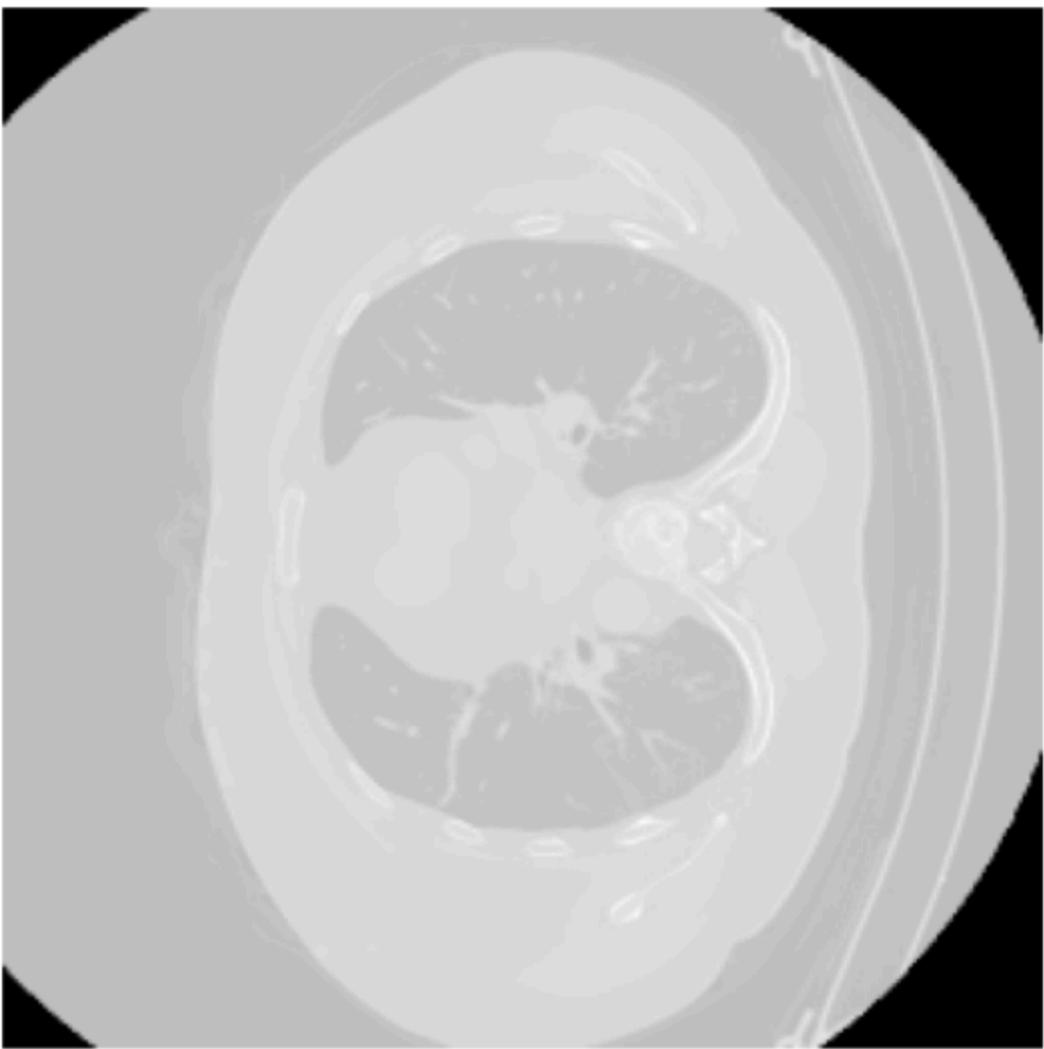


Image Preprocessing

1. Preprocessing dengan fastN1MeansDenoising

```
1. def preprocess_ct_psnr(img_tensor, denoise_h=1):
2.     img = img_tensor.squeeze().numpy()
3.     img_u8 = (img * 255).astype(np.uint8)
4.
5.     # Denoising dengan fastN1Means
6.     img_denoised = cv2.fastN1MeansDenoising(
7.         img_u8, None, h=denoise_h,
8.         templateWindowSize=7, searchWindowSize=21
9.     )
10.
11.    out = img_denoised.astype(np.float32) / 255.0
12.
13.    ## Enhacing image dengan Gamma
14.    # gamma=1.0
15.    # out = np.power(out, gamma)
16.
17.    ## Enhancing image dengan clahe
18.    # out = (out * 255).clip(0,255).astype(np.uint8)
19.    # clahe = cv2.createCLAHE(clipLimit=2.5, tileGridSize=(8, 8))
20.    # out = clahe.apply(out)
21.
22.
23.    return torch.from_numpy(out).unsqueeze(0)
24.
25.
```

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation

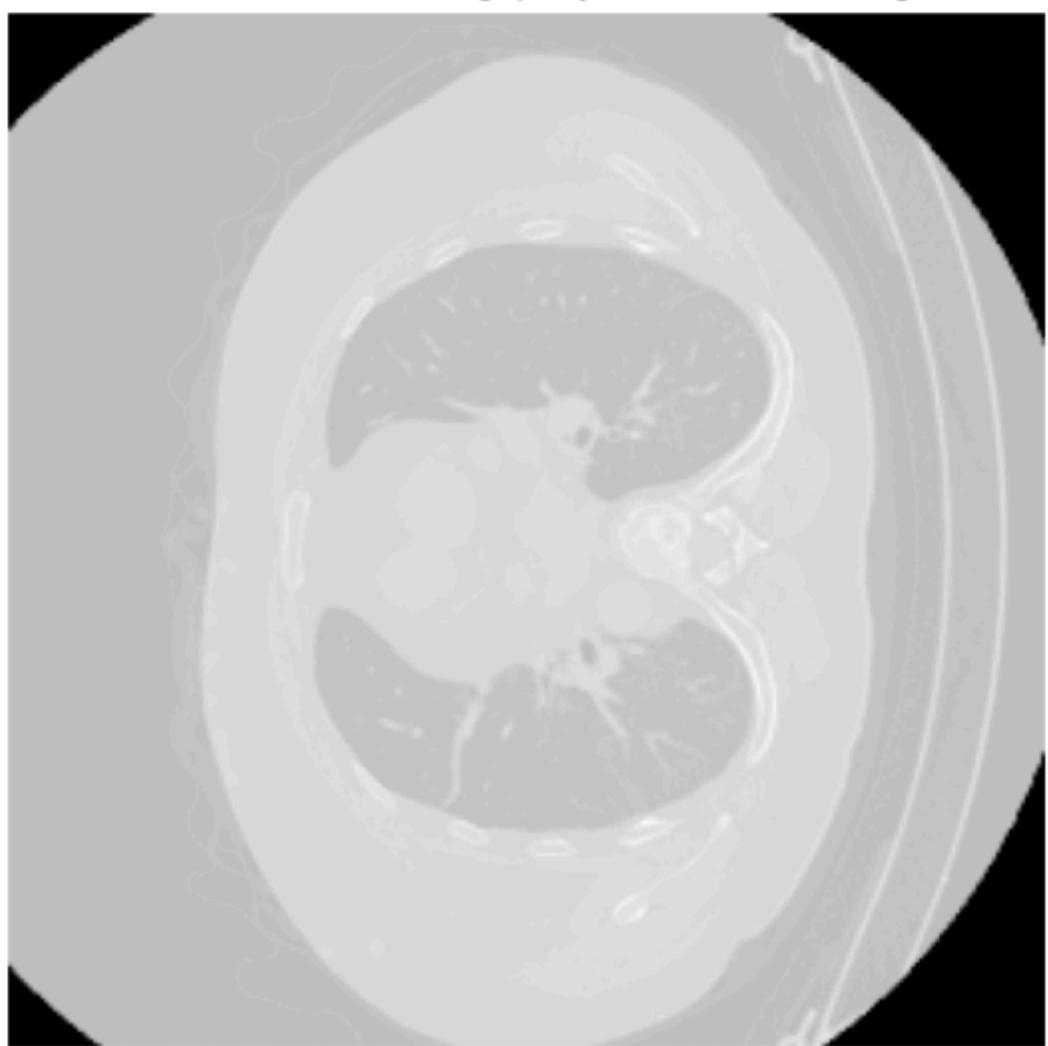
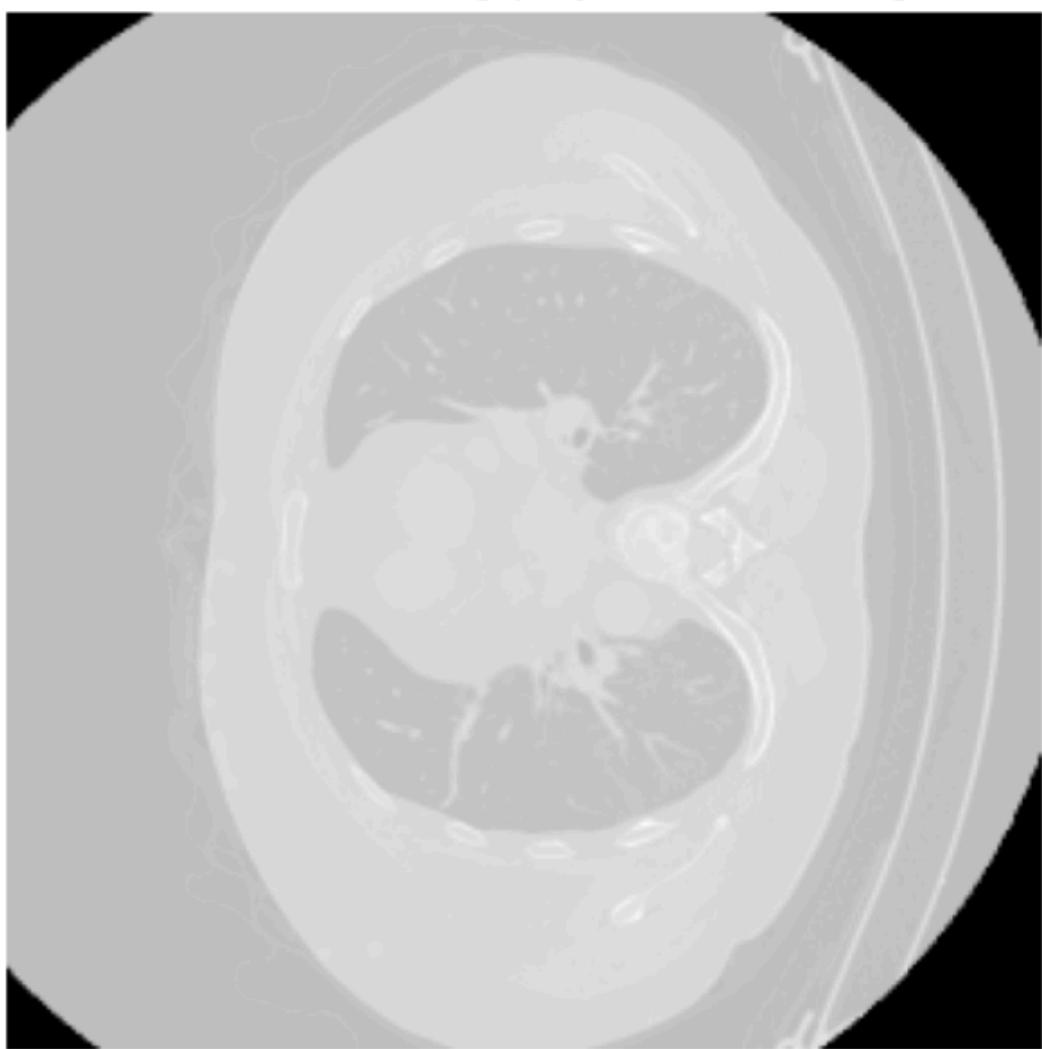


	Image	PSNR	SSIM	MSE	RMSE
0	1	50.83	0.9961	0.0	0.0
1	2	49.57	0.9930	0.0	0.0
2	3	50.21	0.9964	0.0	0.0
3	4	49.99	0.9939	0.0	0.0
4	5	49.40	0.9931	0.0	0.0
5	6	51.34	0.9967	0.0	0.0
6	7	50.40	0.9943	0.0	0.0
7	8	51.26	0.9972	0.0	0.0
8	9	49.33	0.9931	0.0	0.0
9	10	53.23	0.9973	0.0	0.0
10	11	49.73	0.9886	0.0	0.0
11	12	49.86	0.9910	0.0	0.0
12	13	50.66	0.9892	0.0	0.0
13	14	50.64	0.9933	0.0	0.0
14	15	50.48	0.9907	0.0	0.0
15	16	52.07	0.9984	0.0	0.0
16	17	50.58	0.9956	0.0	0.0
17	18	53.09	0.9965	0.0	0.0
18	19	49.12	0.9849	0.0	0.0
19	20	53.10	0.9963	0.0	0.0

2. Prerpocessing dengan *fastNIMeansDenoising h = 1* untuk menghilangkan noise dan *Gamma = 1* untuk enhancing gambar

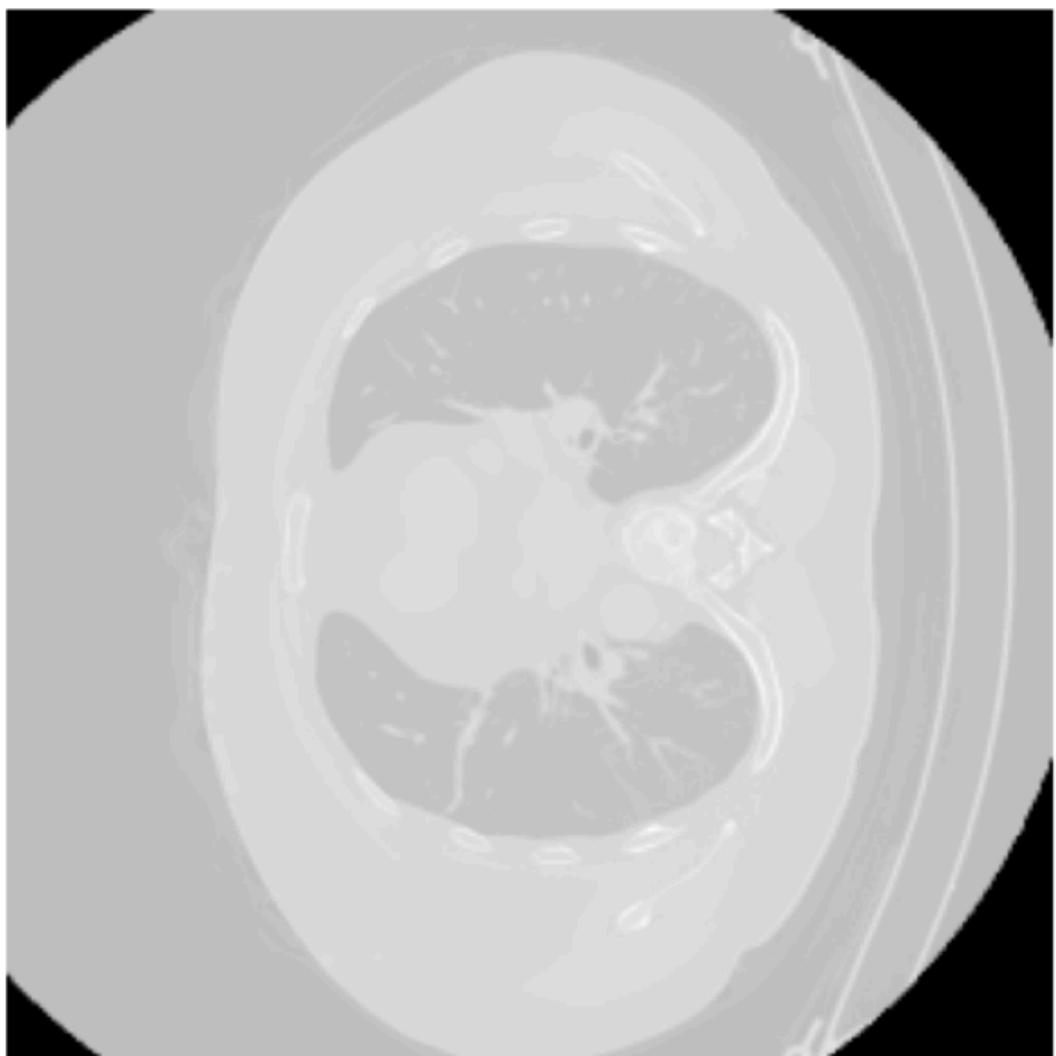
gambar train_1_a_1.[nii.gz](#) sebelum preprocessing

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



gambar train_1_a_1.nii.gz setelah preprocessing

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



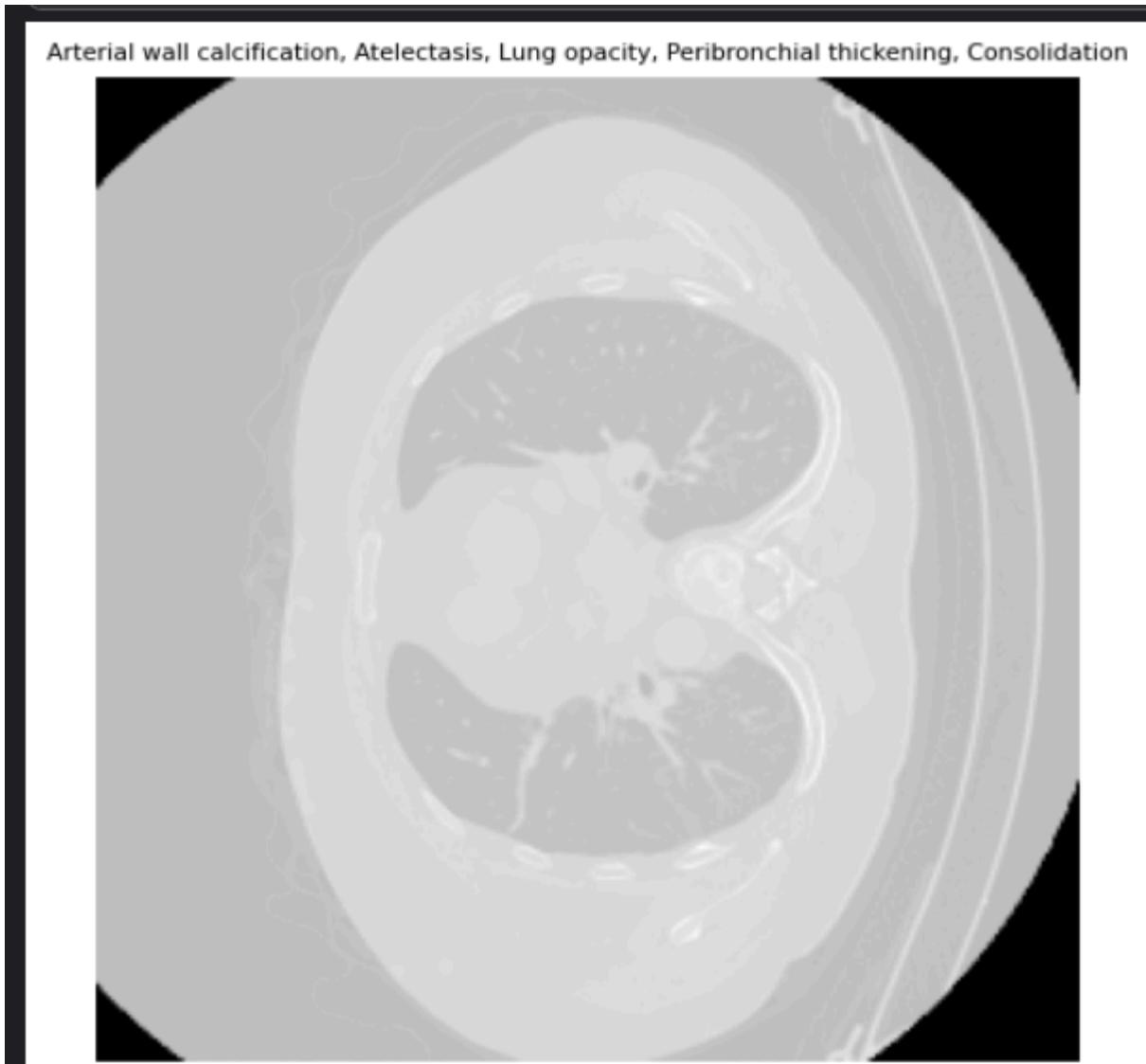
Metric verifikasi 20 data pertama

Image		PSNR	SSIM	MSE	RMSE
0	1	50.83	0.9961	0.0	0.0
1	2	49.57	0.9930	0.0	0.0
2	3	50.21	0.9964	0.0	0.0
3	4	49.99	0.9939	0.0	0.0
4	5	49.40	0.9931	0.0	0.0
5	6	51.34	0.9967	0.0	0.0
6	7	50.40	0.9943	0.0	0.0
7	8	51.26	0.9972	0.0	0.0
8	9	49.33	0.9931	0.0	0.0
9	10	53.23	0.9973	0.0	0.0
10	11	49.73	0.9886	0.0	0.0
11	12	49.86	0.9910	0.0	0.0
12	13	50.66	0.9892	0.0	0.0
13	14	50.64	0.9933	0.0	0.0
14	15	50.48	0.9907	0.0	0.0
15	16	52.07	0.9984	0.0	0.0
16	17	50.58	0.9956	0.0	0.0
17	18	53.09	0.9965	0.0	0.0
18	19	49.12	0.9849	0.0	0.0
19	20	53.10	0.9963	0.0	0.0

