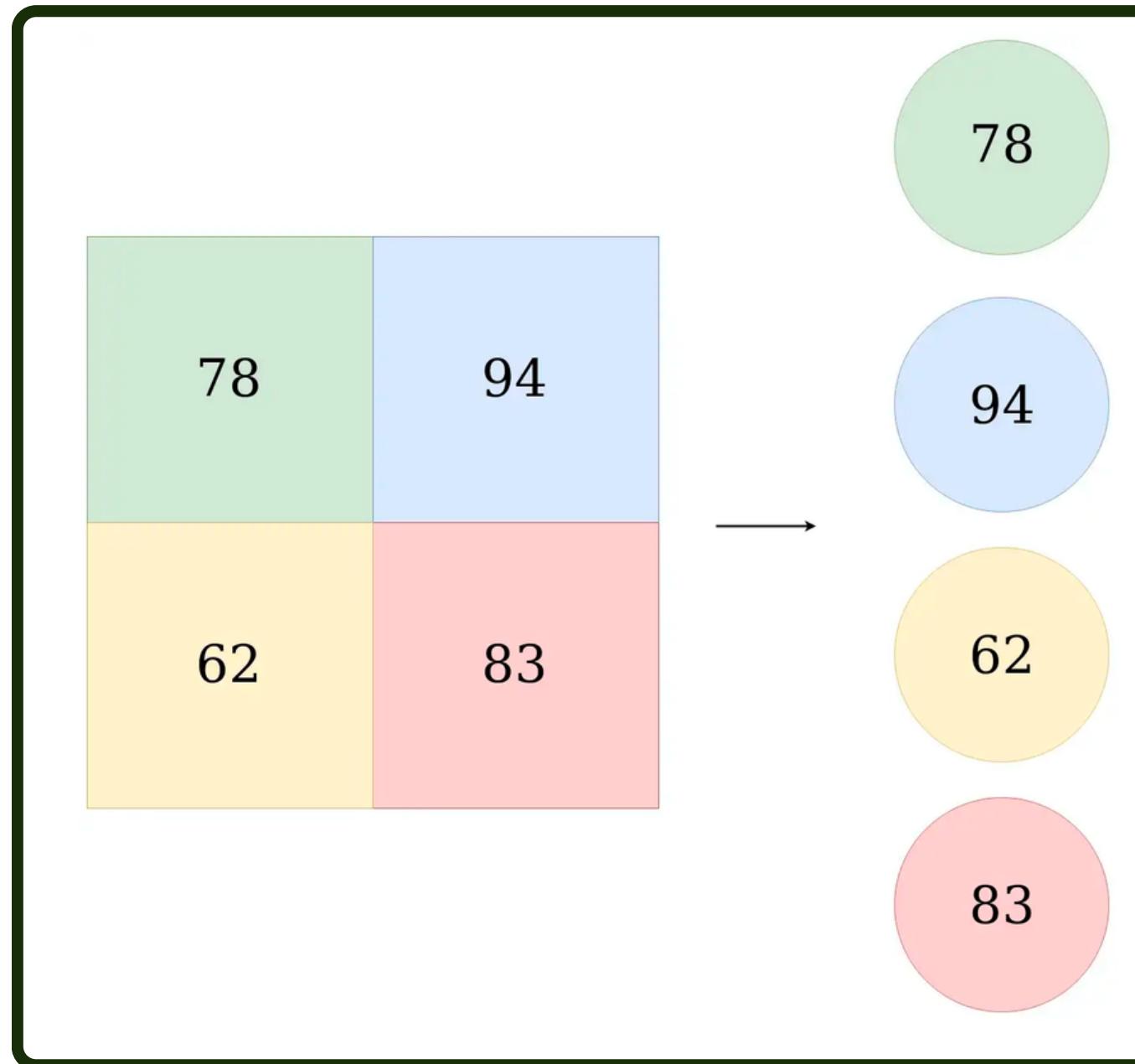
2x2 Max Pooling



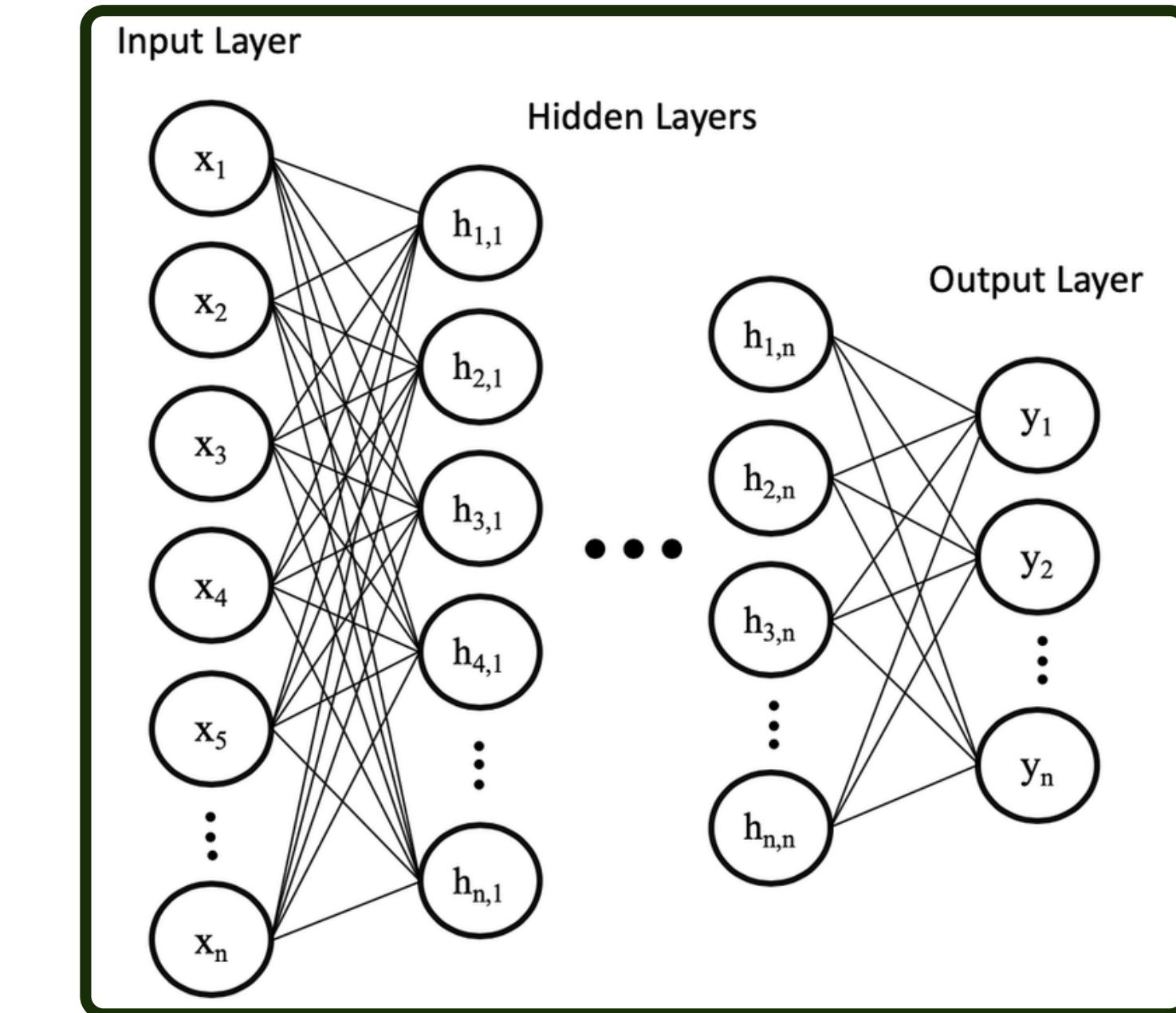
2x2 Average Pooling

FULLY CONNECTED LAYER

- Akhir dari arsitektur model CNN.
- Setiap neuron dari lapisan sebelumnya terhubung dan digunakan sebagai **pengklasifikasi CNN**.
- Bekerja seperti ***multilayer perceptron*** konvensional dan jenis **Feedforward Neural Network (FNN)**.