3. Morphological opening + Gamma + Clahe + Bilateral + unsharp mask

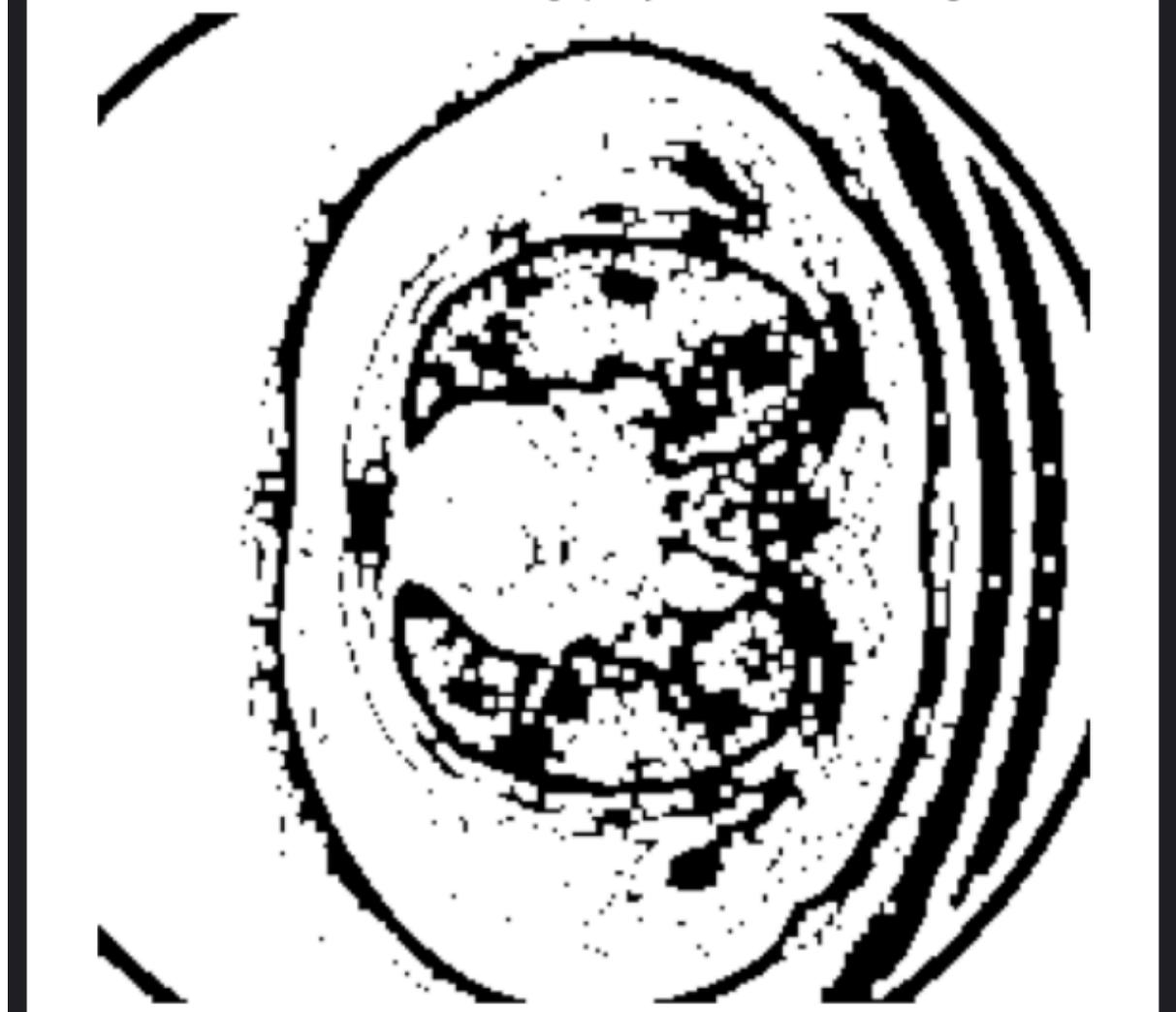
```
4.                      bilateral_d=7, bilateral_sigmaColor=55,
5.                      bilateral_sigmaSpace=55,
6.                      unsharp_amount=0.5, unsharp_radius=1.0):
7.      # img_tensor: (1,H,W) atau (H,W), float 0-1
8.      if img_tensor.ndim == 3:
9.          img = img_tensor.squeeze(0).numpy()
10.         else:
11.             img = img_tensor.numpy()
12. # 1) To uint8
13. img_u8 = (img * 255).clip(0,255).astype(np.uint8)
14.
15. # 2) Morphological opening
16. binary = cv2.adaptiveThreshold(img_u8, 255,
17.                                 cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
18.                                 cv2.THRESH_BINARY, 11, 2)
19. binary = binary.astype(np.float32) / 255.0
20. kernel_open = np.ones((3, 3), np.uint8)
21. img_u8 = cv2.morphologyEx(binary, cv2.MORPH_OPEN, kernel_open )
22.
23. # 3) Gamma (light)
24. img_u8 = np.power(img_u8, gamma)
25. img_u8 = (img_u8 * 255).clip(0,255).astype(np.uint8)
26.
27. # 4) CLAHE (local contrast but moderate)
28. clahe = cv2.createCLAHE(clipLimit=clahe_clip, tileGridSize=clahe_tile)
29. img_clahe = clahe.apply(img_u8)
30.
31. # 5) Bilateral filter (mild)
32. img_bilat = cv2.bilateralFilter(img_clahe, d=bilateral_d,
33.                                 sigmaColor=bilateral_sigmaColor,
34.                                 sigmaSpace=bilateral_sigmaSpace)
35.
36. # 6) Unsharp mask (light sharpening to restore edges)
37. blurred = cv2.GaussianBlur(img_bilat, (0,0), unsharp_radius)
38. img_unsharp = cv2.addWeighted(img_bilat, 1+unsharp_amount, blurred,
-unsharp_amount, 0)
39.
40. # 7) Kembali ke float 0-1
41. out = (img_unsharp.astype(np.float32) / 255.0)
42. return torch.from_numpy(out).unsqueeze(0)
43.
44.
```

gambar train_1_a_1.nii.gz sebelum preprocessing



gambar train_1_a_1.nii.gz setelah preprocessing

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



Metric evaluasi

Image		PSNR	SSIM	MSE	RMSE
0	1	6.61	0.3546	0.22	0.47
1	2	5.42	0.1449	0.29	0.54
2	3	7.31	0.3752	0.19	0.43
3	4	6.48	0.2459	0.23	0.47
4	5	6.26	0.2024	0.24	0.49
5	6	7.32	0.4138	0.19	0.43
6	7	5.83	0.1094	0.26	0.51
7	8	7.35	0.4029	0.18	0.43
8	9	5.58	0.0542	0.28	0.53
9	10	9.77	0.2260	0.11	0.32
10	11	4.27	0.1114	0.37	0.61
11	12	6.24	0.0781	0.24	0.49
12	13	3.73	0.1019	0.42	0.65
13	14	6.91	0.0982	0.20	0.45
14	15	3.94	0.0994	0.40	0.64
15	16	7.94	0.0615	0.16	0.40
16	17	5.32	0.0975	0.29	0.54
17	18	9.95	0.2423	0.10	0.32
18	19	3.62	0.0748	0.43	0.66
19	20	10.02	0.2488	0.10	0.32

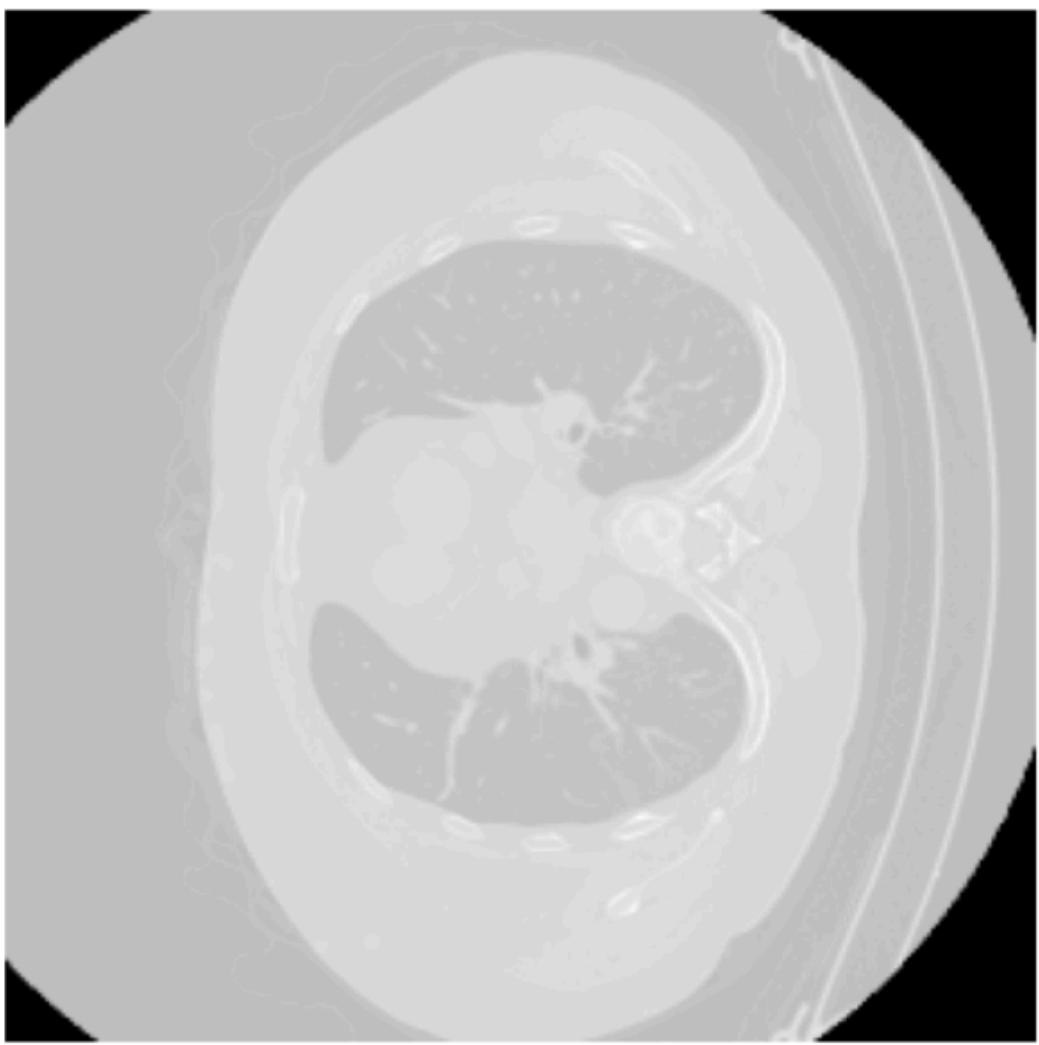
4. *fastN1MeanDenoising + gamma + clahe*

Kode program

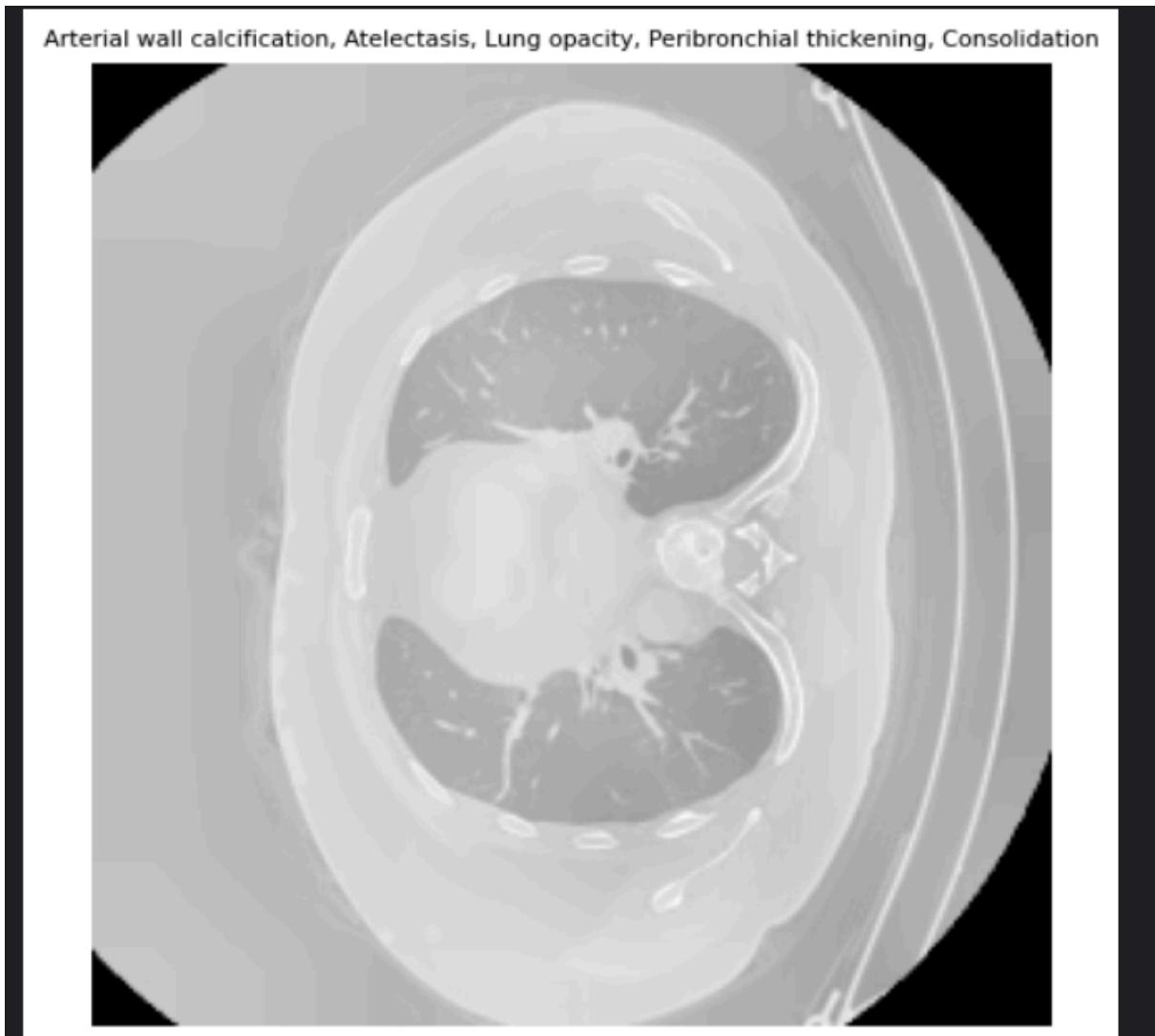
```
1. def preprocess_ct_psnr(img_tensor, denoise_h=1):
2.     img = img_tensor.squeeze().numpy()
3.     img_u8 = (img * 255).astype(np.uint8)
4.
5.     # Denoising dengan fastN1Means
6.     img_denoised = cv2.fastNIMeansDenoising(
7.         img_u8, None, h=denoise_h,
8.         templateWindowSize=7, searchWindowSize=21
9.     )
10.
11.    out = img_denoised.astype(np.float32) / 255.0
12.
13.    # Enhacing image dengan Gamma
14.    gamma=1.0
15.    out = np.power(out, gamma)
16.
17.    # Enhancing image dengan clahe
18.    out = (out * 255).clip(0,255).astype(np.uint8)
19.    clahe = cv2.createCLAHE(clipLimit=1.7, tileGridSize=(8, 8))
20.    out = clahe.apply(out)
21.
22.
23.    return torch.from_numpy(out).unsqueeze(0)
24.
25.
```

gambar train_1_a_1[.nii.gz](#) sebelum preprocessing

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



gambar train_1_a_1.nii.gz setelah preprocessing



41...	Image	PSNR	SSIM	MSE	RMSE
0	1	-45.53	0.0003	35729.511719	189.020004
1	2	-45.19	0.0003	33010.660156	181.690002
2	3	-45.65	0.0006	36759.238281	191.729996
3	4	-45.29	0.0005	33817.828125	183.899994
4	5	-43.70	0.0004	23439.310547	153.100006
5	6	-45.35	0.0005	34290.480469	185.179993
6	7	-44.71	0.0003	29599.640625	172.050003
7	8	-45.50	0.0010	35488.820312	188.380005
8	9	-38.58	0.0005	7208.100098	84.900002
9	10	-38.14	0.0000	6514.910156	80.709999
10	11	-39.08	0.0004	8091.229980	89.949997
11	12	-37.51	0.0001	5635.450195	75.070000
12	13	-39.57	0.0006	9065.230469	95.209999
13	14	-37.35	0.0001	5435.399902	73.730003
14	15	-39.33	0.0002	8564.030273	92.540001
15	16	-39.12	0.0000	8165.799805	90.360001
16	17	-39.31	0.0001	8527.780273	92.349998
17	18	-38.30	0.0000	6755.540039	82.190002
18	19	-39.09	0.0008	8116.520020	90.089996
19	20	-38.02	0.0000	6342.770020	79.639999

⚡ Penyebab utamanya:

CLAHE (Contrast Limited Adaptive Histogram Equalization) itu **bukan operasi linear** dan sangat mengubah distribusi piksel.

Kalau kamu bandingkan hasil CLAHE dengan citra asli, nilainya bisa jauh berbeda secara

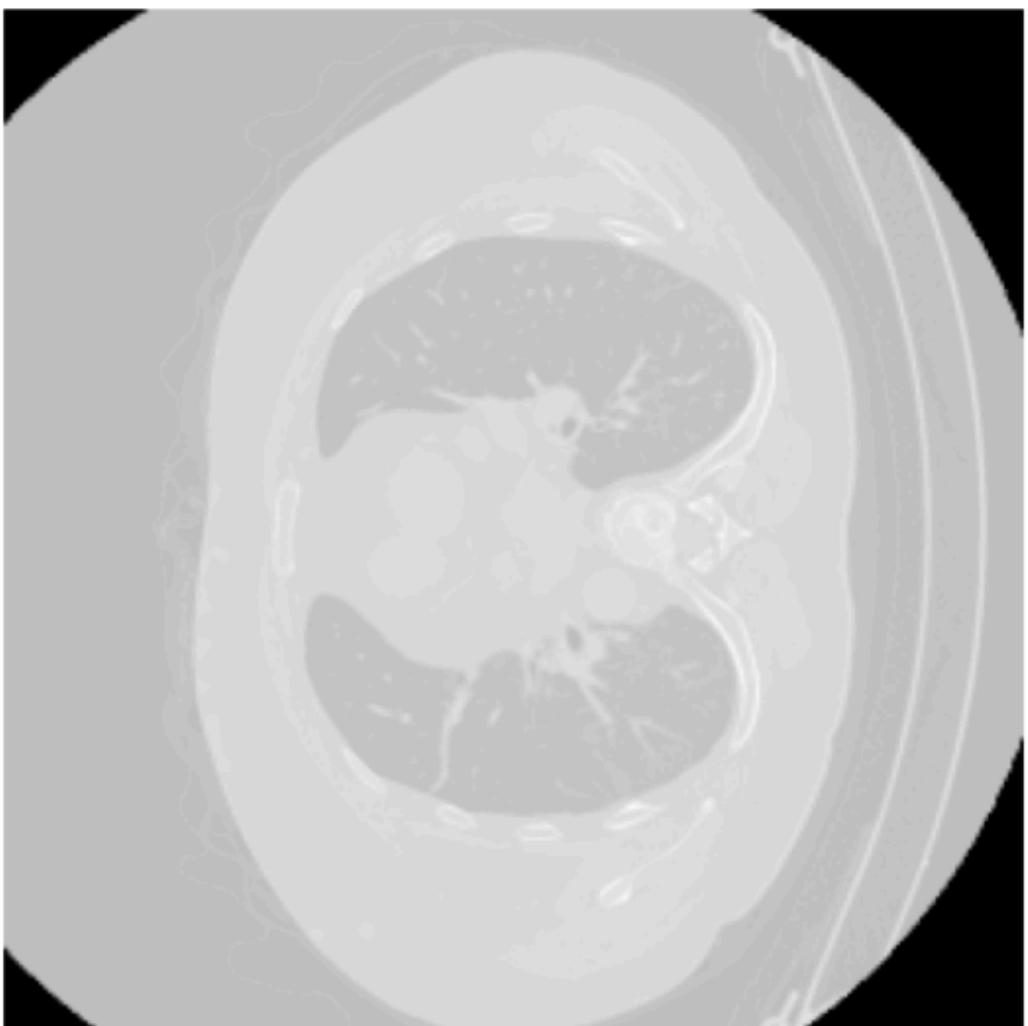
numerik → **MSE jadi besar** → PSNR (yang didefinisikan sebagai $10 \log_{10} \frac{MAX_I^2}{MSE}$) bisa **negatif**.

- ◆ Jadi negatifnya PSNR bukan berarti gambar jadi jelek, tapi artinya **hasilnya terlalu jauh dari referensi asli secara pixel-level**.
Padahal secara visual, bisa jadi lebih jelas (karena kontras ditingkatkan).

5. sama kek no 4, tapi clahe_limit = 2.5



Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



5...	Image	PSNR	SSIM	MSE	RMSE
0	1	-45.34	0.0003	34185.218750	184.889999
1	2	-45.01	0.0003	31663.519531	177.940002
2	3	-45.48	0.0004	35318.339844	187.929993
3	4	-45.09	0.0004	32273.679688	179.649994
4	5	-43.64	0.0004	23122.490234	152.059998
5	6	-45.20	0.0003	33078.101562	181.869995
6	7	-44.70	0.0003	29507.919922	171.779999
7	8	-45.32	0.0006	34064.738281	184.570007
8	9	-39.08	0.0004	8097.839844	89.989998
9	10	-39.05	0.0000	8040.979980	89.669998
10	11	-39.50	0.0002	8914.650391	94.419998
11	12	-38.76	0.0000	7507.790039	86.650002
12	13	-40.30	0.0004	10725.120117	103.559998
13	14	-38.53	0.0000	7120.899902	84.389999
14	15	-39.90	0.0001	9778.450195	98.889999
15	16	-39.73	0.0000	9393.349609	96.919998
16	17	-39.63	0.0001	9193.089844	95.879997
17	18	-38.95	0.0000	7845.160156	88.570000
18	19	-39.55	0.0006	9021.290039	94.980003
19	20	-38.93	0.0000	7814.060059	88.400002

6. Enhacing dulu pake gamma + clahe baru denoising pake fastN1Mean

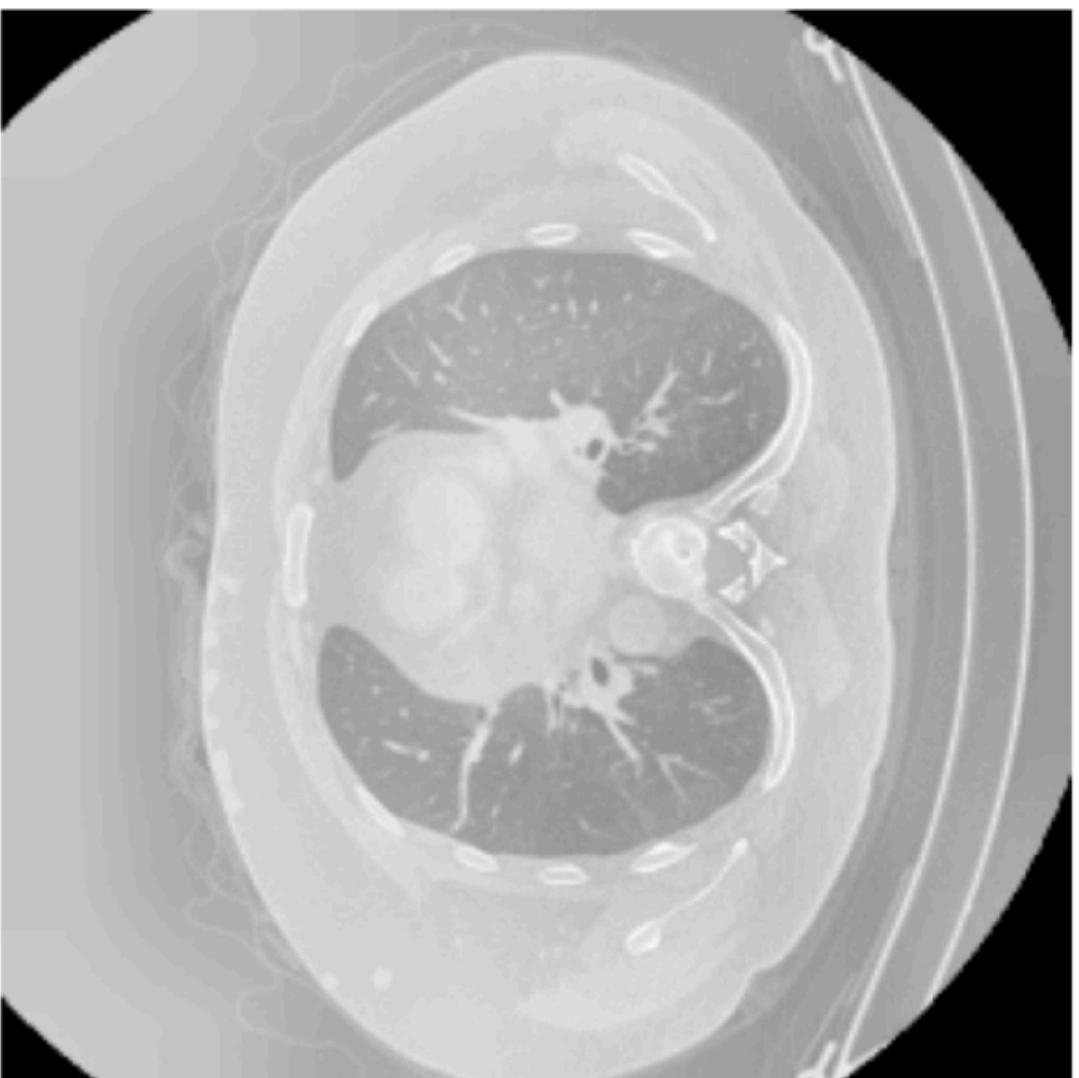
```

1. def preprocess_ct_psnr(img_tensor, denoise_h=1):
2.     img = img_tensor.squeeze().numpy()
3.     # img_u8 = (img * 255).astype(np.uint8)
4.
5.

```

```
6. # Enhacing image dengan Gamma
7. gamma=1.0
8. out = np.power(img, gamma)
9.
10. # Enhancing image dengan clahe
11. out = (out * 255).clip(0,255).astype(np.uint8)
12. clahe = cv2.createCLAHE(clipLimit=2.5, tileGridSize=(8, 8))
13. out = clahe.apply(out)
14.
15. # Denoising dengan fastN1Means
16. img_denoised = cv2.fastNIMeansDenoising(
17.     out, None, h=denoise_h,
18.     templateWindowSize=7, searchWindowSize=21
19. )
20.
21. out = img_denoised.astype(np.float32) / 255.0
22.
23.
24. return torch.from_numpy(out).unsqueeze(0)
25.
26.
```

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation



Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation

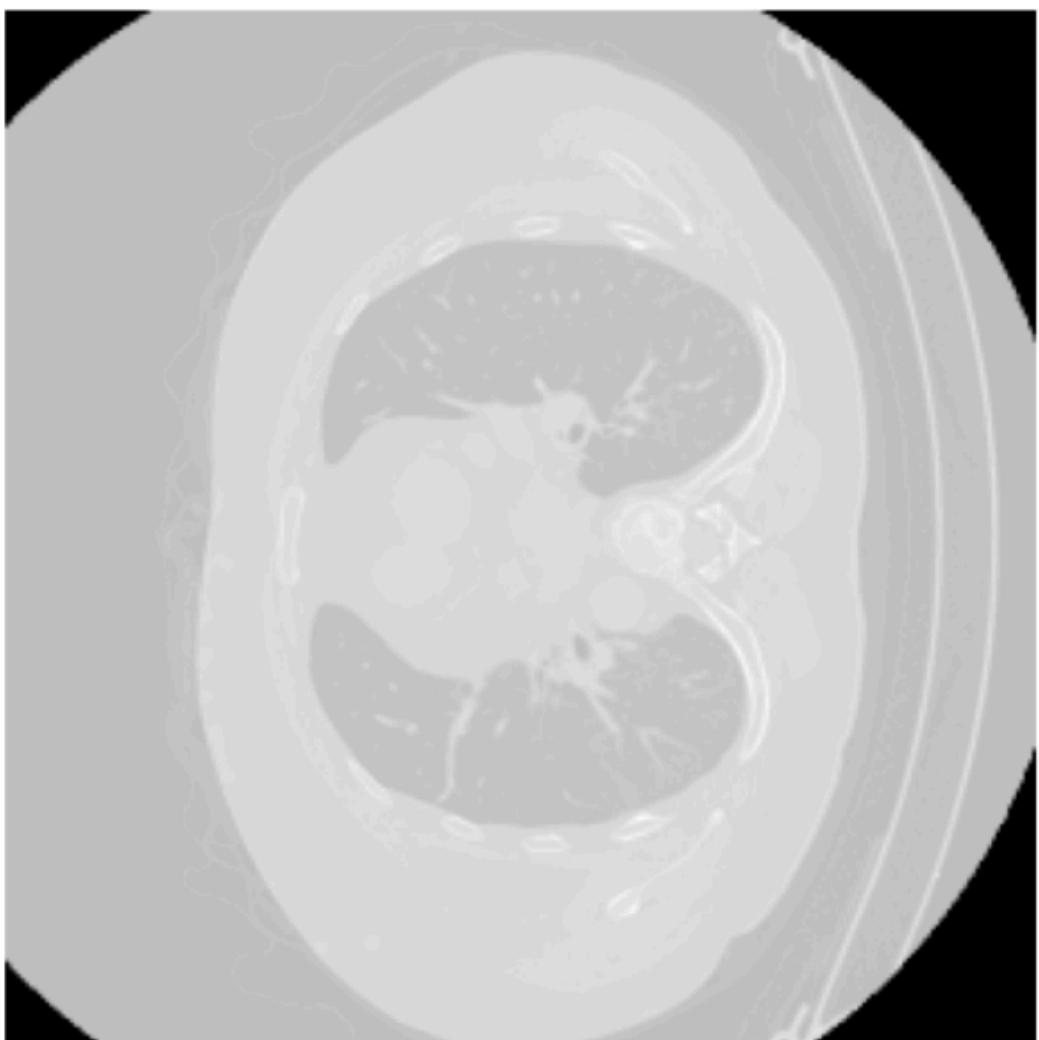


Image		PSNR	SSIM	MSE	RMSE
0	1	22.92	0.8670	0.01	0.07
1	2	23.57	0.8348	0.00	0.07
2	3	21.49	0.8744	0.01	0.08
3	4	22.69	0.8620	0.01	0.07
4	5	26.23	0.8544	0.00	0.05
5	6	22.69	0.8792	0.01	0.07
6	7	24.93	0.8301	0.00	0.06
7	8	23.18	0.8699	0.00	0.07
8	9	20.14	0.8030	0.01	0.10
9	10	17.78	0.5636	0.02	0.13
10	11	21.48	0.6926	0.01	0.08
11	12	16.34	0.5603	0.02	0.15
12	13	18.34	0.6762	0.01	0.12
13	14	16.88	0.5786	0.02	0.14
14	15	19.38	0.6930	0.01	0.11
15	16	19.92	0.7524	0.01	0.10
16	17	21.00	0.7742	0.01	0.09
17	18	18.83	0.5545	0.01	0.11
18	19	21.98	0.6554	0.01	0.08
19	20	18.29	0.5510	0.01	0.12

Model Dev

1. CTTXNet model

- 1.
 2. class ConvTokenizer(nn.Module):
 3. """Convolutional tokenizer: converts (B,C,H,W) -> (B, N, E)

```

tokens"""
4.     def __init__(self, in_chans=1, embed_dim=256):
5.         super().__init__()
6.         # two conv stages to reduce spatial size and increase channels
7.         self.conv1 = nn.Conv2d(in_chans, embed_dim//2,
8.             kernel_size=7, stride=4, padding=3, bias=False)
9.         self.bn1 = nn.BatchNorm2d(embed_dim//2)
10.        self.conv2 = nn.Conv2d(embed_dim//2, embed_dim,
11.            kernel_size=3, stride=2, padding=1, bias=False)
12.        self.bn2 = nn.BatchNorm2d(embed_dim)
13.
14.    def forward(self, x):
15.        # x: (B, C, H, W)
16.        x = F.gelu(self.bn1(self.conv1(x)))
17.        x = F.gelu(self.bn2(self.conv2(x))) # -> (B, E, H', W')
18.        B, E, H2, W2 = x.shape
19.        tokens = x.flatten(2).transpose(1, 2) # -> (B, N, E) where
20.        N=H'*W'
21.        return tokens, (H2, W2)
22.
23.
24.
25. class FeedForward(nn.Module):
26.     def __init__(self, dim, hidden_dim=None, dropout=0.1):
27.         super().__init__()
28.         hidden_dim = hidden_dim or dim * 4
29.         self.net = nn.Sequential(
30.             nn.Linear(dim, hidden_dim),
31.             nn.GELU(),
32.             nn.Dropout(dropout),
33.             nn.Linear(hidden_dim, dim),
34.             nn.Dropout(dropout),
35.         )
36.
37.     def forward(self, x):
38.         return self.net(x)
39.
40.
41. class TransformerEncoderBlock(nn.Module):
42.     def __init__(self, dim, num_heads=4, mlp_ratio=4.0,
43.                  dropout=0.1):
44.         super().__init__()
45.         self.norm1 = nn.LayerNorm(dim)
46.         self.attn = nn.MultiheadAttention(embed_dim=dim,
47.                                         num_heads=num_heads, dropout=dropout, batch_first=True)
48.         self.drop_path = nn.Identity() # placeholder for stochastic
49.                                     depth if needed
50.         self.norm2 = nn.LayerNorm(dim)
51.         self.mlp = FeedForward(dim, int(dim * mlp_ratio),
52.                               dropout=dropout)
53.
54.     def forward(self, x):
55.         # x: (B, N, E)
56.         # MultiheadAttention with batch_first=True expects (B, N, E)
57.         x_res = x

```

```

50.     x = self.norm1(x)
51.     attn_out, _ = self.attn(x, x, x, need_weights=False)
52.     x = x_res + attn_out # residual
53.     x_res = x
54.     x = self.norm2(x)
55.     x = x_res + self.mlp(x)
56.     return x
57.
58.
59. class SequencePooling(nn.Module):
60.     """Simple sequence pooling: average pooling across tokens
61.     (N->1)"""
62.     def __init__(self):
63.         super().__init__()
64.
65.     def forward(self, x):
66.         # x: (B, N, E) -> pooled (B, E)
67.         return x.mean(dim=1)
68.
69. class CTXNet(nn.Module):
70.     def __init__(self,
71.                  in_chans=1,
72.                  num_classes=18,
73.                  embed_dim=256,
74.                  depth=6,
75.                  num_heads=16,
76.                  mlp_ratio=6.0,
77.                  dropout=0.1):
78.         super().__init__()
79.         self.tokenizer = ConvTokenizer(in_chans=in_chans,
80.                                         embed_dim=embed_dim)
81.         # optional learnable position embedding (small)
82.         self.pos_embed = None # we'll init lazily once we know token
83.         count
84.         # transformer blocks
85.         self.blocks = nn.ModuleList([
86.             TransformerEncoderBlock(dim=embed_dim,
87.                                     num_heads=num_heads, mlp_ratio=mlp_ratio, dropout=dropout)
88.             for _ in range(depth)
89.         ])
90.
91.         self.norm = nn.LayerNorm(embed_dim)
92.         self.pool = SequencePooling()
93.
94.         # classifier head
95.         self.head = nn.Sequential(
96.             nn.Linear(embed_dim, embed_dim // 2),
97.             nn.GELU(),
98.             nn.Dropout(0.1),
99.             nn.Linear(embed_dim // 2, num_classes)
99.         )

```

```

100.
101.    def forward(self, x):
102.        # x: (B, C, H, W)
103.        B = x.shape[0]
104.        tokens, (Hn, Wn) = self.tokenizer(x)      # tokens: (B, N, E)
105.        N = tokens.shape[1]
106.
107.        # create pos emb if needed
108.        if self.pos_embed is None or self.pos_embed.shape[1] != N:
109.            # small learnable pos emb
110.            self.pos_embed = nn.Parameter(torch.zeros(1, N,
111.                tokens.shape[2]).to(tokens.device))
112.            nn.init.trunc_normal_(self.pos_embed, std=0.02)
113.        tokens = tokens + self.pos_embed
114.
115.        # transformer blocks (B,N,E)
116.        for blk in self.blocks:
117.            tokens = blk(tokens)
118.
119.        tokens = self.norm(tokens)
120.        pooled = self.pool(tokens)  # (B, E)
121.        logits = self.head(pooled)  # (B, num_classes)
122.        return logits
123.
124.
125.
126.    CTTXNet = CTXNet(in_chans=1, num_classes=18,
127.                      embed_dim=128, depth=3, num_heads=16).to('cuda')
128.    summary(CTTXNet)

```

batch = 16

epoch = 5

lr = 1e-3

Evaluasi :

Epoch 1

loss: 0.710617 [16/ 100]

Test Error:

Accuracy: 80.2%, Avg loss: 0.495111

Epoch 2

loss: 0.600416 [16/ 100]

Test Error:

Accuracy: 83.4%, Avg loss: 0.445460

Epoch 3

loss: 0.585182 [16/ 100]

Test Error:

Accuracy: 83.2%, Avg loss: 0.432131

Epoch 4

loss: 0.590293 [16/ 100]

Test Error:

Accuracy: 82.7%, Avg loss: 0.438456

Epoch 5

...

Test Error:

Accuracy: 83.7%, Avg loss: 0.448541

[82]

✓ 44.5s

...

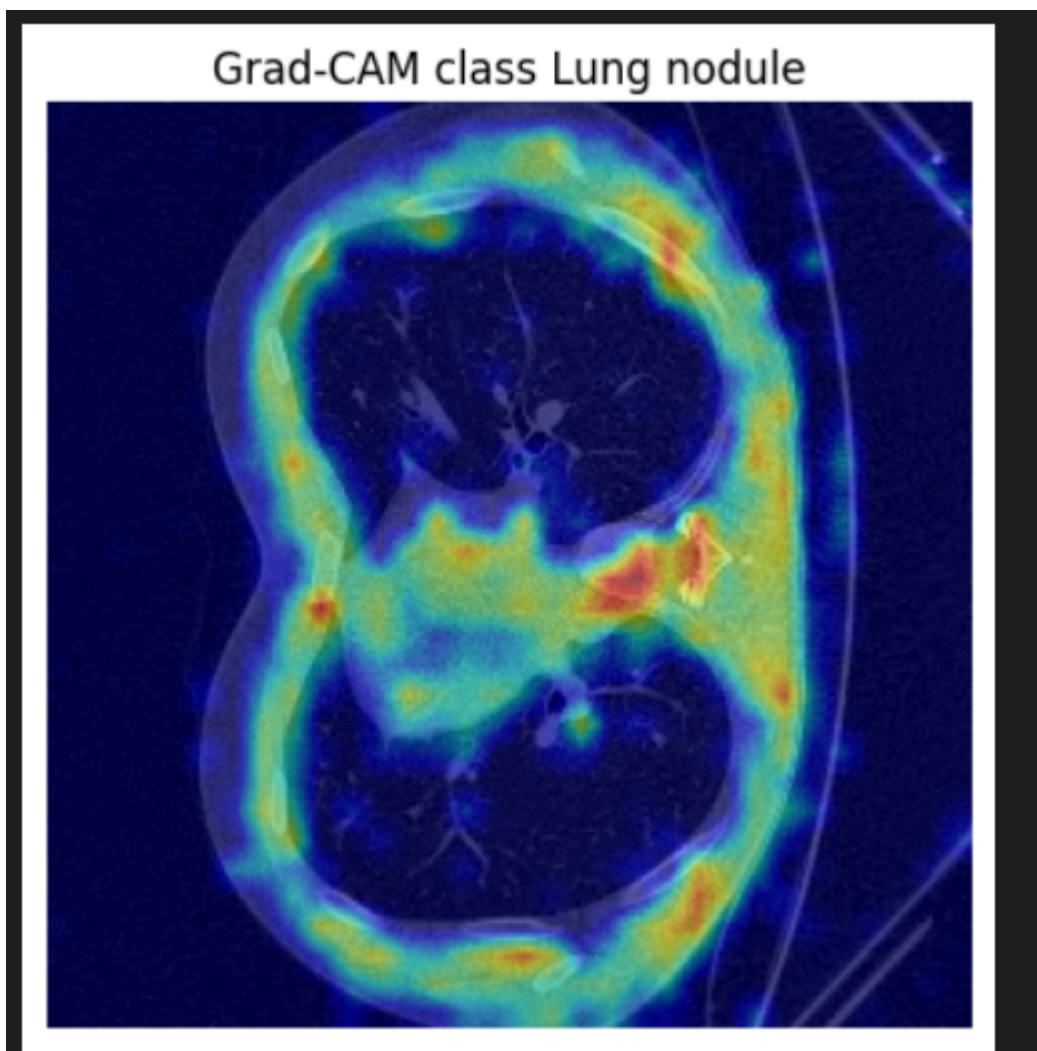
Lung nodule



...

Predicted: ['Lung nodule'], Actual: ['Lung nodule']

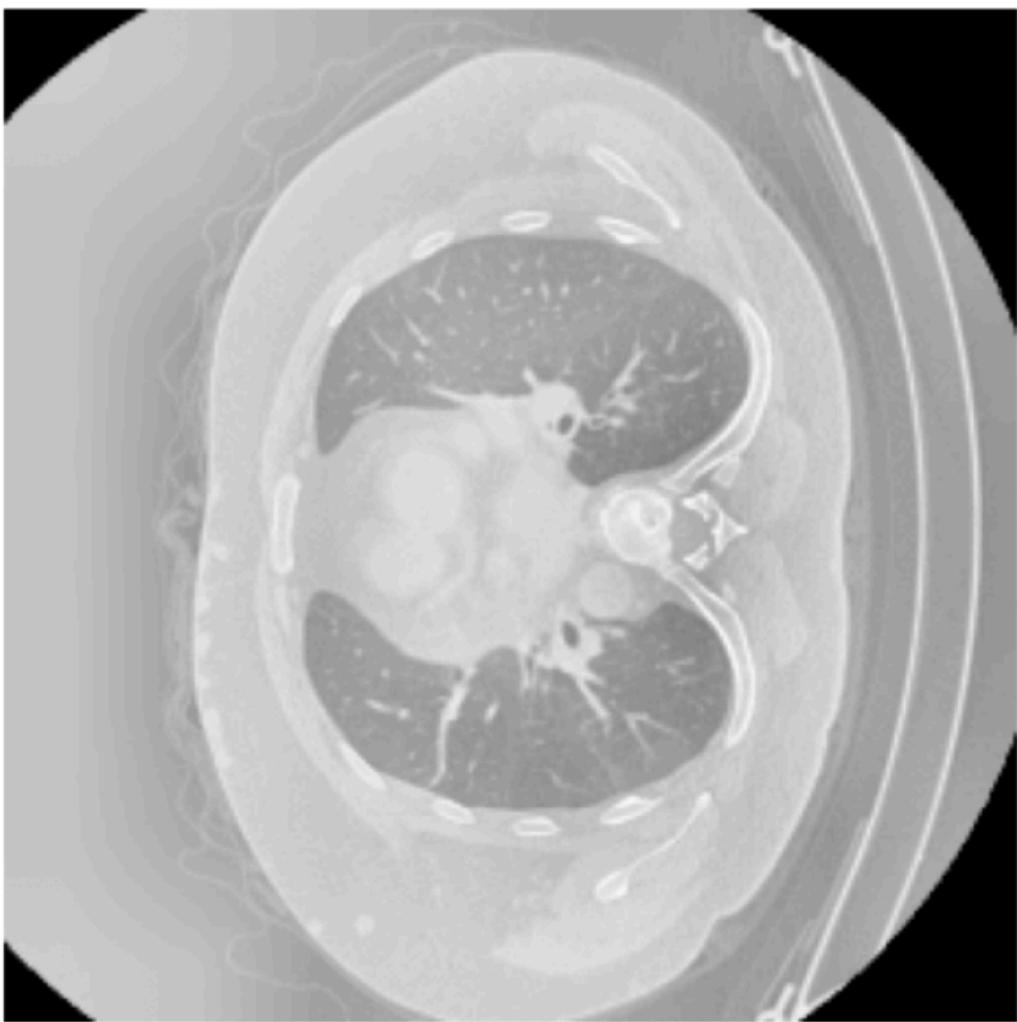
Explainable AI GAD-CAM

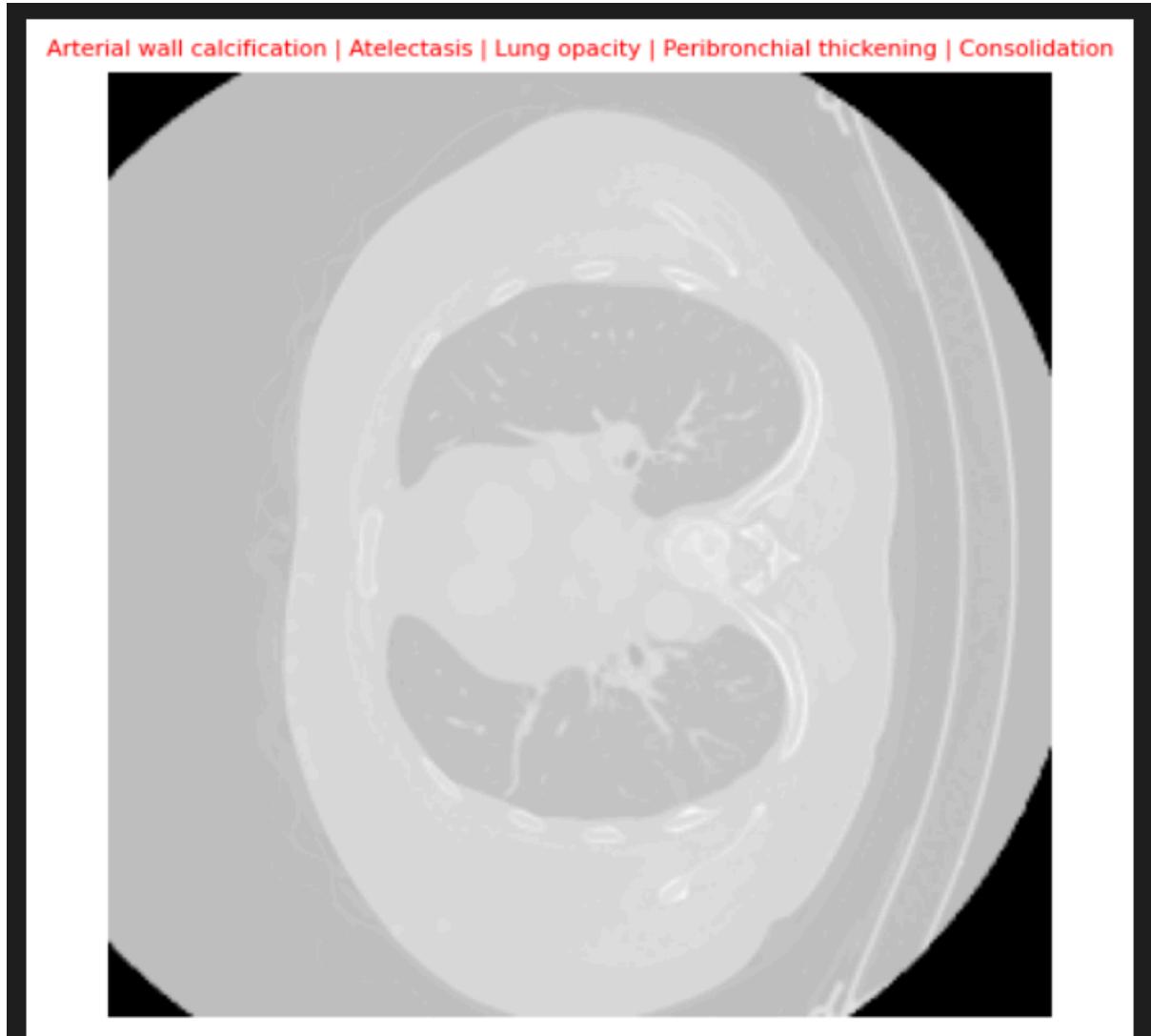


Coba Preprocessing image lagi, clip_limit pada clahe naikan ke 3.0

```
1. def preprocess_ct_psnr(img_tensor, denoise_h=1):
2.     img = img_tensor.squeeze().numpy()
3.     # img_u8 = (img * 255).astype(np.uint8)
4.
5.
6.     # Enhacing image dengan Gamma
7.     gamma=1.0
8.     out = np.power(img, gamma)
9.
10.    # Enhancing image dengan clahe
11.    out = (out * 255).clip(0,255).astype(np.uint8)
12.    clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
13.    out = clahe.apply(out)
14.
15.    # Denoising dengan fastN1Means
16.    img_denoised = cv2.fastNIMeansDenoising(
17.        out, None, h=denoise_h,
18.        templateWindowSize=7, searchWindowSize=21
19.    )
20.
21.    out = img_denoised.astype(np.float32) / 255.0
22.
23.
24.    return torch.from_numpy(out).unsqueeze(0)
25.
```