Flatten



fully-connected layer

MFCC MODEL

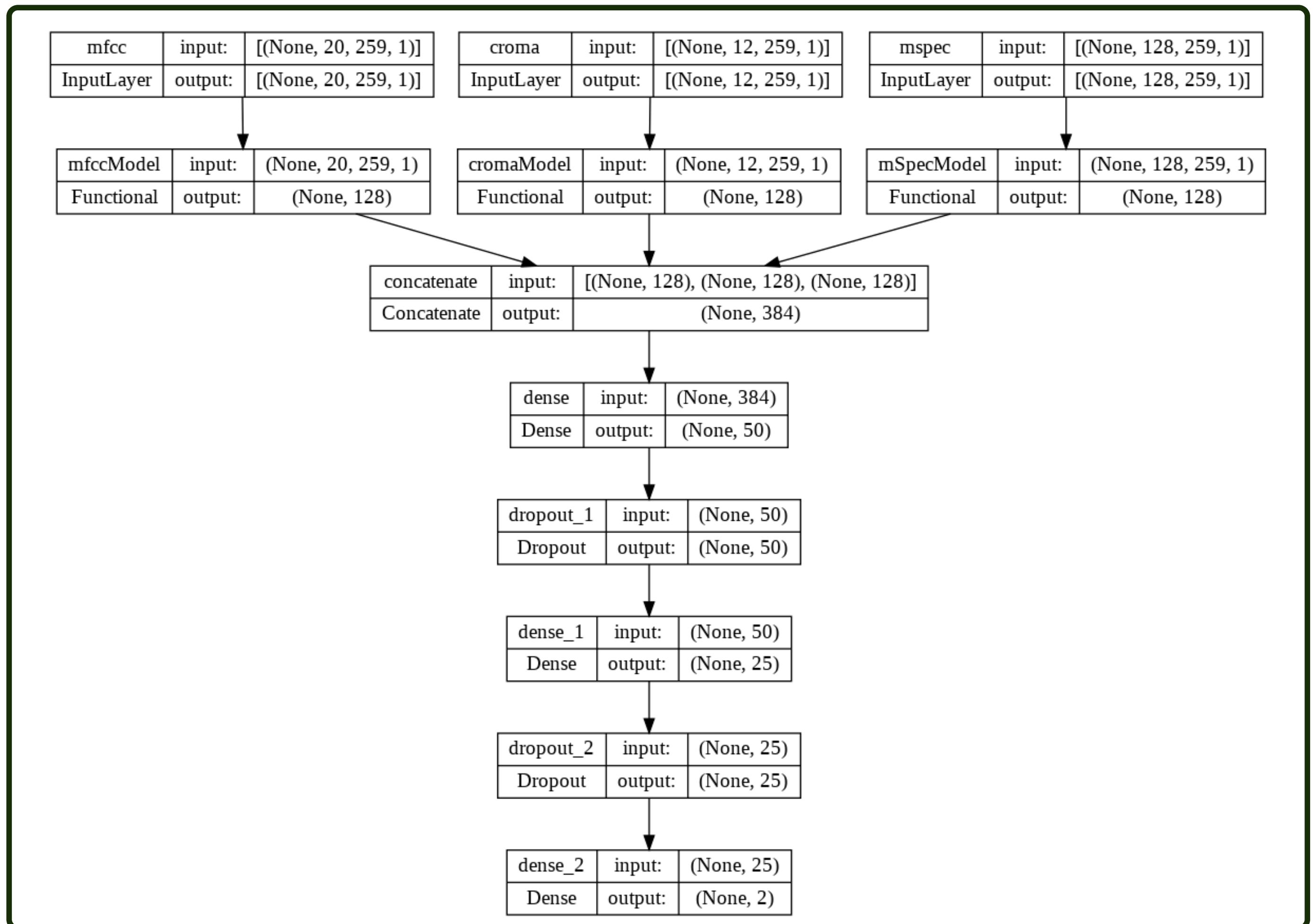
Layer (type)	Output Shape	Param #
<hr/>		
mfccInput (InputLayer)	[(None, 20, 259, 1)]	0
conv2d (Conv2D)	(None, 20, 87, 32)	832
batch_normalization (BatchN ormalization)	(None, 20, 87, 32)	128
activation (Activation)	(None, 20, 87, 32)	0
max_pooling2d (MaxPooling2D)	(None, 10, 43, 32)	0
conv2d_1 (Conv2D)	(None, 10, 22, 64)	18496
batch_normalization_1 (Bathc hNormalization)	(None, 10, 22, 64)	256
activation_1 (Activation)	(None, 10, 22, 64)	0
max_pooling2d_1 (MaxPooling 2D)	(None, 5, 11, 64)	0
conv2d_2 (Conv2D)	(None, 5, 11, 96)	24672
batch_normalization_2 (Bathc hNormalization)	(None, 5, 11, 96)	384
activation_2 (Activation)	(None, 5, 11, 96)	0
max_pooling2d_2 (MaxPooling 2D)	(None, 2, 5, 96)	0
conv2d_3 (Conv2D)	(None, 2, 5, 128)	49280
batch_normalization_3 (Bathc hNormalization)	(None, 2, 5, 128)	512
activation_3 (Activation)	(None, 2, 5, 128)	0
global_max_pooling2d (Globa lMaxPooling2D)	(None, 128)	0
<hr/>		