Arterial wall calcification | Atelectasis | Lung opacity | Peribronchial thickening | Consolidation





#	Image	# PSNR	# SSIM	# MSE	# RMSE
0	1	22.0	0.8354	0.01	0.08
1	2	22.57	0.7942	0.01	0.07
2	3	20.98	0.8524	0.01	0.09
3	4	22.25	0.8344	0.01	0.08
4	5	25.62	0.8218	0.0	0.05
5	6	22.13	0.8568	0.01	0.08
6	7	24.36	0.7952	0.0	0.06
7	8	22.73	0.8446	0.01	0.07
8	9	19.33	0.7622	0.01	0.11
9	10	16.79	0.5084	0.02	0.14

#	Image	# PSNR	# SSIM	# MSE	# RMSE
10	11	20.55	0.642	0.01	0.09
11	12	15.38	0.503	0.03	0.17
12	13	17.5	0.6287	0.02	0.13
13	14	15.9	0.5227	0.03	0.16
14	15	18.36	0.6456	0.01	0.12
15	16	19.34	0.7075	0.01	0.11
16	17	20.28	0.7304	0.01	0.1
17	18	17.86	0.4982	0.02	0.13
18	19	21.33	0.603	0.01	0.09
19	20	17.58	0.4994	0.02	0.13

Epoch 1

loss: 0.679748 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.518273

Epoch 2

loss: 0.589148 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.455573

Epoch 3

loss: 0.575900 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.438323

Epoch 4

loss: 0.584326 [16/ 100]

Test Error:

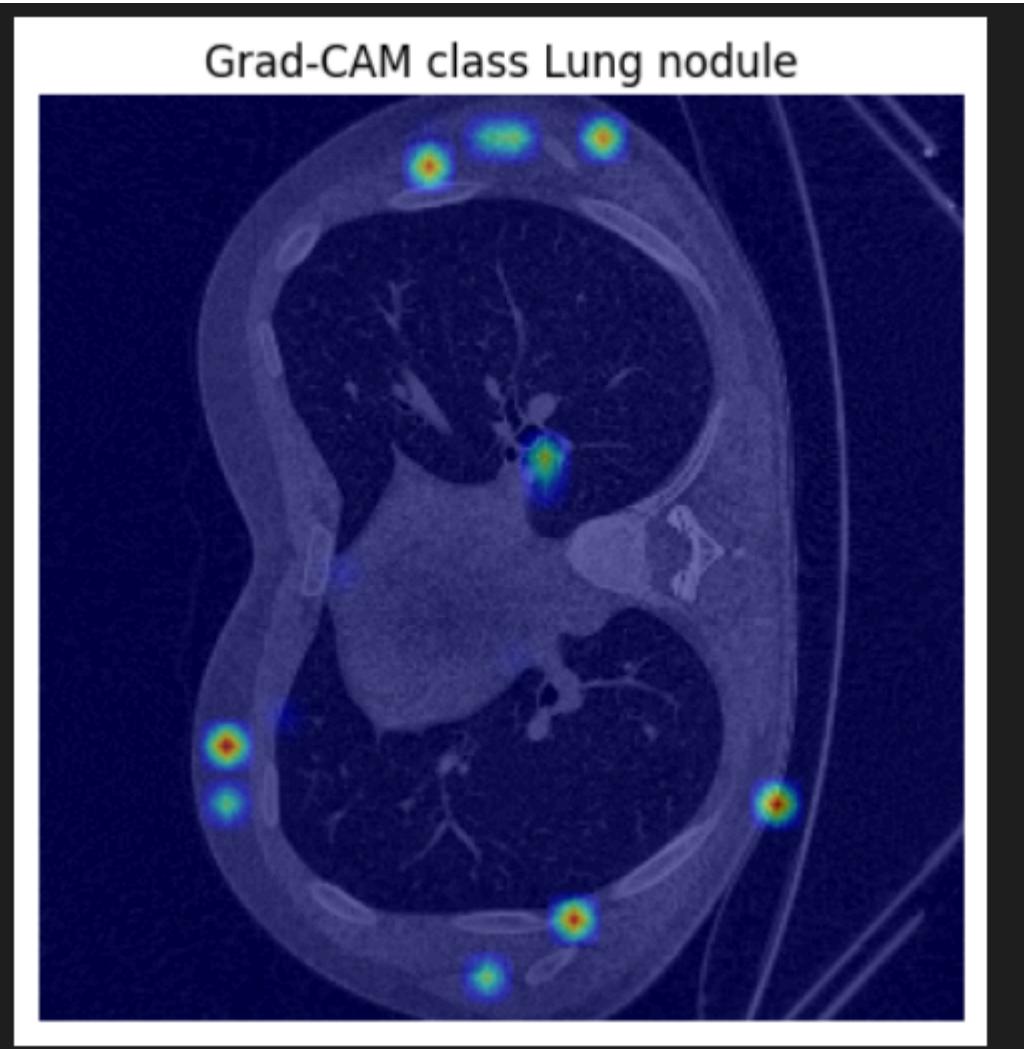
Accuracy: 83.3%, Avg loss: 0.449317

Epoch 5

...

Test Error:

Accuracy: 84.1%, Avg loss: 0.451600

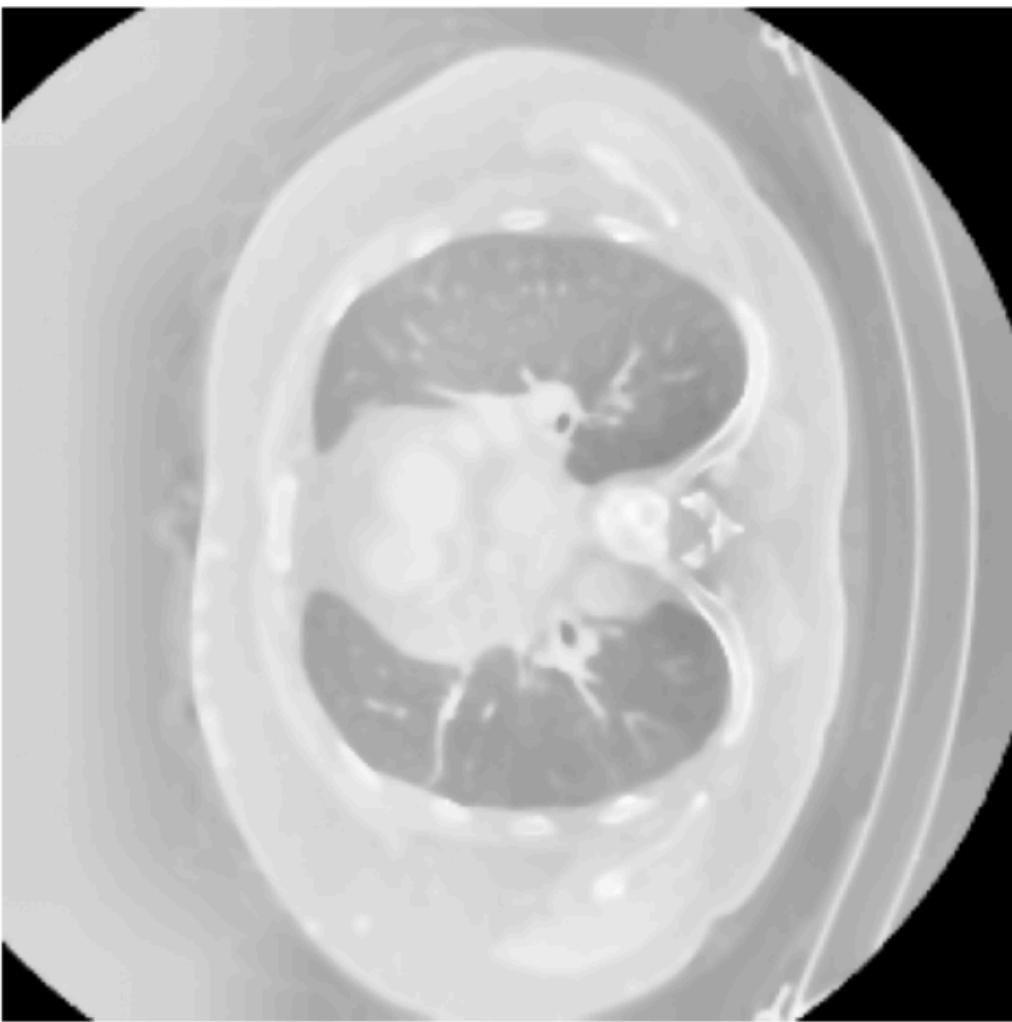


Coba tambahkan bilateral filtering d = 5, sigmaColor & sigmaSpace = 30

```
1. def preprocess_ct_psnr(img_tensor, denoise_h=1):
2.     img = img_tensor.squeeze().numpy()
3.
4.     # Enhacing image dengan Gamma
5.     gamma=1.0
6.     out = np.power(img, gamma)
7.
8.
9.     # Enhancing image dengan clahe
10.    out = (out * 255).clip(0,255).astype(np.uint8)
11.    clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
12.    out = clahe.apply(out)
13.
14.    # Denoising dengan fastN1Means
```

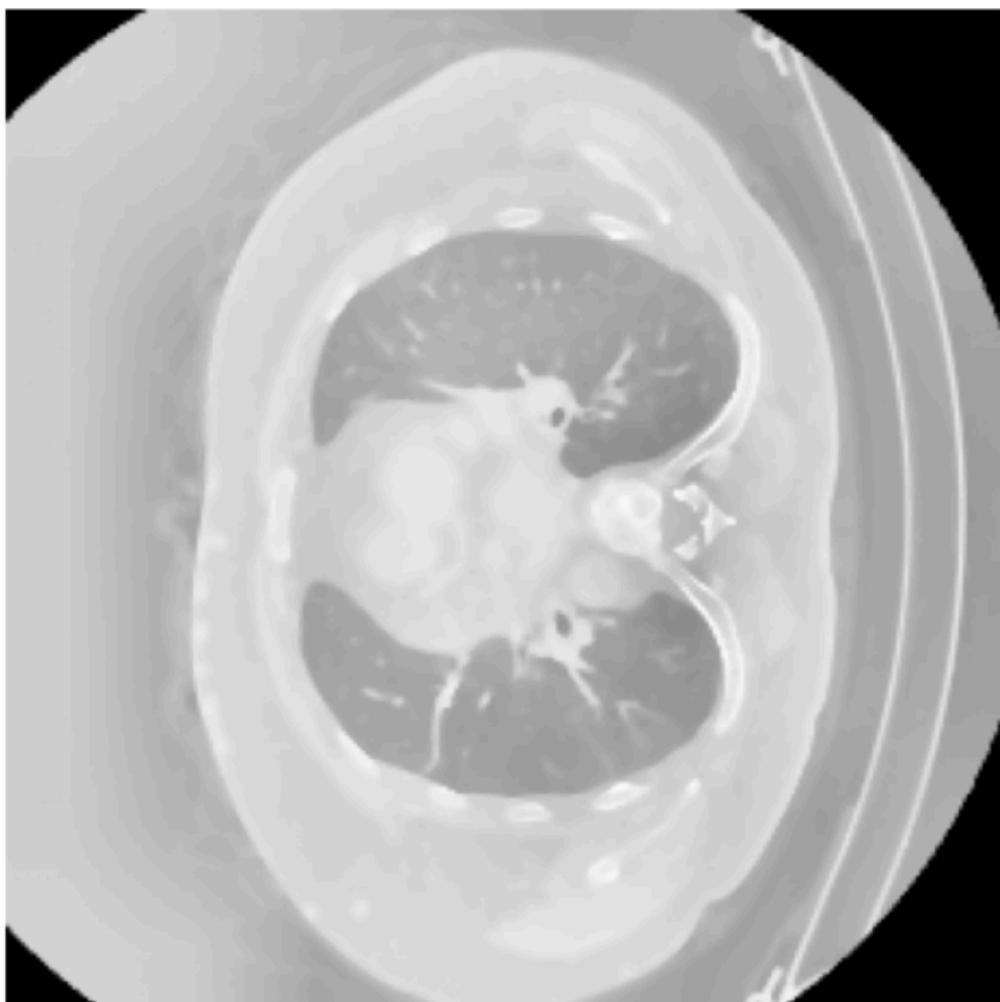
```
15. img_denoised = cv2.fastNIMeansDenoising(  
16.     out, None, h=denoise_h,  
17.     templateWindowSize=7, searchWindowSize=21  
18. )  
19.  
20. # Smooth sisa noise pake bilateral filter  
21. img_bila = cv2.bilateralFilter(out, d=5, sigmaColor=30, sigmaSpace=30)  
22.  
23. out = img_bila.astype(np.float32) / 255.0  
24.  
25. return torch.from_numpy(out).unsqueeze(0)  
26.
```

Arterial wall calcification | Atelectasis | Lung opacity | Peribronchial thickening | Consolidation



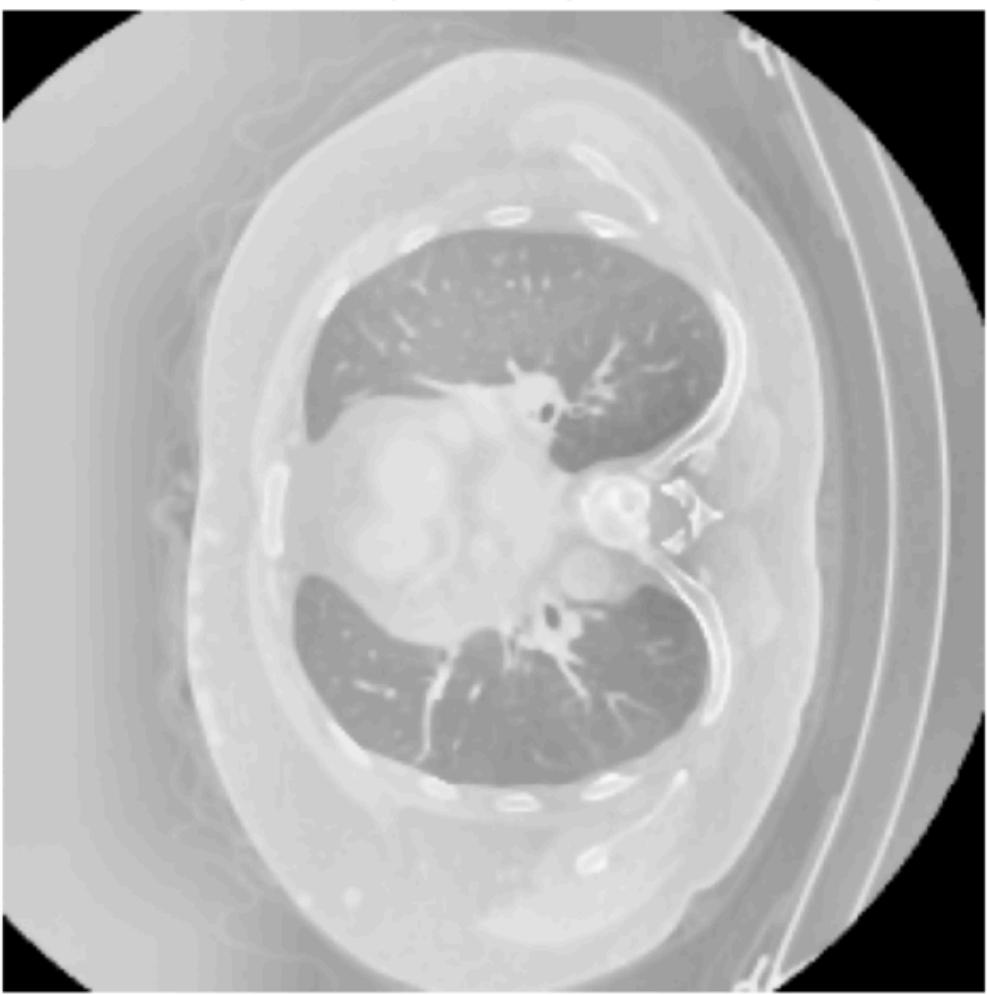
gambar hasil terlihat jadi blur ketimbang sebelumnya coba turunkan
sigmaColor&sigmaSpace jadi 20

Arterial wall calcification | Atelectasis | Lung opacity | Peribronchial thickening | Consolidation



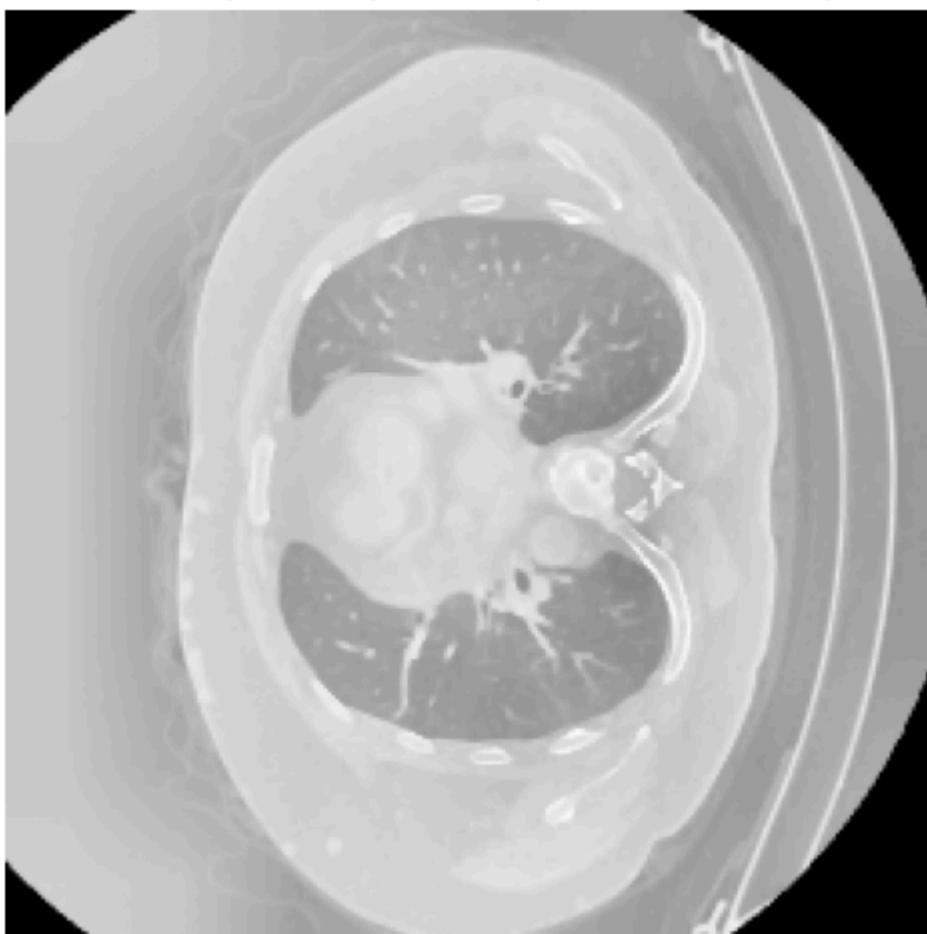
hasil masih ngeblur, coba turunkan d ke 3

Arterial wall calcification | Atelectasis | Lung opacity | Peribronchial thickening | Consolidation



hasil tampak lebih baik, tapi keknya ga sebagus kalau ga pake
bilateralfilter, coba turunkan **Sigma ke 15**

Arterial wall calcification | Atelectasis | Lung opacity | Peribronchial thickening | Consolidation



coba cek accuracy model aja deh apakah lebih baik atau buruk dari yg ga pake bilateral

Epoch 1

loss: 0.693583 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.510726

Epoch 2

loss: 0.620899 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.462935

Epoch 3

loss: 0.610267 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.438313

Epoch 4

loss: 0.602020 [16/ 100]

Test Error:

Accuracy: 83.7%, Avg loss: 0.433409

Epoch 5

...

Test Error:

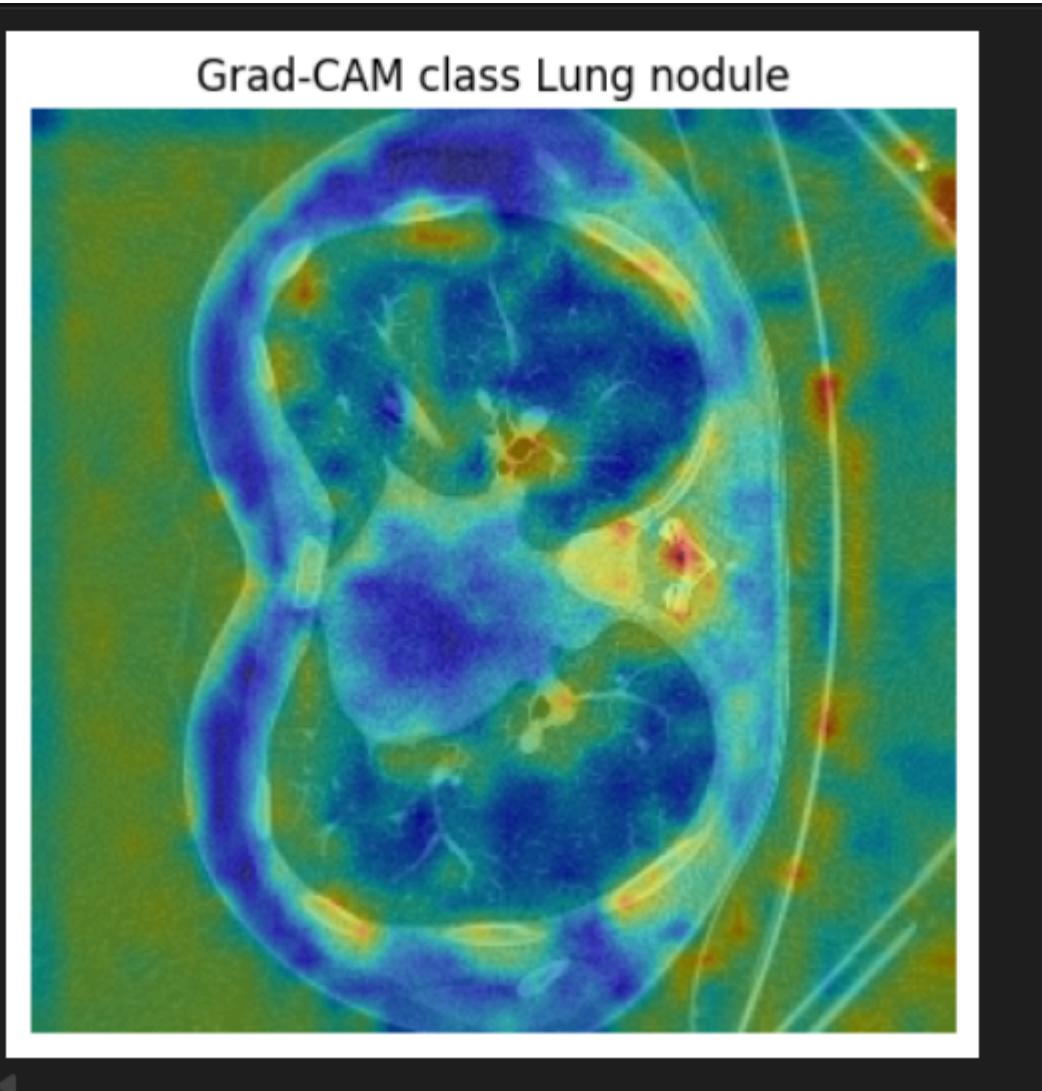
Accuracy: 83.7%, Avg loss: 0.436243

terlihat accuracy nya hanya 83,7 yang berarti tidak lebih baik dari tidak menggunakan bilateral

Data sekarang training 100 dan test 50 , skrg coba 500 train, 100 val

Accuracy stagnant di 80,1

Accuracy: 80.1%, Avg loss: 0.474842



Coba kita gedein batch nya dan kecilkan learning rate

Batch = 32, lr = 1e-5

loss: 0.681962 [32/ 500]

Test Error:

Accuracy: 64.6%, Avg loss: 0.658118

Accuracy makin jelek, coba kembalikan lr ke 1e-3

Epoch 1

loss: 0.662226 [32/ 500]

Test Error:

Accuracy: 80.1%, Avg loss: 0.484777

Epoch 2

loss: 0.551225 [32/ 500]

Test Error:

Accuracy: 80.1%, Avg loss: 0.478153

Epoch 3

loss: 0.541216 [32/ 500]

Test Error:

Accuracy: 80.1%, Avg loss: 0.473307

Epoch 4

loss: 0.541369 [32/ 500]

Test Error:

Accuracy: 80.1%, Avg loss: 0.473107

Epoch 5

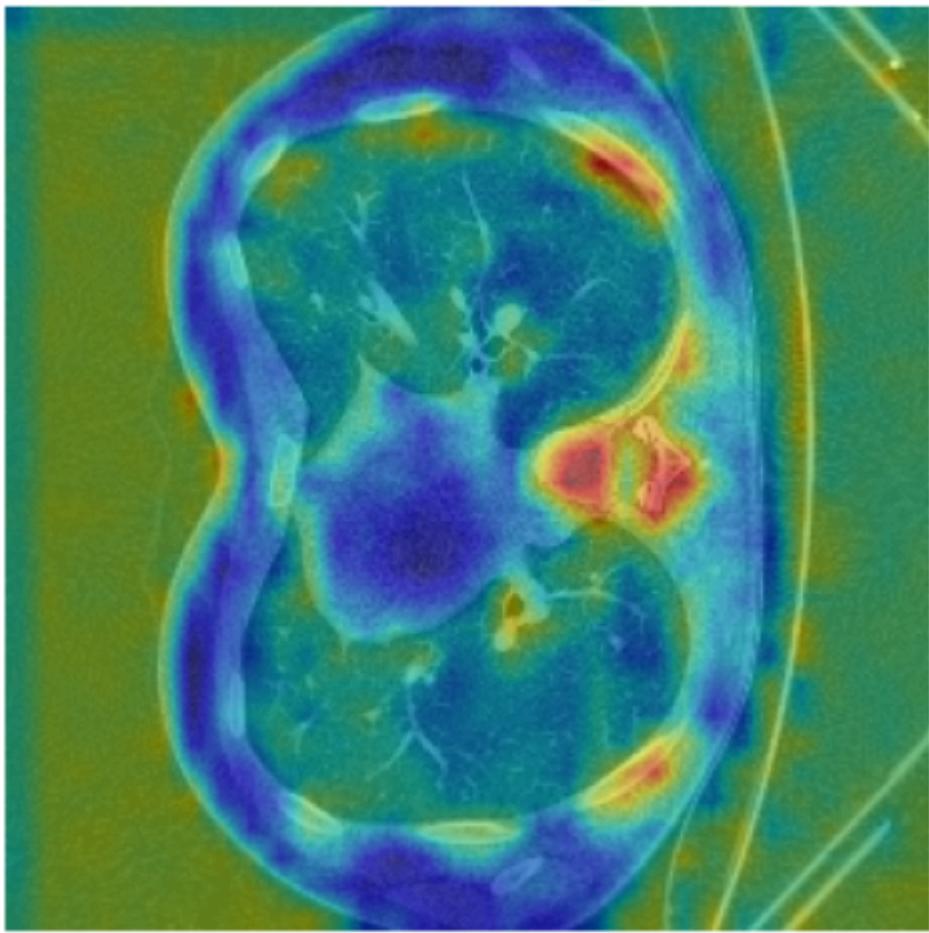
...

Test Error:

Accuracy: 80.1%, Avg loss: 0.473683

kembali stagnant 80,1%

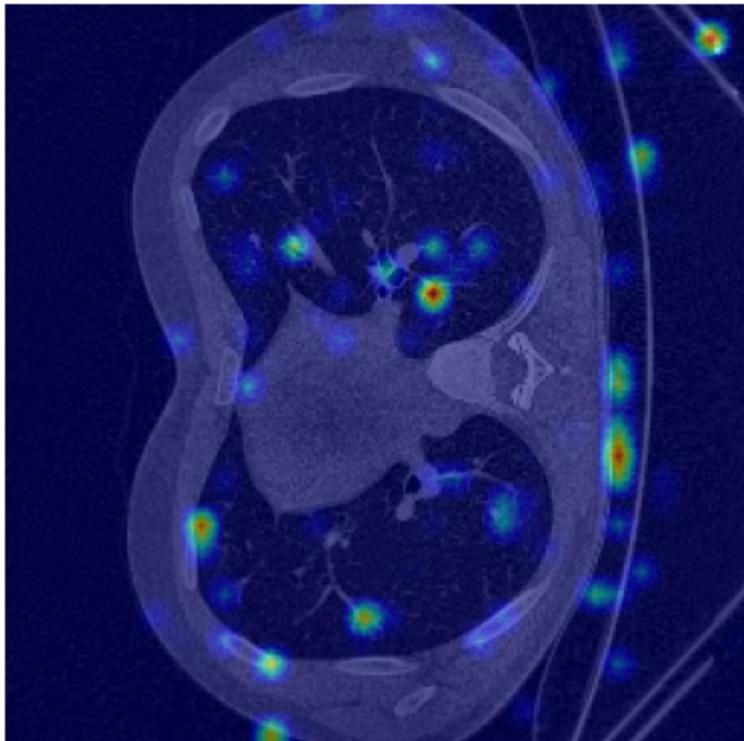
Grad-CAM class Lung nodule



Pake model Training 500 train 100 val dengan data 1000

Accuracy total nya 80,1 % juga

Grad-CAM class Lung nodule



tapi hasilnya lebih bagus

Metric evaluasi data Training

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.83	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.83	0.0
Arterial wall calcification	0.73	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.73	0.0
Cardiomegaly	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.88	0.0
Pericardial effusion	0.90	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.90	0.0
Coronary artery wall calcification	0.77	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.77	0.0
Hiatal hernia	0.85	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.85	0.0
Lymphadenopathy	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Emphysema	0.81	0.0	0.0	0.99	0.0	0.0	0.00	0.0	0.81	0.0
Atelectasis	0.73	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.73	0.0
Lung nodule	0.53	0.49	0.51	0.55	0.5	0.44	0.48	0.50	0.57	0.06
Lung opacity	0.66	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.66	0.0

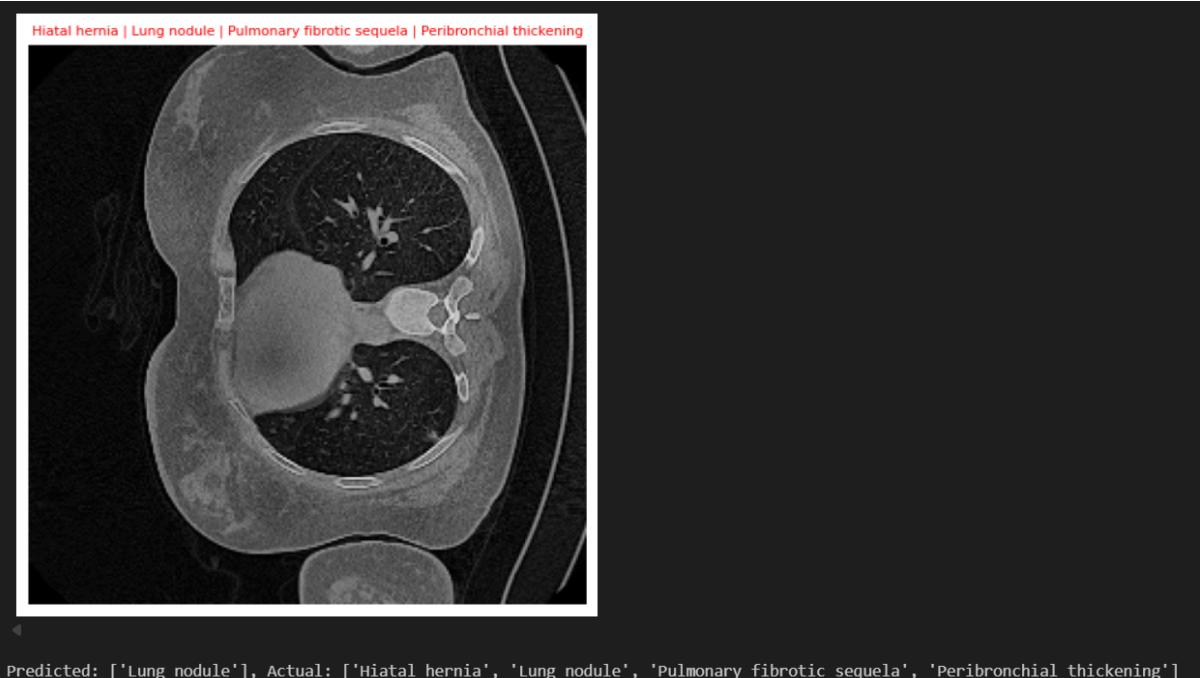
y										
Pulmonary fibrotic sequela	0.75	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.75	0.0
Pleural effusion	0.82	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.82	0.0
Mosaic attenuation pattern	0.91	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.91	0.0
Peribronchial thickening	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.91	0.0
Consolidation	0.77	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.91	0.0
Bronchiectasis	0.90	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.90	0.0
Interlobular septal thickening	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0

Metric evaluasi data validasi

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.88	0.0
Arterial wall calcification	0.71	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.71	0.0
Cardiomegaly	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0
Pericardial effusion	0.92	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.92	0.0
Coronary artery wall calcification	0.73	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.73	0.0
Hiatal hernia	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0
Lymphadenopathy	0.74	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.74	0.0
Emphysema	0.77	0.0	0.0	0.99	0.0	0.0	0.00	0.0	0.7	0.0
Atelectasis	0.78	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.78	0.0
Lung nodule	0.51	0.49	0.47	0.54	0.48	0.45	0.52	0.50	0.52	0.02
Lung	0.61	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.61	0.0

opacity										
Pulmonary fibrotic sequela	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Pleural effusion	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0
Mosaic attenuation pattern	0.92	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.92	0.0
Peribronchial thickening	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0
Consolidation	0.79	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.79	0.0
Bronchiectasis	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0
Interlobular septal thickening	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0

Terlihat karena ketidak seimbangan subset data yang diambil, akibatnya model overfitting ke label Lung Nodule, dan ini bisa dibuktikan dengan gambar ini



Predicted: ['Lung nodule'], Actual: ['Hiatal hernia', 'Lung nodule', 'Pulmonary fibrotic sequela', 'Peribronchial thickening']

Bisa dilihat pada gambar berlabel 'Hiatal hernia', 'Lung nodule', 'Pulmonary fibrotic sequela', 'Peribronchial thickening', model hanya memprediksi bahwa dia mengidap 'Lung nodule'



Predicted: ['Lung nodule'], Actual: ['Lung nodule']

Namun, di gambar yang memang hanya berlabel lung nodule, model memprediksinya dengan tepat

1000 data train 400 val, Shuffle = False

Epoch 1

loss: 0.699469 [32/ 1000]

Test Error:

Accuracy: 80.3%, Avg loss: 0.462028

Epoch 2

loss: 0.547850 [32/ 1000]

Test Error:

Accuracy: 80.2%, Avg loss: 0.459586

Epoch 3

loss: 0.539254 [32/ 1000]

Test Error:

Accuracy: 80.2%, Avg loss: 0.457123

Epoch 4

loss: 0.530114 [32/ 1000]

Test Error:

Accuracy: 80.2%, Avg loss: 0.455126

Epoch 5

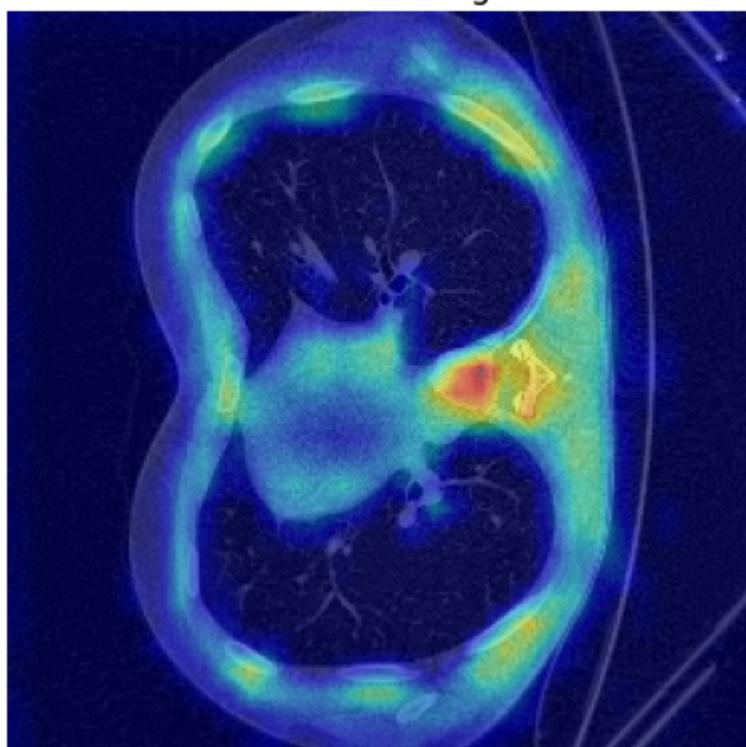
...

Test Error:

Accuracy: 80.3%, Avg loss: 0.454239

Accuracy test 80,3%

Grad-CAM class Lung nodule



Grad-CAM class Pericardial effusion



hasil gambar menunjukan model bisa mendekksi long nodule, tapi tidak dengan class lain, Pericardial effusion contohnya

Metric evaluasi Training

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.83	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.83	0.0
Arterial wall calcification	0.73	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.73	0.0
Cardiomegaly	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.88	0.0
Pericardial effusion	0.90	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.90	0.0
Coronary artery wall calcification	0.77	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.77	0.0
Hiatal hernia	0.85	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.85	0.0
Lymphadenopathy	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Emphysema	0.81	0.0	0.0	0.99	0.0	0.0	0.00	0.0	0.81	0.0
Atelectasis	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Lung nodule	0.54	0.50	0.22	0.81	0.31	0.18	0.77	0.59	0.55	0.05
Lung	0.60	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.60	0.0

opacity										
Pulmonary fibrotic sequela	0.75	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.75	0.0
Pleural effusion	0.82	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.82	0.0
Mosaic attenuation pattern	0.91	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.91	0.0
Peribronchial thickening	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.88	0.0
Consolidation	0.77	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.77	0.0
Bronchiectasis	0.90	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.90	0.0
Interlobular septal thickening	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0

Metric evaluasi data val

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.88	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.88	0.0

Arteri al wall calcifi cation	0.71	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.71	0.0
Cardi ome gal	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0
Peric ardial effusi on	0.92	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.92	0.0
Coron ary artery wall calcifi catio	0.73	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.73	0.0
Hiatal hernia	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0
Lymp haden opathy	0.74	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.74	0.0
Emphysem a	0.78	0.0	0.0	0.99	0.0	0.0	0.00	0.0	0.77	0.0
Atelec tasis	0.78	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.78	0.0
Lung nodul e	0.50	0.48	0.19	0.80	0.27	0.19	0.80	0.51	0.51	-0.00 4
Lung opacit y	0.61	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.61	0.0
Pulm onary fibroti c seque la	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Pleur al effusi	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0

on										
Mosaic attenuation pattern	0.92	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.92	0.0
Peribronchial thickening	0.87	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.87	0.0
Consolidation	0.79	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.79	0.0
Bronchiectasis	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0
Interlobular septal thickening	0.89	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.89	0.0

Dapat dilihat bahwa 1000 data oertama pun data masih tidak seimbang, coba kita ambil 500 train dan 100 val data secara acak

Coba Shuffle nya true

di sini menambahkan pos_weight pada loss function BCE untuk menangani data label yang imbalance

Epoch 1

loss: 1.252962 [32/ 500]

Test Error:

Accuracy: 39.8%, Avg loss: 1.064612

Epoch 2

loss: 1.059134 [32/ 500]

Test Error:

Accuracy: 46.3%, Avg loss: 1.058887

Epoch 3

loss: 1.131776 [32/ 500]

Test Error:

Accuracy: 62.4%, Avg loss: 1.048508

Epoch 4

loss: 0.974374 [32/ 500]

Test Error:

Accuracy: 57.8%, Avg loss: 1.045594

Epoch 5

...

Test Error:

Accuracy: 60.1%, Avg loss: 1.042969

Metric evaluasi training

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.88	0.44	0.07	0.98	0.12	0.01	0.92	0.55	0.89	0.14
Arterial wall calcification	0.54	0.37	0.73	0.46	0.49	0.53	0.25	0.62	0.8	0.19
Cardiomegaly	0.85	0.37	0.36	0.91	0.37	0.08	0.63	0.62	0.91	0.28
Pericardial effusion	0.52	0.08	0.68	0.51	0.14	0.48	0.31	0.91	0.96	0.09
Coronary	0.58	0.36	0.61	0.57	0.46	0.42	0.38	0.63	0.78	0.17

artery wall calcifi- cation										
Hiatal hernia	0.22	0.17	0.95	0.07	0.29	0.99	0.04	0.82	0.88	0.04
Lymp- haden- opathy	0.39	0.29	0.87	0.22	0.44	0.77	0.12	0.7	0.82	0.109
Emphysema	0.78	0.26	0.12	0.92	0.17	0.07	0.87	0.73	0.83	0.07
Atelectasis	0.49	0.32	0.78	0.38	0.46	0.61	0.21	0.67	0.82	0.16
Lung nodule	0.52	0.47	0.28	0.73	0.35	0.26	0.71	0.52	0.55	0.02
Lung opacity	0.54	0.42	0.65	0.47	0.51	0.52	0.34	0.57	0.7	0.12
Pulmonary fibrotic sequela	0.57	0.34	0.4	0.65	0.37	0.34	0.59	0.65	0.70	0.05
Pleural effusion	0.72	0.2	0.3	0.78	0.26	0.21	0.62	0.79	0.89	0.12
Mosaic attenuation pattern	0.85	0.19	0.31	0.90	0.23	0.09	0.68	0.8	0.94	0.17
Peribronchi- al thickening	0.72	0.17	0.48	0.74	0.25	0.25	0.51	0.82	0.93	0.15
Cons	0.33	0.20	0.93	0.20	0.33	0.79	0.06	0.79	0.93	0.13

oldation										
Bronchiectasis	0.63	0.15	0.51	0.65	0.24	0.34	0.48	0.84	0.91	0.11
Interlobular septal thickening	0.59	0.15	0.62	0.59	0.24	0.4	0.37	0.84	0.93	0.13