CSTFT MODEL

Layer (type)	Output Shape	Param #
<hr/>		
cromaInput (InputLayer)	[(None, 12, 259, 1)]	0
conv2d_4 (Conv2D)	(None, 12, 87, 32)	832
batch_normalization_4 (Bathc hNormalization)	(None, 12, 87, 32)	128
activation_4 (Activation)	(None, 12, 87, 32)	0
max_pooling2d_3 (MaxPooling 2D)	(None, 6, 43, 32)	0
conv2d_5 (Conv2D)	(None, 6, 22, 64)	18496
batch_normalization_5 (Bathc hNormalization)	(None, 6, 22, 64)	256
activation_5 (Activation)	(None, 6, 22, 64)	0
max_pooling2d_4 (MaxPooling 2D)	(None, 3, 11, 64)	0
conv2d_6 (Conv2D)	(None, 3, 11, 128)	32896
batch_normalization_6 (Bathc hNormalization)	(None, 3, 11, 128)	512
activation_6 (Activation)	(None, 3, 11, 128)	0
global_max_pooling2d_1 (Glo balMaxPooling2D)	(None, 128)	0
<hr/>		

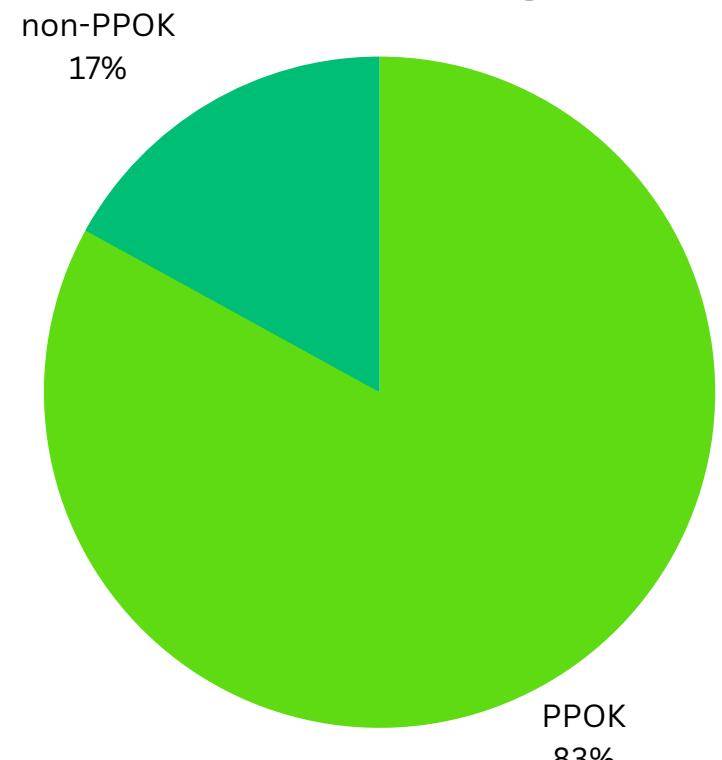
MelSpectrogram MODEL

Layer (type)	Output Shape	Param #
<hr/>		
mSpecInput (InputLayer)	[(None, 128, 259, 1)]	0
conv2d_7 (Conv2D)	(None, 64, 87, 32)	832
batch_normalization_7 (Bathc hNormalization)	(None, 64, 87, 32)	128
activation_7 (Activation)	(None, 64, 87, 32)	0
max_pooling2d_5 (MaxPooling 2D)	(None, 32, 43, 32)	0
conv2d_8 (Conv2D)	(None, 16, 22, 64)	18496
batch_normalization_8 (Bathc hNormalization)	(None, 16, 22, 64)	256
activation_8 (Activation)	(None, 16, 22, 64)	0
max_pooling2d_6 (MaxPooling 2D)	(None, 8, 11, 64)	0
conv2d_9 (Conv2D)	(None, 8, 11, 96)	24672
batch_normalization_9 (Bathc hNormalization)	(None, 8, 11, 96)	384
activation_9 (Activation)	(None, 8, 11, 96)	0
max_pooling2d_7 (MaxPooling 2D)	(None, 4, 5, 96)	0
conv2d_10 (Conv2D)	(None, 4, 5, 128)	49280
batch_normalization_10 (Bathc hNormalization)	(None, 4, 5, 128)	512
activation_10 (Activation)	(None, 4, 5, 128)	0
global_max_pooling2d_2 (Glo balMaxPooling2D)	(None, 128)	0
<hr/>		