Evaluasi Validasi

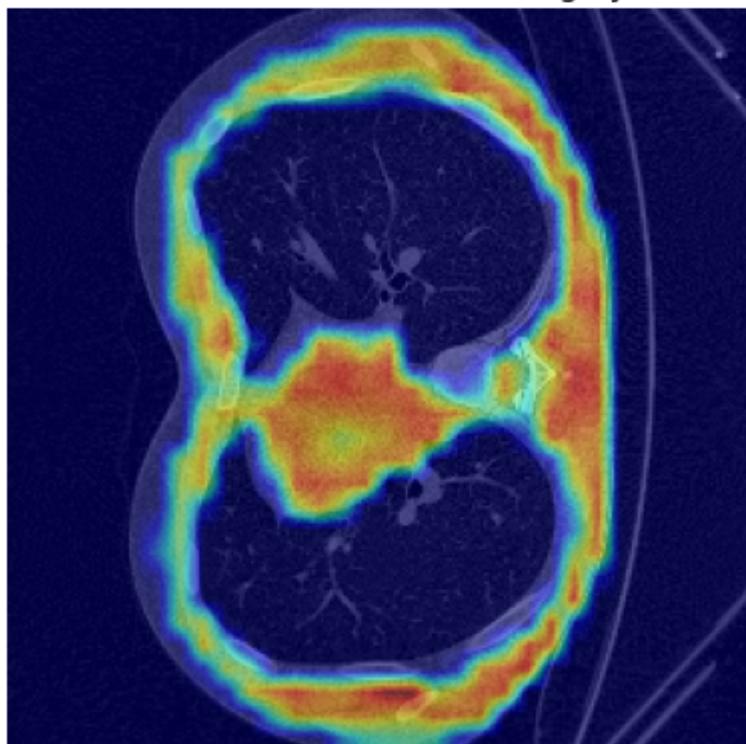
Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.61	0.16	0.461 53846 11834 3195	0.643 67816 08455 543	0.239 99999 60560 0006	0.356 32183 90395 0326	0.538 46153 80473 372	0.837 83783 76113 952	0.888 88888 87477 954	0.073 28996 63291 1351
Arterial wall calcification	0.54	0.405 79710 13904 642	0.874 99999 97265 625	0.397 05882 34710 208	0.554 45544 11057 74	0.602 94117 63819 205	0.124 99999 99609 375	0.594 20289 84646 083	0.870 96774 16545 265	0.274 40174 50483 129
Cardiomegaly	0.539 99999 9946	0.206 89655 16884 661	0.999 99999 91666 666	0.477 27272 72184 918	0.342 85713 99183 674	0.522 72727 26678 719	0.0	0.793 10344 81391 2	0.999 99999 97619 048	0.314 23889 24126 067
Pericardial effusion	0.129 99999 99870 0001	0.103 09278 34945 2652	0.999 99999 89999 999	0.033 33333 33296 2963	0.186 91588 61210 5864	0.966 66666 65592 594	0.0	0.896 90721 64023 808	0.999 99999 66666 667	0.058 62103 81760 538
Coronary artery wall calcification	0.569 99999 9943	0.379 31034 47621 879	0.758 62068 93935 791	0.492 95774 64094 426	0.505 74712 18760 735	0.507 04225 34497 124	0.241 37931 02615 9334	0.620 68965 50653 983	0.833 33333 31349 206	0.231 29324 24553 63
Hiatal hernia	0.219 99999 99780 0002	0.142 85714 28414 4427	0.999 99999 92307 692	0.103 44827 58501 7836	0.249 99999 77644 2305	0.896 55172 40348 791	0.0	0.857 14285 70486 657	0.999 99999 88888 888	0.121 56613 47709 655
Lymph	0.459	0.301	0.879	0.319	0.044	0.679	0.119	0.698	0.888	0.195

hadeno pathy	99999 99540 0004	36986 29724 1514	99999 9648 3336	99999 99573 3336	89795 87944 60646	99999 99093 334	99999 9952 987	63013 68905 987	88888 85596 707	06857 86602 1737
Emphysem a	0.339 99999 9966 4046	0.171 05263 15564 874	0.812 49999 94921 381	0.249 99999 99702 913	0.282 60869 27173 143	0.749 99999 99107 125	0.187 49999 98828 807	0.828 94736 83119 166	0.874 99999 96354 166	0.053 64969 22049 344
Atelec tasis	0.439 99999 99560 0003	0.356 32183 90395 0326	0.999 99999 96774 194	0.188 40579 70741 441	0.525 42372 48506 177	0.811 59420 27809 284	0.0	0.643 67816 08455 543	0.999 99999 92307 692	0.259 10055 98539 0706
Lung nodul e	0.469 99999 9953	0.407 40740 72565 1575	0.229 16666 66189 236	0.692 30769 21745 562	0.293 33332 86471 112	0.307 69230 76331 361	0.770 83333 31727 43	0.592 59259 23731 138	0.493 15068 48639 52	-0.08 83670 72735 8293
Lung opacit y	0.639 99999 9936	0.536 23188 39802 563	0.902 43902 41701 368	0.457 62711 85665 039	0.672 72726 79289 257	0.542 37288 12640 046	0.097 56097 55859 6073	0.463 76811 58748 1626	0.870 96774 16545 265	0.382 90834 25266 1204
Pulmonary fibrotic sequela	0.509 99999 9949	0.306 12244 89171 179	0.499 99999 98333 333	0.514 28571 42122 449	0.379 74683 06361 1603	0.485 71428 56448 98	0.499 99999 98333 333	0.693 87755 08788 005	0.705 88235 28027 681	0.013 09569 28146 8872
Pleural effusion	0.629 99999 99370 001	0.232 55813 94808 0042	0.714 28571 37755 102	0.616 27906 96957 815	0.350 87718 91535 8573	0.383 72093 01879 3946	0.285 71428 55102 0406	0.767 44186 02866 414	0.929 82456 12403 816	0.231 68513 64884 415
Mosaic attenuation pattern	0.439 99999 99560 0003	0.153 84615 38224 8523	0.909 09090 82644 627	0.382 02247 18671 885	0.263 15789 21918 2834	0.617 97752 80204 52	0.090 90909 08264 4627	0.846 15384 60236 687	0.971 42857 11510 204	0.190 96897 34713 449
Peribronchi al thickening	0.739 99999 99260 001	0.222 22222 21399 1769	0.545 45454 49586 776	0.764 04494 37343 77	0.315 78946 94044 3214	0.235 95505 61532 6348	0.454 54545 41322 3135	0.777 77777 74897 119	0.931 50684 91874 648	0.218 12626 87698 9355
Consolidati on	0.559 99999 99440 001	0.131 57894 73337 9502	0.312 49999 98046 875	0.607 14285 70705 782	0.185 18518 09465 022	0.392 85714 28103 742	0.687 49999 95703 125	0.868 42105 24030 471	0.822 58064 50286 16	-0.06 06927 02788 05855
Bronc	0.619	0.060	0.222	0.659	0.095	0.340	0.777	0.939	0.895	-0.07

hiecta sis	99999 9938	60606 05876	22222 19753	34065 92682	23809 18253	65934 06219	77777 69135	39393 91092	52238 79260	20834 24734	
Interlo bular septal thicke ning	0.909 99999 9909	0.333 33333 22222	0.124 99999 98437	0.978 26086 94588	0.181 81817 75206	0.021 73913 04324	0.874 99999 89062	0.666 66666 44444	0.927 83505 14507	0.164 22081 02696	0762

terlihat model kali ini lebih lumayan seimbang dan bisa melakukan prediksi untuk label lainnya, di sini kita akan lihat prediksi gambar dengan MCC tertinggi dan terendah

Grad-CAM class Cardiomegaly



dengan mcc train 0,28 dan val nya 0,31

Grad-CAM class Bronchiectasis



dengan mcc 0,11 pada train dan -0,07 pada val

Gunakan model efficientb0

Epoch 1

loss: 1.052851 [32/ 500]

Test Error:

Accuracy: 43.9%, Avg loss: 1.072745

Epoch 2

loss: 1.018156 [32/ 500]

Test Error:

Accuracy: 43.4%, Avg loss: 1.110487

Epoch 3

loss: 0.788935 [32/ 500]

Test Error:

Accuracy: 63.5%, Avg loss: 1.117259

Epoch 4

loss: 0.756849 [32/ 500]

Test Error:

Accuracy: 59.3%, Avg loss: 1.038264

Epoch 5

...

Test Error:

Accuracy: 68.3%, Avg loss: 1.009007

Done!

Metric evaluasi training

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.921 99999 99815 6	0.644 06779 65010 054	0.678 57142 84502 551	0.952 70270 26812 455	0.660 86956 01058 603	0.047 29729 72962 3204	0.321 42857 13711 735	0.355 93220 33295 0304	0.959 18367 34476 376	0.617 10375 76569 398
Arterial wall calcification	0.863 99999 99827 2	0.873 33333 32751 111	0.859 99999 99754 285	0.793 93938 89325 986	0.139 99999 9996 222	0.126 66666 66582 9874	0.272 22222 22070 054	0.940 62499 99706 456	0.727 77777 77373 089	0.700 11573 11738 089
Cardiomegaly	0.899 99999 9982	0.562 49999 99296 876	0.749 99999 9875 26	0.920 45454 54336 471	0.642 85713 78673 467	0.079 54545 45436 333	0.249 99999 99583 125	0.437 49999 99453 551	0.964 28571 42627 18	0.594 29443 59687 18
Pericardial effusion	0.961 99999 99807 6	0.666 66666 64444 444	0.689 65517 21759 809	0.978 76857 74739 114	0.677 96609 64665 325	0.021 23142 25048 57083	0.310 34482 74791 9145	0.333 33333 32222 222	0.980 85106 38089 181	0.657 88770 28419 604
Coronary artery wall calcification	0.819 99999 99836	0.639 17525 76990 115	0.861 11111 10513 117	0.803 37078 64942 873	0.733 72780 57168 867	0.196 62921 34776 2277	0.138 88888 88792 4383	0.360 82474 22494 42	0.934 64052 28452 732	0.617 48700 29297 19
Hiatal hernia	0.795 99999 99840 8	0.445 16129 02938 6053	0.811 76470 57868 512	0.792 77108 43182 465	0.574 99999 53774 306	0.207 22891 56576 5714	0.188 23529 40955 0174	0.554 83870 96416 233	0.953 62318 83781 559	0.490 99846 22943 456
Lymphadenopathy	0.731 99999 99853 6	0.29	0.87	0.22	0.44	0.77	0.12	0.7	0.82	0.109
Emphysema	0.869 99999 99826	0.677 41935 47294 485	0.482 75862 06341 657	0.951 57384 98558 941	0.563 75838 43268 322	0.048 42615 01198 92826	0.517 24137 92508 919	0.322 58064 51092 6115	0.897 26027 39521 174	0.499 60186 44551 454
Atelectasis	0.669 99999 99866	0.445 73643 40912 505	0.839 41605 83328 892	0.582 27847 64523 634	0.393 93939 39285 416	0.160 58394 15941 1796	0.554 26356 58699 898	0.606 06060 60439 102	0.909 09090 90533 433	0.397 57678 66787 894
Lung	0.709	0.708	0.618	0.786	0.660	0.213	0.381	0.291	0.710	0.412

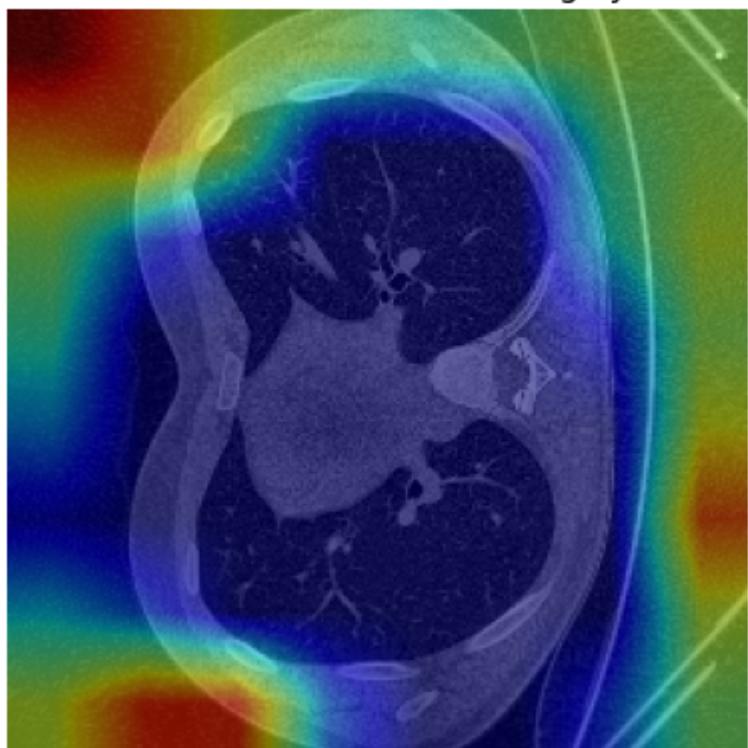
node	99999 99858	54271 35322 34	42105 26044 552	76470 58534 277	42154 06595 769	23529 41098 0752	57894 73516 851	45728 64175 1467	96345 51258 815	28379 20328 778
Lung opacity	0.731 99999 99853 6	0.645 34883 71717 82	0.603 26086 95324 314	0.806 96202 52909 189	0.623 59550 05886 252	0.193 03797 46774 355	0.396 73913 04132 207.3 4	0.354 65116 27700 784	0.777 43902 43665 414	0.416 45799 36874 762
Pulmonary fibrotic sequela	0.733 99999 99853 2	0.616 82242 98488 951	0.417 72151 89609 037	0.880 11695 90385 931	0.498 11320 26947 669	0.119 88304 09321 6716	0.582 27848 09758 051	0.383 17757 00576 4697	0.765 90330 78685 521	0.337 62471 95569 9686
Pleural effusion	0.883 99999 99823 2	0.542 55319 14316 433	0.772 72727 26101 929	0.900 92165 89654 165	0.637 49999 50734 377	0.099 07834 10115 4198	0.227 27272 72382 9203	0.457 44680 84619 738	0.963 05418 71683 976	0.583 61106 09945 767
Mosaic attenuation pattern	0.917 99999 99816 4	0.451 61290 31529 6565	0.799 99999 97714 285	0.926 88172 04101 746	0.577 31958 28972 262	0.073 11827 95683 2004	0.199 99999 99428 5714	0.548 38709 66857 44	0.984 01826 48177 165	0.562 71869 78560 278
Peribronchial thickening	0.919 99999 99816	0.573 77049 17092 179	0.714 28571 41399 417	0.942 35033 25733 403	0.636 36363 13074 381	0.057 64966 74044 867	0.285 71428 56559 767	0.426 22950 81268 476	0.968 10933 93856 922	0.596 50467 74756 931
Consolidation	0.851 99999 99829 599	0.565 21739 12551 985	0.730 33707 85696 252	0.878 34549 87620 84	0.637 25489 69795 273	0.121 65450 12135 8505	0.269 66292 13180 1545	0.434 78260 86578 45	0.937 66233 76379 828	0.553 25774 24377 602
Bronchiectasis	0.893 99999 99821 2	0.523 80952 37263 795	0.589 28571 41804 847	0.932 43243 24114 317	0.554 62184 36635 831	0.067 56756 75660 4577	0.410 71428 56409 4387	0.476 19047 61148 904	0.947 36842 10309 526	0.495 80448 17949 3986
Interlobular septal thickening	0.917 99999 99816 4	0.624 99999 98697 917	0.566 03773 57422 57	0.959 73154 36026 905	0.594 05940 08352 122	0.040 26845 63749 3807	0.433 96226 40690 6374	0.374 99999 99218 75	0.949 11504 42267 895	0.549 41064 16414 718

Evaluasi Validasi

Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.799 99999 992	0.294 11764 68858 1316	0.384 61538 43195 266	0.862 06896 54181 53	0.333 33332 82000 0006	0.137 93103 44669 045	0.615 38461 49112 425	0.705 88235 25259 516	0.903 61445 77224 562	0.220 85609 74824 6096
Arterial wall calcification	0.739 99999 99260 001	0.568 18181 80526 86	0.781 24999 97558 594	0.720 58823 51881 489	0.657 89473 17936 289	0.279 41176 46647 924	0.218 74999 99316 4063	0.431 81818 17200 413	0.874 99999 98437 5	0.471 59896 26269 355
Cardiomegaly	0.869 99999 9913	0.473 68421 02770 083	0.749 99999 9375	0.886 36363 62629 133	0.580 64515 61706 556	0.113 63636 36234 5042	0.249 99999 97916 6665	0.526 31578 91966 759	0.962 96296 28440 787	0.527 13032 84099 097
Pericardial effusion	0.719 99999 9928	0.218 74999 99316 4063	0.699 99999 92999 999	0.722 22222 21419 754	0.333 33332 95464 8526	0.277 77777 77469 136	0.299 99999 96999 9996	0.781 24999 97558 594	0.955 88235 28006 056	0.271 53942 64756 3833
Coronary artery wall calcification	0.769 99999 99230 001	0.593 74999 98144 531	0.655 17241 35671 819	0.816 90140 83356 477	0.622 95081 44799 786	0.183 09859 15235 0727	0.344 82758 60879 9047	0.406 24999 98730 469	0.852 94117 63451 558	0.459 20715 48212 7816
Hiatal hernia	0.459 99999 99540 0004	0.174 60317 45754 5982	0.846 15384 55029 586	0.402 29885 05284 714	0.289 47368 12984 765	0.597 70114 93565 861	0.153 84615 37278 1063	0.825 39682 52658 1	0.945 94594 56902 849	0.173 06286 16679 0671
Lymphadenopathy	0.519 99999 99480 001	0.338 02816 89664 749	0.959 99999 9616	0.373 33333 32835 556	0.499 99999 60438 368	0.626 66666 65831 112	0.039 99999 9984	0.661 97183 08926 801	0.965 51724 10463 734	0.318 09087 29663 0295
Emphysema	0.869 99999 9913	0.999 99999 66666 667	0.187 49999 98828 125	0.999 99999 98809 525	0.315 78947 06925 208	0.0	0.812 49999 94921 874	0.0	0.865 97938 13540 227	0.402 95301 71379 9636
Atelectasis	0.629 99999 99370 001	0.448 27586 19916 7657	0.838 70967 71488 033	0.536 23188 39802 563	0.584 26965 82502 209	0.463 76811 58748 1626	0.161 29032 25286 1603	0.551 72413 78359 097	0.880 95238 07426 304	0.351 34221 42596 3025
Lung nodule	0.579 99999 9942	0.799 99999 92	0.166 66666 66319 4443	0.961 53846 13535 503	0.275 86206 60166 4687	0.038 46153 84541 4201	0.833 33333 31597 222	0.199 99999 98	0.555 55555 54938 272	0.213 50420 50734 4903

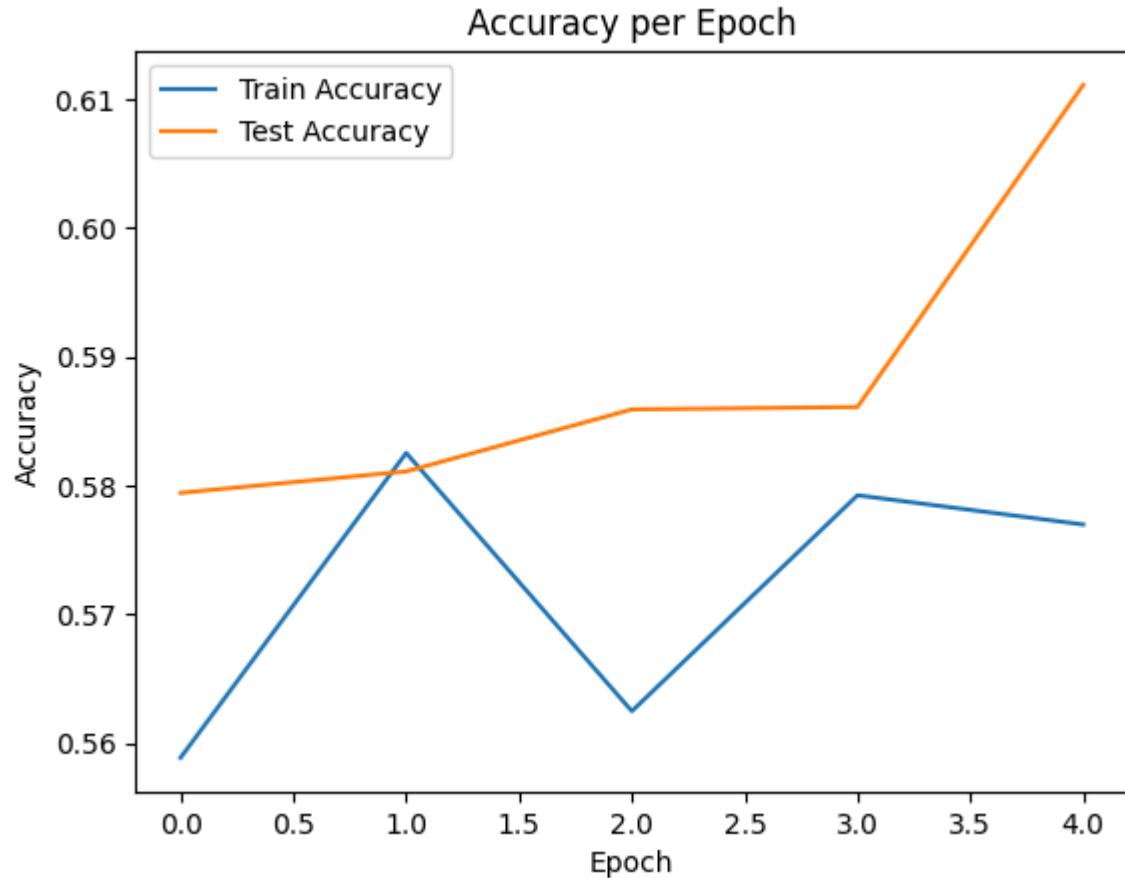
Lung opacity	0.689 99999 9931	0.613 63636 34969 008	0.658 53658 52052 35	0.711 86440 66590 061	0.635 29411 25038 062	0.288 13559 31715 0245	0.341 46341 45508 626	0.386 36363 62758 264	0.749 99999 98660 715	0.367 00309 24544 0427
Pulmonary fibrotic sequela	0.529 99999 9947	0.373 13432 83025 173	0.833 33333 30555 556	0.399 99999 99428 572	0.515 46391 31469 87	0.599 99999 99142 858	0.166 66666 66111 111	0.626 86567 15482 29	0.848 48484 82277 318	0.227 40083 83084 3708
Pleural effusion	0.849 99999 99150 001	0.481 48148 13031 55	0.928 57142 79081 632	0.837 20930 22282 315	0.634 14633 66567 519	0.162 79069 76554 8945	0.071 42857 13775 5101	0.518 51851 83264 746	0.986 30136 97279 04	0.598 51407 15168 469
Mosaic attenuation pattern	0.739 99999 99260 001	0.258 06451 60457 856	0.727 27272 66115 702	0.741 57303 36245 424	0.380 95237 69047 619	0.258 42696 62630 9813	0.272 72727 24793 388	0.741 93548 36316 336	0.956 52173 89918 085	0.317 18741 48561 068
Peribronchial thickening	0.769 99999 99230 001	0.269 23076 91272 1894	0.636 36363 57851 239	0.786 51685 38442 117	0.378 37837 39956 1725	0.213 48314 60434 2888	0.363 63636 33057 851	0.730 76923 04881 657	0.945 94594 58181 155	0.301 65217 52188 4213
Consolidation	0.649 99999 9935	0.228 57142 85061 2244	0.499 99999 96875	0.678 57142 84906 463	0.313 72548 57670 1276	0.321 42857 13903 062	0.499 99999 96875	0.771 42857 12081 632	0.876 92307 67881 657	0.137 25270 32615 0305
Bronchiectasis	0.899 99999 991	0.333 33333 22222 222	0.111 11111 09876 543	0.978 02197 79145 032	0.166 66666 26388 8896	0.021 97802 19756 0681	0.888 88888 79012 344	0.666 66666 44444 444	0.917 52577 31012 86	0.149 53209 38866 1085
Interlobular septal thickening	0.709 99999 99290 001	0.181 81818 17630 854	0.749 99999 90624 999	0.706 52173 90536 39	0.292 68292 35455 086	0.293 47826 08376 6543	0.249 99999 96874 9997	0.818 18181 79338 842	0.970 14925 35865 45	0.263 39407 35253 188

Grad-CAM class Cardiomegaly



XAI untuk class dengan MCC val tertinggi

Model CTTXNET Shuffle 1500 data (1300 train 200 val) epoch 5 lr 1e-5



Evaluasi Training

#	ACC	Precision	Recall	Specificity	F1	FPR
0	0.785833333267848	0.2807017543736534	0.4076433120759463	0.8427612655719774	0.332467527620307	0.15723873441843492
1	0.609999999949167	0.39965694681990294	0.663817637987516	0.5877502944571525	0.49892931486251	0.4122497055310689
2	0.77916666666601736	0.28618421051690185	0.644444443967078	0.7962441314479227	0.3963553487981072	0.2037586854268776
3	0.8249999999931251	0.18781725887371487	0.4252873562729555	0.8562443845385783	0.2605633760134398	0.14375561545243706
4	0.624999999947917	0.3840579710075352	0.6583850931472551	0.612756264229923	0.485125853458729	0.3872437357586874
5	0.593333333283889	0.19361277444723237	0.5359116021803364	0.603532875362085	0.2844574740930496	0.3964671246281014
6	0.48916666666259034	0.3065789473643871	0.730407523488075	0.4018161180431122	0.43188136746762923	0.598183881945371
7	0.5949999999950417	0.219088937088523	0.4449339206852452	0.630010277485817	0.2936046467326512	0.3699897250390555
8	0.5791666666618404	0.3636363636303531	0.6470588235103806	0.5523255813889264	0.46560846099179765	0.4476744185994456
9	0.46666666666277784	0.46260869564815127	0.9602888086469262	0.04334365325010304	0.6244131411442561	0.956656346734417

#	ACC	Precision	Recall	Specificity	F1	FPR
10	0.643333333279723	0.5024390243657346	0.24009324008764352	0.8677042801443877	0.3249211326058575	0.13229571984264207
11	0.49583333332920143	0.2949852507331123	0.6116207950883297	0.45246277204521806	0.39800949458507265	0.5475372279433272
12	0.7499999999937501	0.2776025236505488	0.5534591194620466	0.7800192122883765	0.3697478946950251	0.2199807877020175
13	0.8941666666592154	0.2911392404694761	0.24468085103779933	0.9493670885990112	0.2658959487640751	0.05063291139194727
14	0.677499999943542	0.16172506738108558	0.44117647055579584	0.7077067669106419	0.23668638659741922	0.292293230799597
15	0.709999999940834	0.2671232876620848	0.3679245282453187	0.78340080970867	0.30952380463750323	0.2165991902812085
16	0.8216666666598195	0.1653543306956414	0.16279069766179916	0.9010270774892529	0.16406249498748796	0.09897292250141015
17	0.575833333285348	0.1350364963479008	0.6788990825065231	0.5655362053110401	0.22526635947818716	0.4344637946797941

# FNR	# FDR	# NPV	# MCC
0.5923566878603594	0.7192982455824869	0.9043209876450172	0.2152453055984208
0.33618233617275833	0.6003430531629443	0.8087520259188209	0.2289738407864476
0.3555555555292181	0.7138157894502034	0.9464285714180086	0.32017150968785474
0.5747126436121021	0.8121827410755237	0.950149551336489	0.1970838305540309
0.341614906821689	0.6159420289743489	0.8302469135674344	0.2410537643503098
0.46408839776441496	0.8063872255328066	0.8798283261676706	0.10119760822415313
0.26959247648057705	0.693421052622455	0.8045454545271694	0.12121581203407038
0.555066079270702	0.780911062889785	0.829499323398789	0.06034408194025865
0.3529411764602076	0.636363636353118	0.7983193277176753	0.17969818904896737
0.039711191335023266	0.5373913043431532	0.5599999999888	0.00906229694421424

# FNR	# FDR	# NPV	# MCC
0.7599067598890464	0.4975609755854848	0.6723618090384688	0.1372701583804053
0.3883792048810893	0.7050147492521384	0.7567049808284156	0.05755427374977732
0.4465408804750603	0.7223974763179054	0.919592298970333	0.2564375177156557
0.7553191488558172	0.7088607594039418	0.9366636931227774	0.21024911396592327
0.5588235293706747	0.8382749325919602	0.908323281050563	0.10212259739499117
0.6320754716682982	0.7328767123036686	0.8524229074795988	0.13450044011617263
0.8372093022606814	0.8346456692256184	0.899347623477173	0.06425834394038624
0.32110091740173385	0.864963503633851	0.9463190183903939	0.14101829197036825

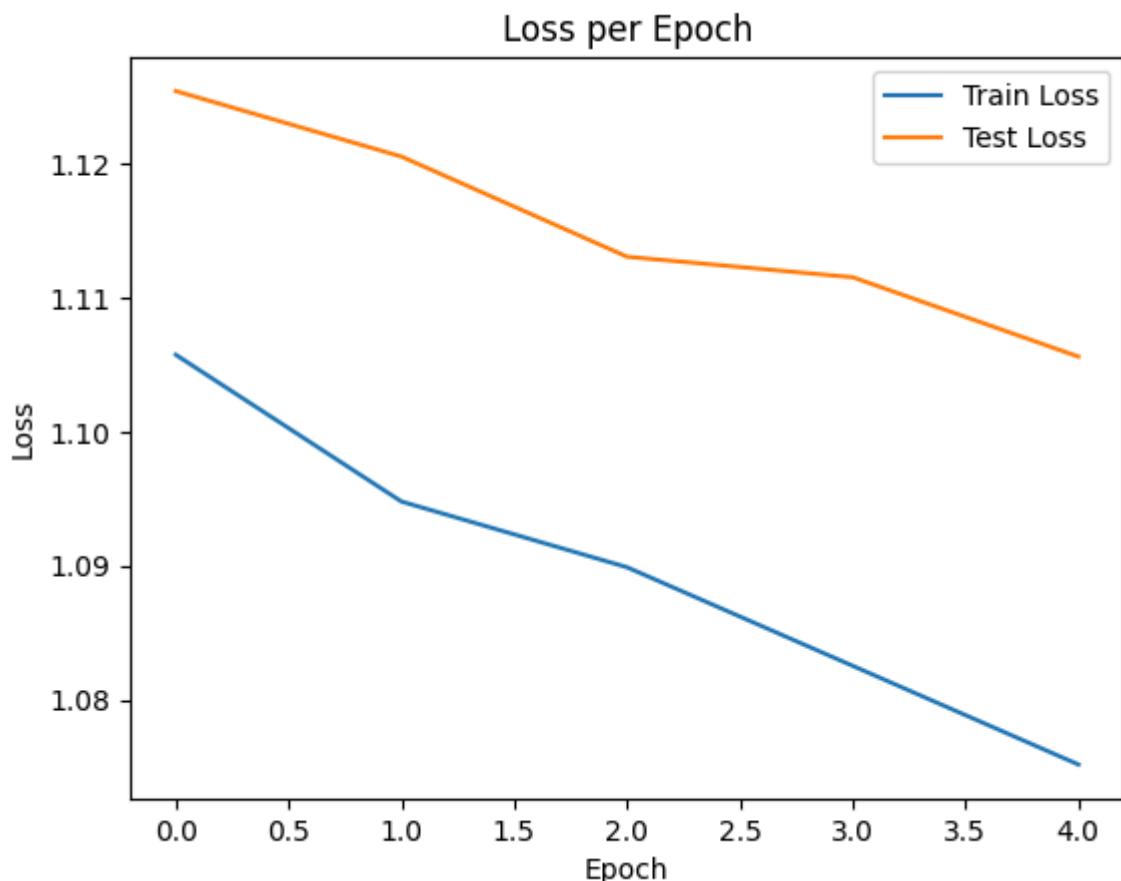
Metric evaluasi test

# ACC	# Precision	# Recall	# Specificity	# F1	# FPR
0	0.603333333132223	0.1574803149482299	0.6249999998046875	0.6007462686343005	0.25157232379731814
1	0.593333333135555	0.40140845067595715	0.6063829786588955	0.587386407481855	0.4830508426235278
2	0.763333333078889	0.3116883116478327	0.571428571292517	0.7945736433800552	0.4033613399025493
3	0.823333333058889	0.20930232553272038	0.3214285713137755	0.8749999999678308	0.25352112191231907
4	0.6466666666451111	0.38541666662651913	0.44047619042375286	0.7268518510182012	0.4111111060876544
5	0.303333333232222	0.1217391304294996	0.799999999714285	0.2377358490476326	0.7622641509146315
6	0.503333333165555	0.3350253806936535	0.7857142856207484	0.39351851850030006	0.46975088545484495
7	0.583333333138889	0.18749999998325895	0.381818187487603	0.628571428557725	0.2514970015403924
8	0.563333333145556	0.32894736839941136	0.632911392324948	0.5384615384371737	0.4329004283622871
9	0.473333333175556	0.45804195802594255	0.977611940255513	0.6626506023697198	0.6238095194346939

# ACC	# Precision	# Recall	# Specificity	# F1	# FPR
10	0.593333333135555	0.4999999989130434	0.1885245901484816	0.870786516805012	0.27380951980017015
11	0.3733333332088886	0.29674796746761184	0.829545454511881	0.1839626414226594	0.4371257445957188
12	0.863333333045555	0.9999999966666667	0.068181816632231	0.999999999609375	0.12765957321865096
13	0.543333333152222	0.13157894735976453	0.799999999698	0.519999999810909	0.2259886981135689
14	0.759999999746666	0.26562499995849614	0.40476190466553286	0.817824573326422	0.32075471213599155
15	0.539999999982	0.21854304634314284	0.6226415093164828	0.5222672064565883	0.323252940788687046
16	0.516666666494444	0.11029411763894096	0.3846153845167653	0.5363984674123985	0.171428579451429
17	0.583333333138889	0.1230796230745562	0.5925925923731138	0.5824175823962484	0.20382165317700518

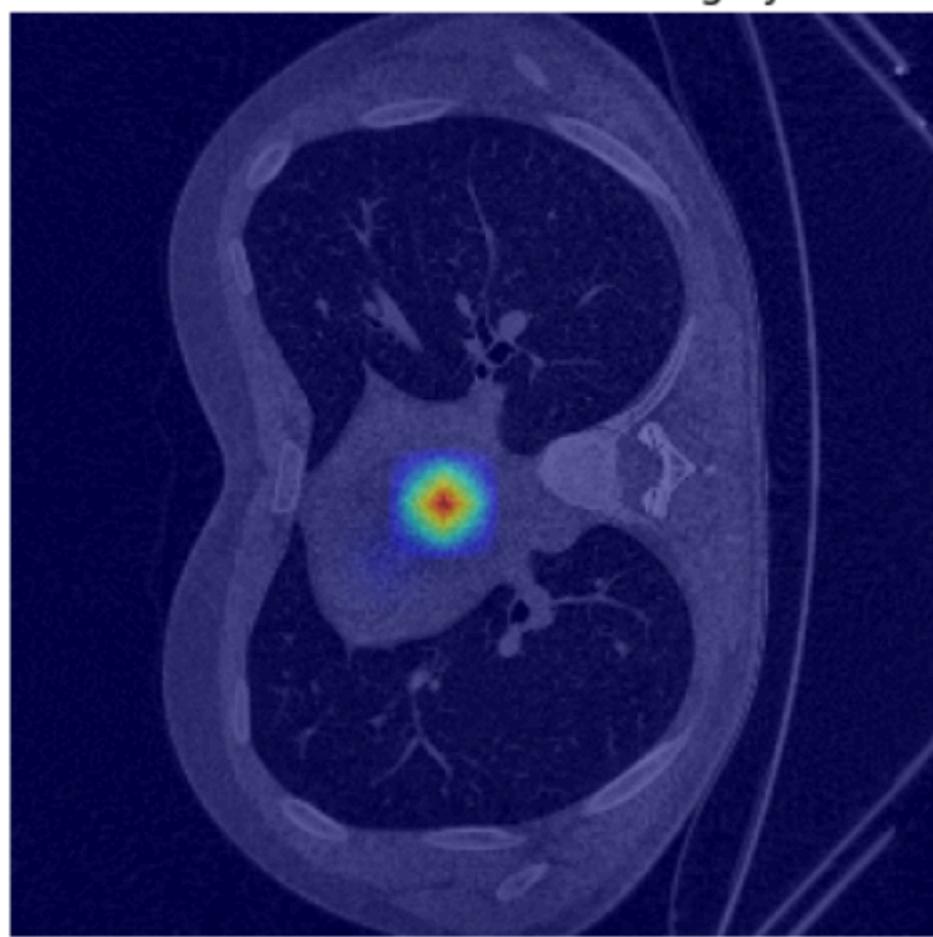
	# FNR	# FDR	# NPV	# MCC
1	0.374999998828125	0.84251968497303	0.930635838096495	0.1410386215657749
3	0.39361702123472164	0.5985915492536202	0.7658227847616568	0.1800083193195915
2	0.4285714284693877	0.688311688222973	0.9192825111695389	0.2907504647362502
1	0.6785714283290816	0.7906976742347215	0.9260700388744719	0.1630674712137648
7	0.5595238094571996	0.6145833332693142	0.769607843099529	0.16105883315842878
5	0.1999999994285714	0.8782608695270321	0.899999998714286	0.02864165750631024
6	0.2142857142602041	0.664974619255585	0.8252427183664813	0.16948540008218163
7	0.61818180694215	0.812499999274554	0.819148936126641	0.008311429258190126
4	0.36708860754846984	0.6710526315347991	0.8040540539997261	0.1509729895676248
7	0.022388059699821786	0.5419580419390924	0.7857142851530612	0.1034180489024629

# FNR	# FDR	# NPV	# MCC
0.8114754097695512	0.4999999989130434	0.6102362204484159	0.08085933631737356
0.17045454543517563	0.7032520324917377	0.722222220884773	0.016007622750131578
0.931818181606405	0.0	0.8619528619238399	0.24242424242424232
0.19999999992	0.8684210525744459	0.9662162161509313	0.17690238084063178
0.5952380950963718	0.73437499885254	0.8940677965722852	0.18853709746150002
0.377358490494838	0.7814569535906319	0.8657718120224314	0.11053487173082109
0.6153846152268244	0.8897058822875216	0.8536585365333135	-0.05335954447015582
0.40740740725651575	0.8769230768556212	0.9352941175920415	0.10107188556977714