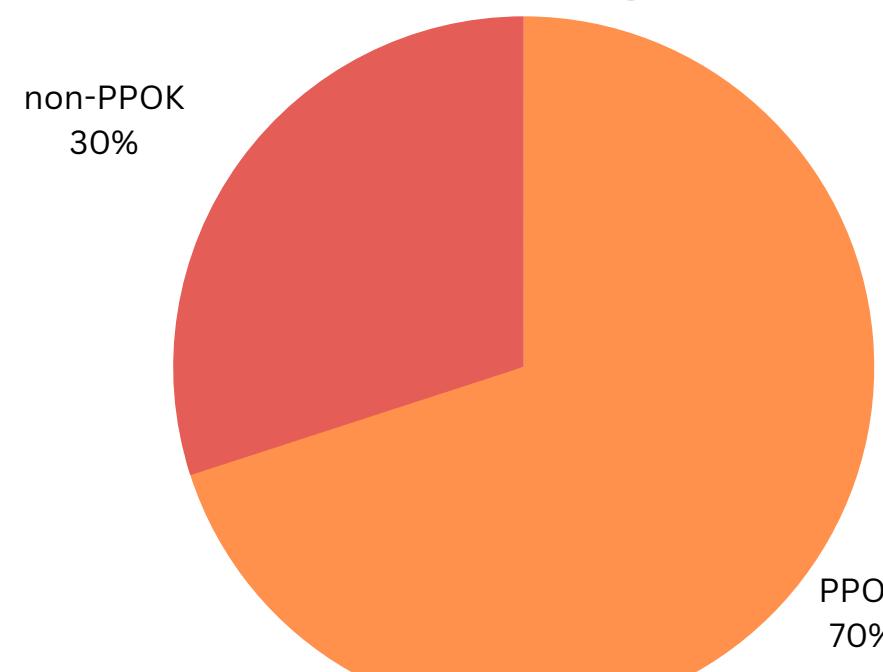


HASIL SEMENTARA

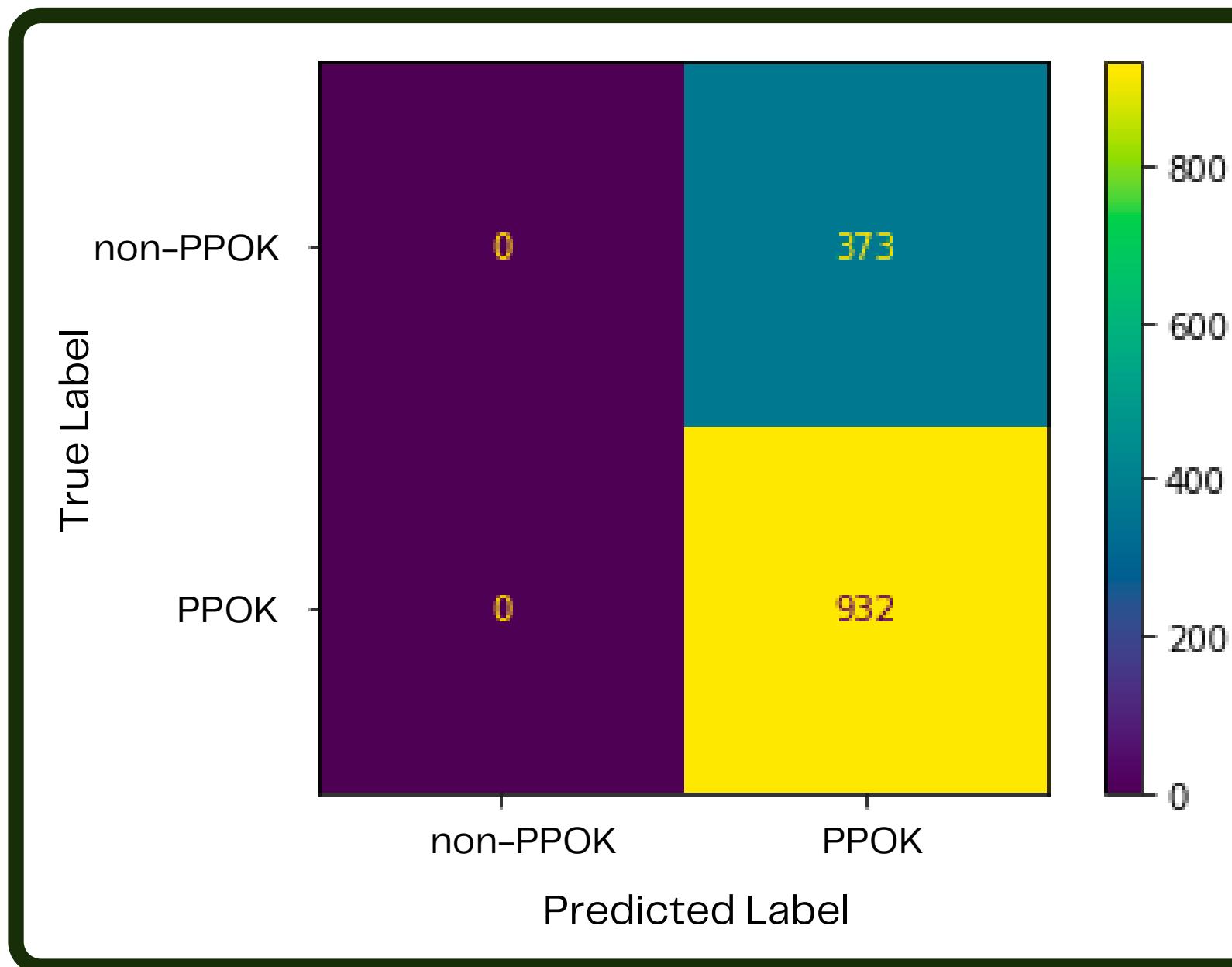
Proporsi Training Data



Proporsi Testing Data



Confusion Matrix



Skor Evaluasi Model

Akurasi : 71%

PPOK

Presisi : 71%

Sensitivitas : 100%

NON-PPOK

Presisi : 0%

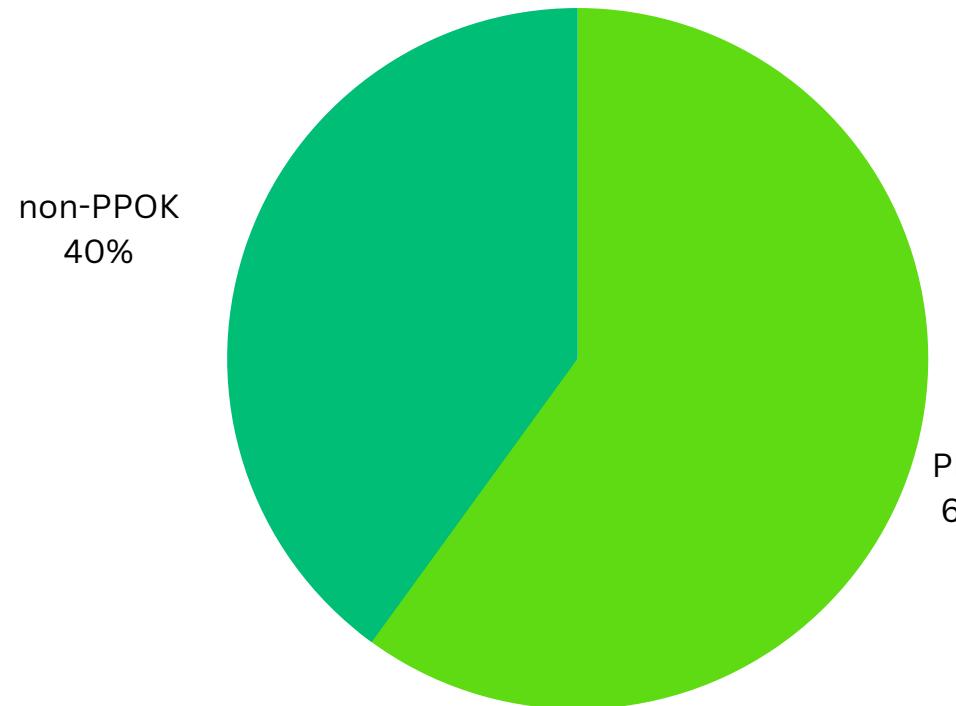
Sensitivitas : 0%

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

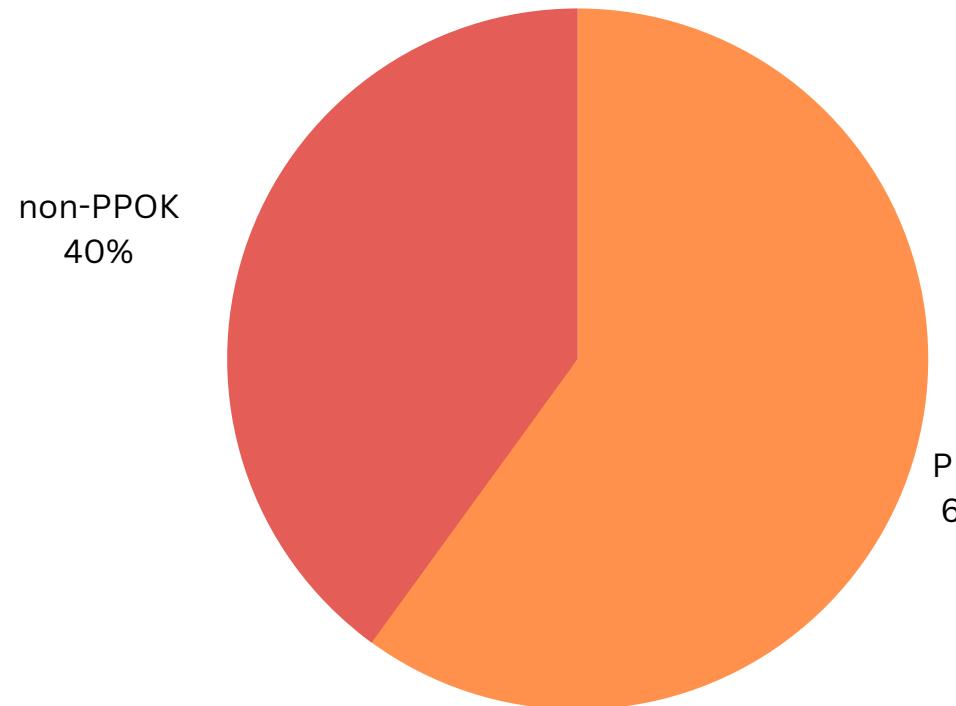
$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

HASIL SEMENTARA

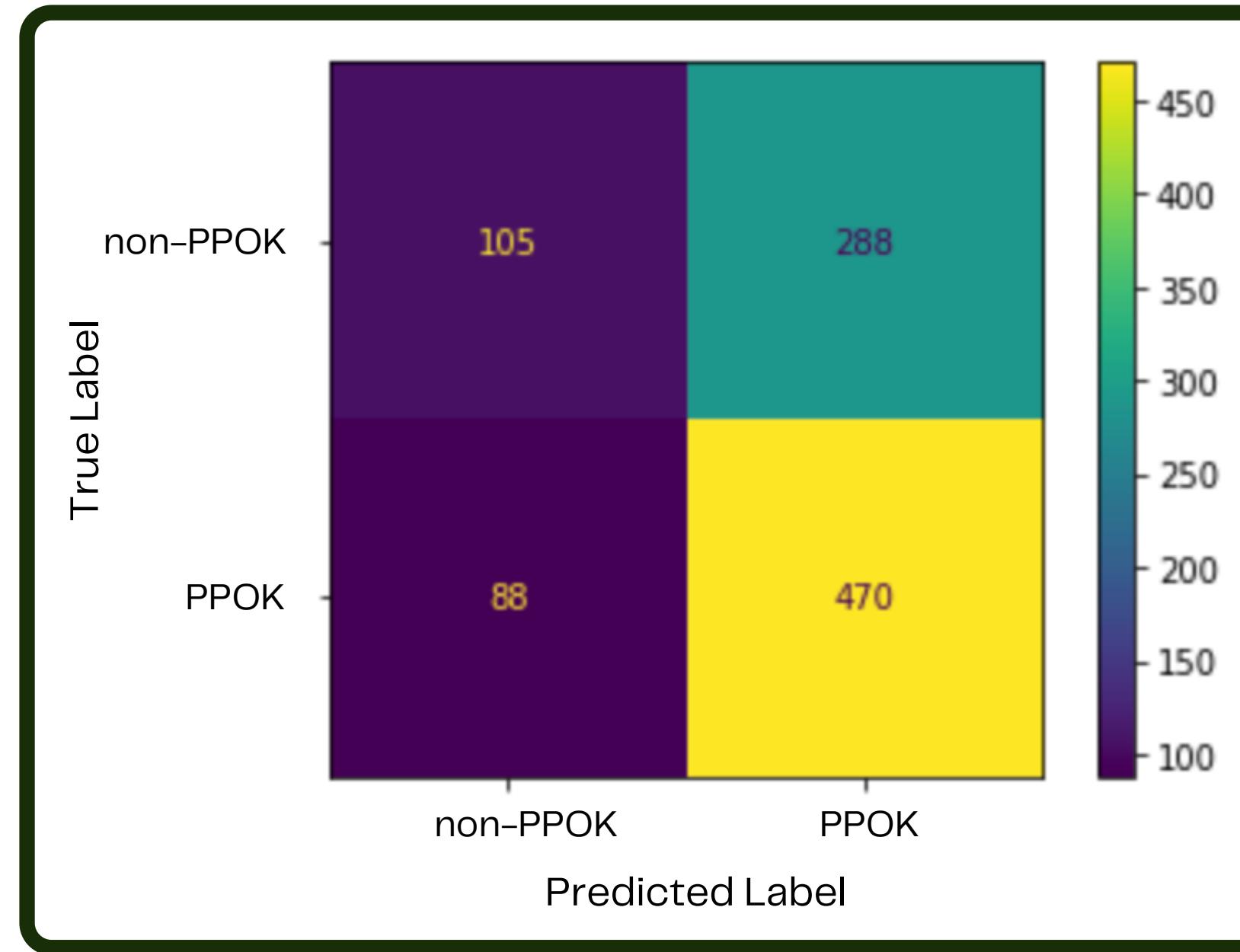
Proporsi Training Data



Proporsi Testing Data



Confusion Matrix



$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Skor Evaluasi Model

Akurasi : 60%

PPOK

Presisi : 62%

Sensitivitas : 84%

NON-PPOK

Presisi : 54%

Sensitivitas : 27%

KESIMPULAN SEMENTARA

1. Didapatkan model deteksi PPOK dengan **akurasi** sebesar **60%** , **presisi** sebesar **62%** dan **sensitivitas** sebesar **84%** untuk kelas PPOK, dan **presisi** sebesar **54%** dan **sensitivitas** sebesar **27%** untuk kelas **non-PPOK**.
2. Model lebih sensitif dalam mendekripsi penyakit PPOK dibandingkan non-PPOK.

RENCANA SELANJUTNYA

1. **Memperbanyak sample data non-PPOK** untuk bisa mengurangi data yang **imbalanced**, sehingga model bisa **lebih sensitif pada deteksi non-PPOK**, tidak hanya PPOK.
2. **Meningkatkan performa model** CNN dengan melakukan perubahan pada arsitektur model CNN.
3. **Menambahkan set data lainnya** yang berkaitan dengan **data suara sektor kesehatan.** *

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TERIMA KASIH

Thank You | 谢谢 | 고맙습니다 | ありがとうございました | Danke | Merci | Gracias