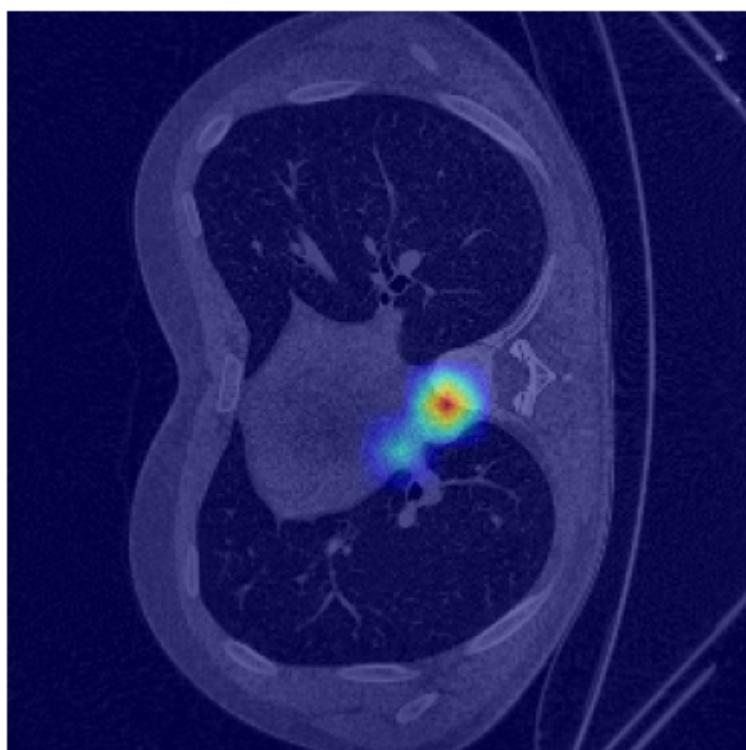


class dengan MCC ter tinggi

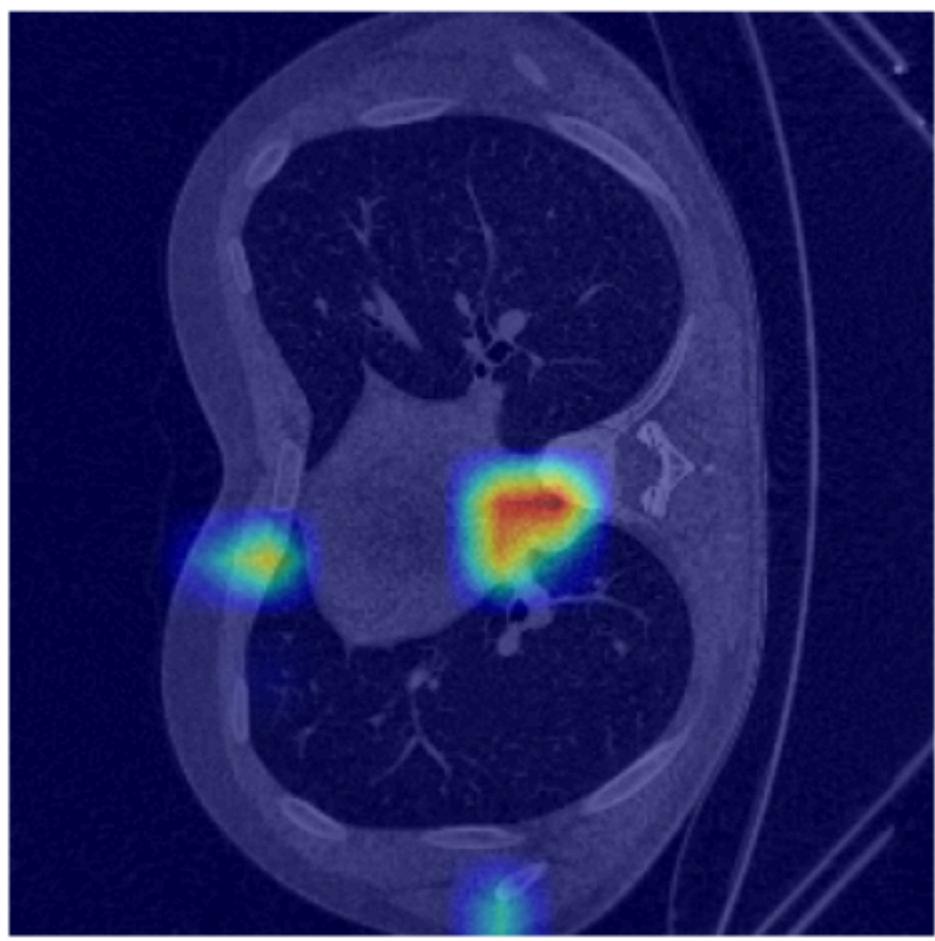
Grad-CAM class Cardiomegaly



Grad-CAM class Pleural effusion

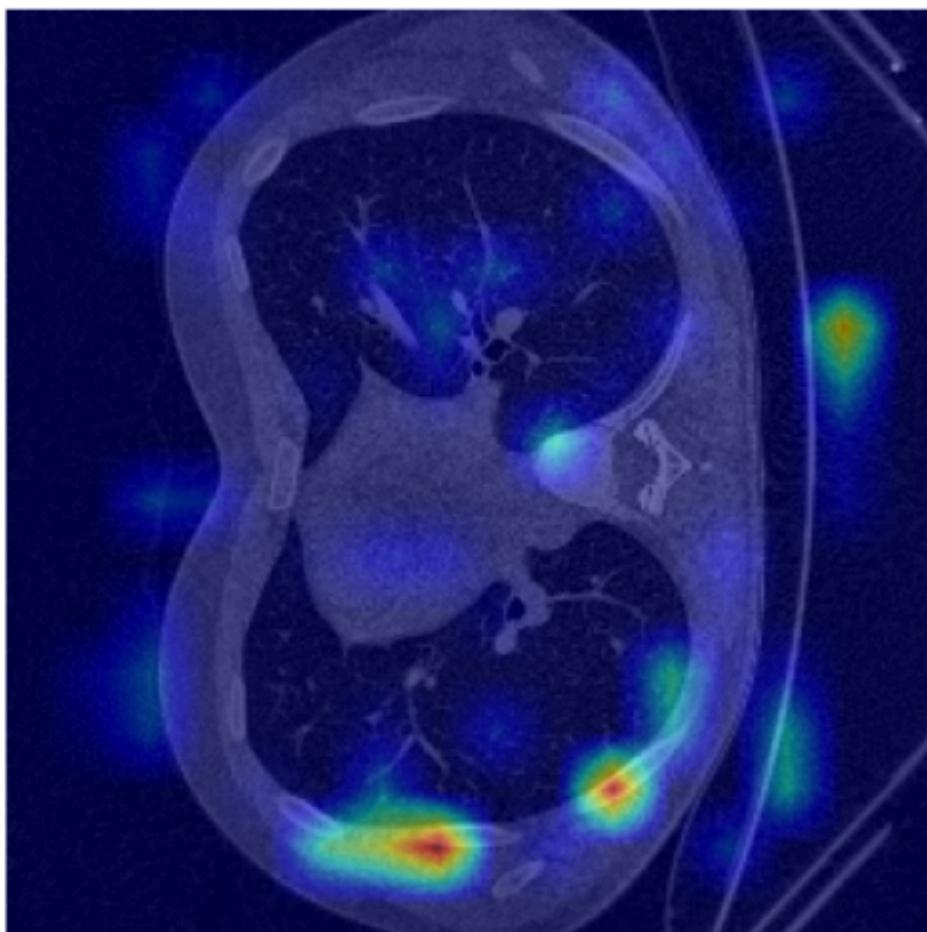


Grad-CAM class Pericardial effusion

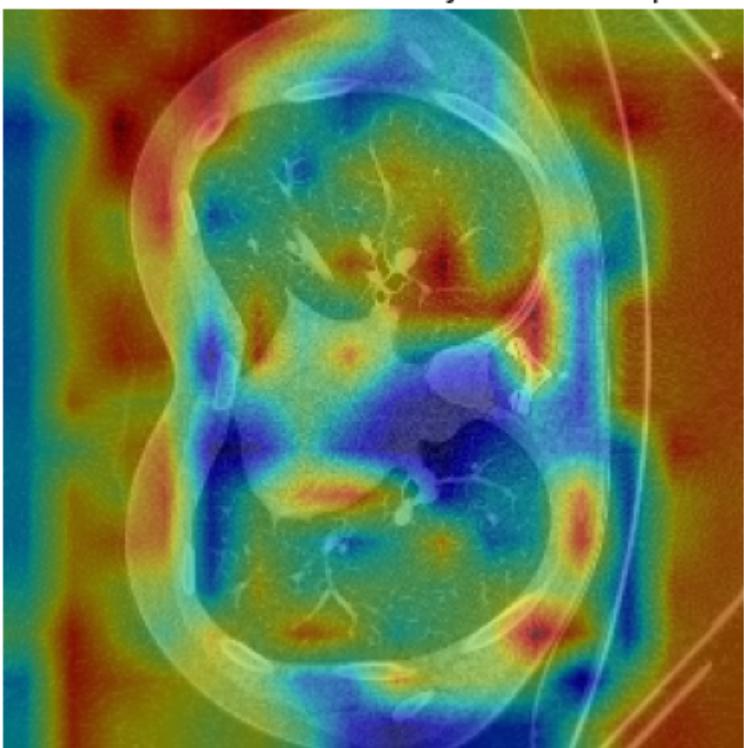


kelas dengan MCC terendah

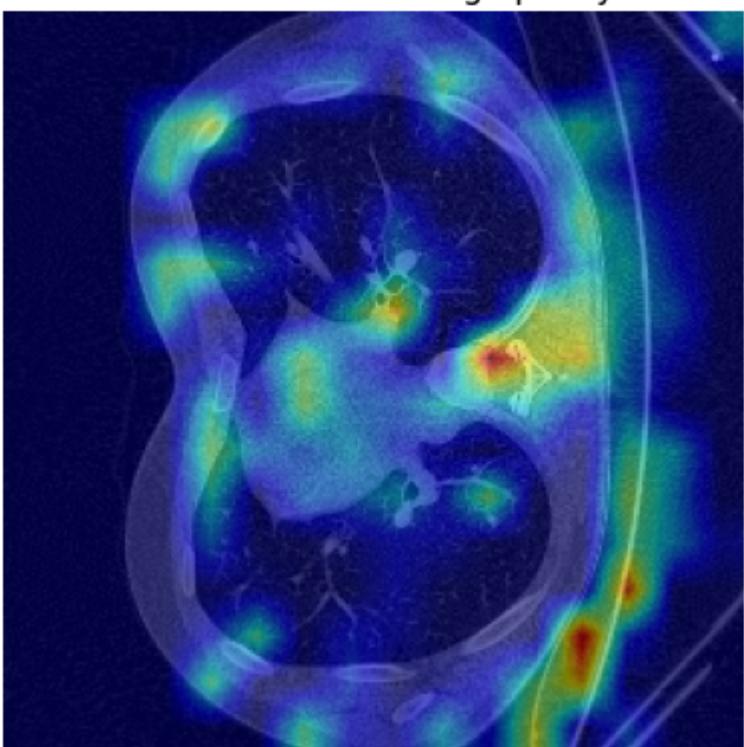
Grad-CAM class Bronchiectasis



Grad-CAM class Pulmonary fibrotic sequela



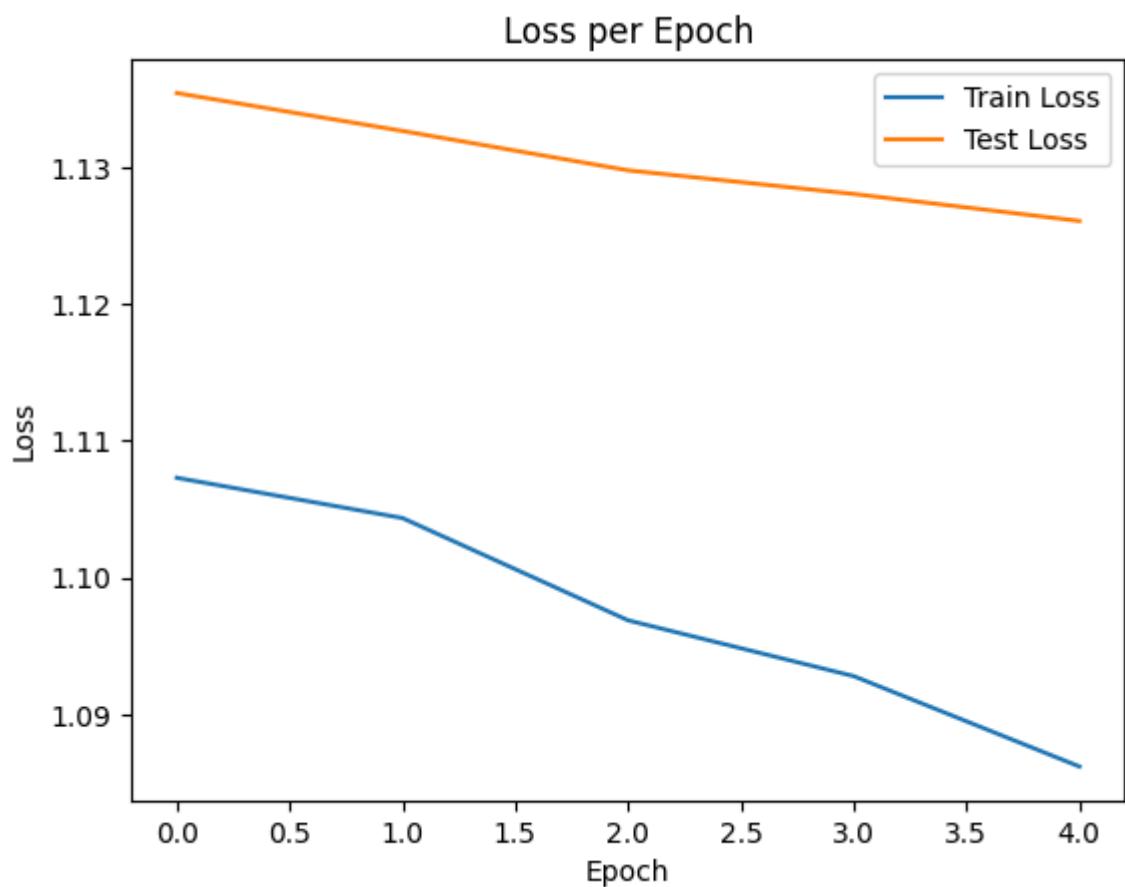
Grad-CAM class Lung opacity

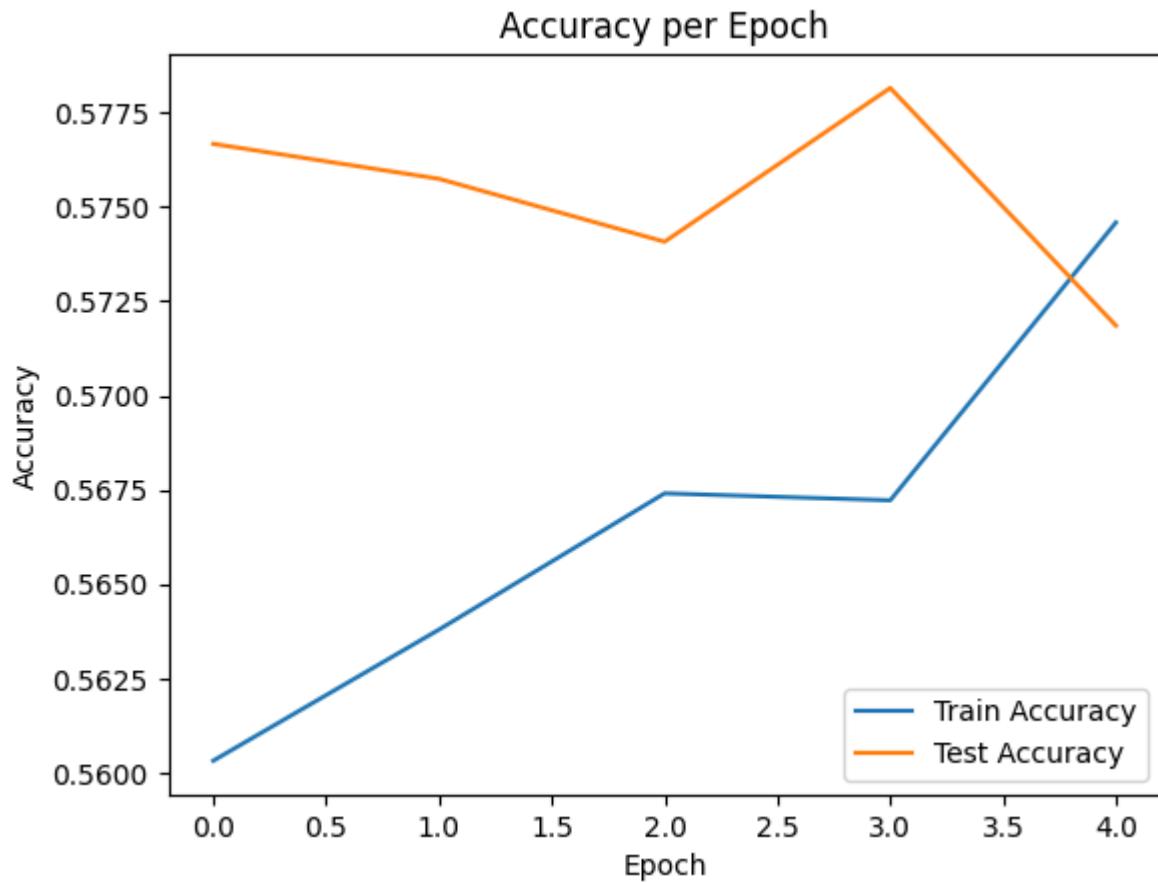


mAP (Train): 0.2741

mAP (Validation): 0.2820

Model efficientb0 1500 data (1300 train, 200 val)





Metric evaluasi

	# ACC	# Precision	# Recall	# Specificity	# F1	# FPR
0	0.7091666666660757	0.2460317460253725	0.5923566878603594	0.7267497602998395	0.3476635742406483	0.2732502396905729
1	0.6449999999946251	0.43068391866117034	0.6638176637987516	0.6372202591208808	0.5224215198788182	0.36277974086734066
2	0.8533333333262223	0.3815028901513582	0.4888888885267484	0.8995305164234787	0.42857142361970824	0.10046948356713176
3	0.90666666666591112	0.3188405796639362	0.2528735631893249	0.957771787951862	0.2820512770816898	0.04222821203915339
4	0.6916666666610904	0.4020887728354546	0.47826086955036456	0.7391799544334945	0.4368794276491525	0.260820045511595
5	0.5083333333290972	0.19703703703411796	0.7348066297936571	0.46810598625644645	0.31074766020937966	0.53189401373374
6	0.7324999999938959	0.489999999951	0.15360501566916598	0.9421112372197263	0.23389021115190733	0.05788876276892294
7	0.754166666660382	0.3316831683004117	0.295154185009024	0.8612538540507579	0.3123543073567303	0.1387461459389646
8	0.5108333333290764	0.33058984910383277	0.708823529390917	0.43255813952985395	0.45088867666393945	0.5674418604585181
9	0.5416666666621528	0.5027397260205104	0.662458736342517	0.4380804953492557	0.5176510854277181	0.5619195046352644

	# ACC	# Precision	# Recall	# Specificity	# F1	# FPR
10	0.537499999955209	0.4033742312264764	0.6130536130393227	0.4954604409793066	0.4865864891908253	0.5045395590077232
11	0.5216666666623195	0.3207547169764763	0.6758409785726043	0.4639175257678818	0.4350393657049221	0.5360824742206635
12	0.8674999999927709	0.4999999998958333	0.1509433962169218	0.9769452449473878	0.2318840543863344	0.0230547550430062
13	0.798333333266807	0.22388059700657162	0.6382978722725215	0.8119349005351544	0.3314917088440524	0.1880650945580413
14	0.6166666666615278	0.18235294117289505	0.6838235293614835	0.6080827067612022	0.28792569326141343	0.3919172932299933
15	0.738333333271807	0.2959999998816	0.34905660375711994	0.8218623481698192	0.3203463153662788	0.17813765182005933
16	0.39166666666340283	0.14011976047736383	0.9069767441157381	0.32959850606601687	0.24273858688837574	0.6704014939246462
17	0.548333333287639	0.14910858994896095	0.844036697170272	0.5187901008201762	0.253443523611889	0.4812098991706581

# FNR	# FDR	# NPV	# MCC
0.4076433120759463	0.7539682539483077	0.9221411192101929	0.23165717281227372
0.33618233617275833	0.5693160813203454	0.8209408194109113	0.2752246146644774
0.51111111073251	0.6184971097908383	0.9328140214125336	0.34940919833916095
0.7471264366957326	0.6811594201911364	0.9425287356238504	0.23464064272342622
0.5217391304185796	0.5979112271384357	0.7943696450331167	0.20668352684448835
0.2651933701510943	0.8029629629510672	0.9085714285541224	0.14638746544162748
0.846394984299486	0.509999999949	0.7545454545385951	0.1529933808172578
0.7048458149469231	0.6683168316500833	0.8396793587090212	0.16371462007256238
0.2911764705796713	0.6694101508824498	0.7898089171806835	0.1304690711219878
0.33754512634769773	0.4972602739657909	0.6021276595616568	0.10267853382175074

# FNR	# FDR	# NPV	# MCC
0.3869463869373672	0.596625766862015	0.6970802919580825	0.1044065503939234
0.3241590213968147	0.6792452830090095	0.7925636007672688	0.1258459320280491
0.8490566037201851	0.4999999998958333	0.8828124999923368	0.22126312492807954
0.36170212762109555	0.7761194029561149	0.9635193132943828	0.2904713088434469
0.316176470564987	0.8176470588074971	0.9376811594067003	0.1871862775907829
0.6509433961957102	0.7039999999718399	0.8547368420962659	0.16051100608102817
0.09302325580674238	0.8598802395106601	0.9671232876447363	0.15928292737853414
0.15596330273798503	0.8508914100348316	0.97084048025779	0.2086162435713583

Metric test

# ACC	# Precision	# Recall	# Specificity	# F1
0	0.543333333152222	0.14285714284742468	0.6562499997949218	0.5298507462488862
1	0.609999999796667	0.4079999996736	0.5425531914316433	0.6407766989980205
2	0.8333333333055555	0.4090909089979339	0.4285714284693877	0.8992248061666966
3	0.746666666417777	0.17567565193573	0.46428571411989794	0.7757352940991273
4	0.5333333333155555	0.33908045975062756	0.7023809522973357	0.46759259257094477
5	0.4033333333198885	0.13265306121772177	0.742857142644898	0.35849056602420787
6	0.5833333333138899	0.3586206896304399	0.6190476189739229	0.569444444180813
7	0.7166666666427778	0.26562499995849614	0.30909090903471076	0.8081632652731362
8	0.659999999978	0.3678160911917453	0.4050632910879667	0.751132216854692
9	0.4899999998366667	0.43790849670340465	0.499999999626865	0.48192771081434166

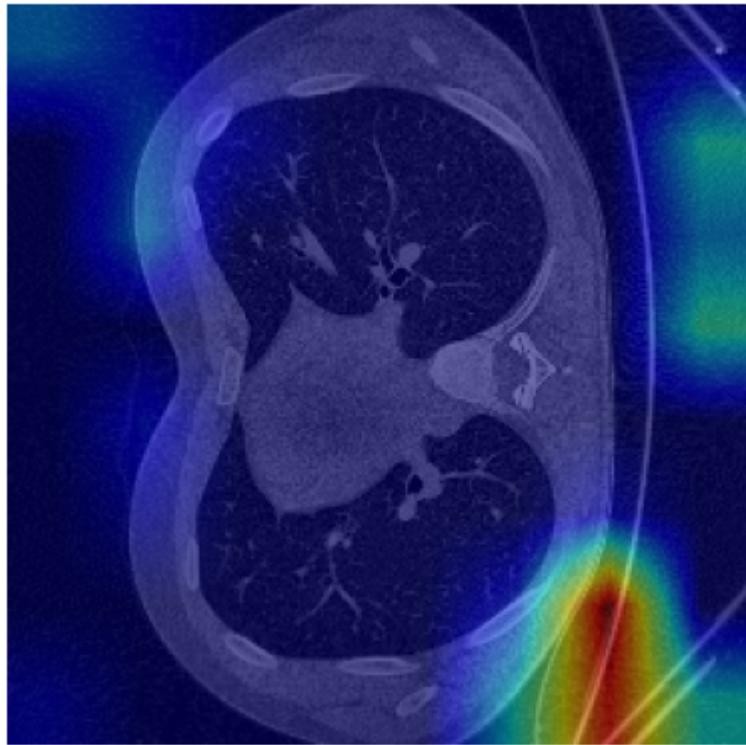
# ACC	# Precision	# Recall	# Specificity	# F1
10	0.5633333333145556	0.46399999996288005	0.4754098360266058	0.623595505829441
11	0.3899999998699997	0.30612244896709706	0.8522727271758782	0.19811320753782485
12	0.8166666666394444	0.3777777769382714	0.3863636362758264	0.890624999652099
13	0.3133333333228889	0.10480349344520508	0.959999999616	0.2545454545361983
14	0.74999999975	0.24615384611597635	0.380952380861678	0.8100775193484466
15	0.716666666427778	0.257575753673095	0.3207547169206123	0.8016194331659263
16	0.7433333333085556	0.1481481481207133	0.205128020507560814	0.8237547892404692
17	0.873333333042222	0.26086956510396975	0.2222222213991769	0.9377289376945886

# FPR	# FNR	# FDR	# NPV	# MCC
0.4701492537138004	0.3437499998925781	0.8571428570845481	0.9281045751027382	0.1149174863984101
0.35922330095343574	0.4574468084619738	0.591999999526401	0.7542857142426123	0.17248716541445802
0.1007751937945436	0.571428571292517	0.5909090907747934	0.9062499999645995	0.32150826221092393
0.2242647058741079	0.5357142855229592	0.8243243242129292	0.9336283185427597	0.1619730067781035
0.5324074073827589	0.2976190475836168	0.6609195401919011	0.8015873015236836	0.15462793428553825
0.6415094339380563	0.2571428570693878	0.8673469387312578	0.9134615383737057	0.06836379908097164
0.4305555555356224	0.3809523809070295	0.6413793103005945	0.7935483870455775	0.16935956801036248
0.19183673468604748	0.6909090907834711	0.734374999885254	0.8389830508119075	0.11075075908273196
0.24886877826928194	0.5949367087854511	0.6321839079733123	0.7793427229681059	0.15160936453708967
0.5180722891254174	0.499999999626865	0.5620915032312358	0.5442176870378083	-0.017972778710452376

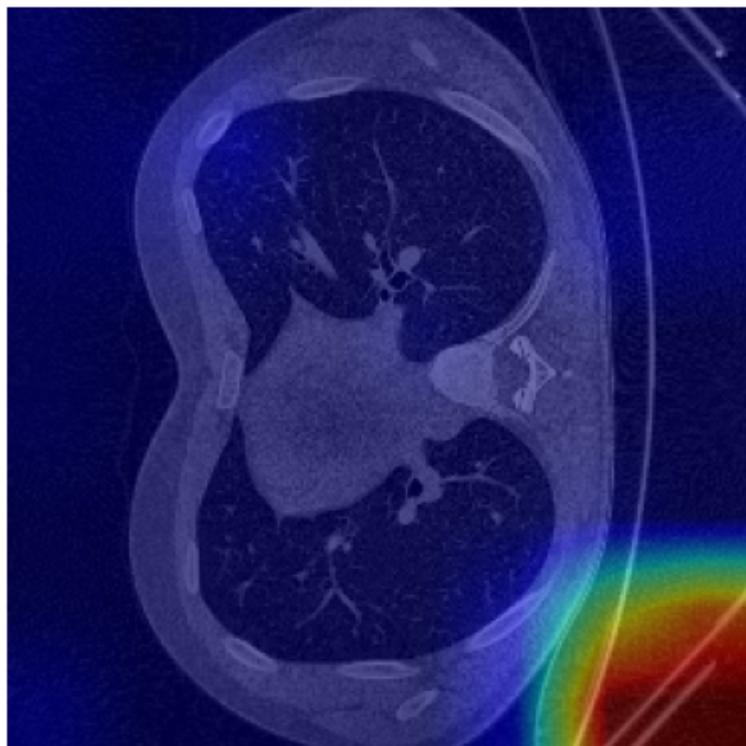
# FPR	# FNR	# FDR	# NPV	# MCC
0.37640449436087614	0.5245901638914271	0.53599999995712	0.6342857142494693	0.09864487176467432
0.8018867924150053	0.14772727271048555	0.6938775509920866	0.7636363634975206	0.05928627991011872
0.10937499999572754	0.6136363634969008	0.6222222220839506	0.8941176470237601	0.27443021509848686
0.7454545454274379	0.039999999984	0.8951965065111268	0.9859154928188852	0.1395110969590091
0.1899224806127937	0.6190476189002267	0.7538461537301776	0.8893617020898144	0.1608959964749993
0.19838056679358781	0.6792452828907084	0.742424242311754	0.8461530461176857	0.11266686338435034
0.17624521072121666	0.7948717946679815	0.8518518516941015	0.8739837398018705	0.025283101011410482
0.06227106226878128	0.777777774897119	0.7391304344612476	0.9241877255984048	0.17204687828828036

Grid cam class val mcc terbesar

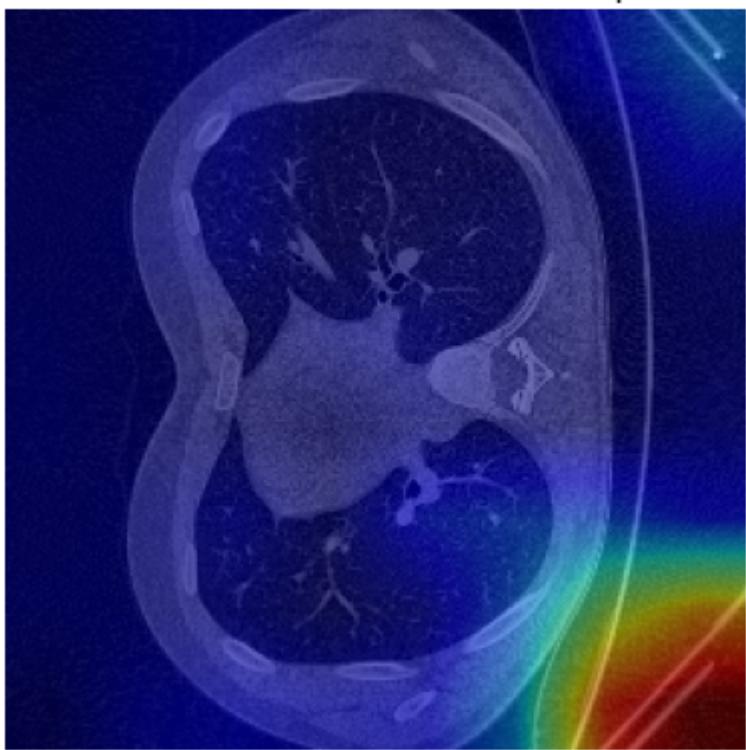
Grad-CAM class Cardiomegaly



Grad-CAM class Arterial wall calcification

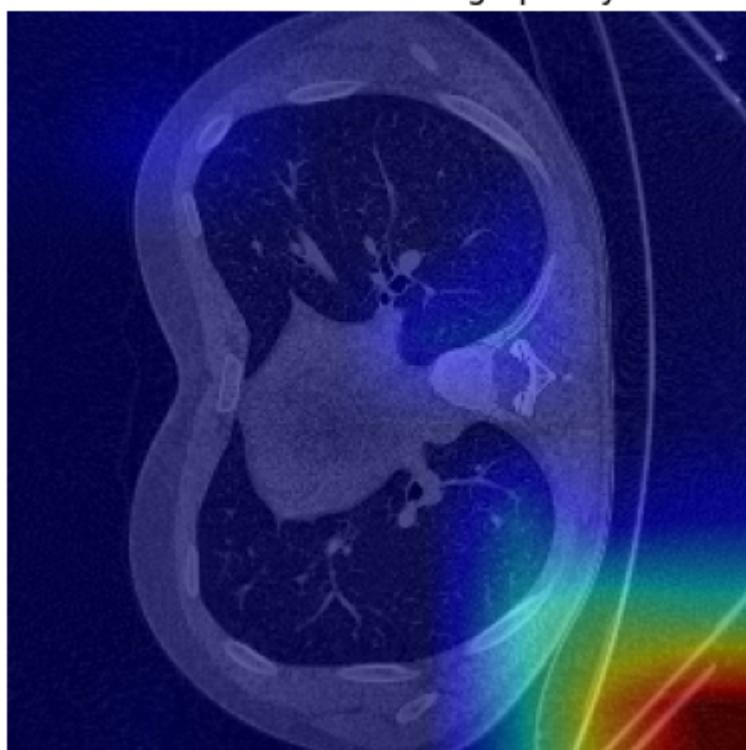


Grad-CAM class Mosaic attenuation pattern

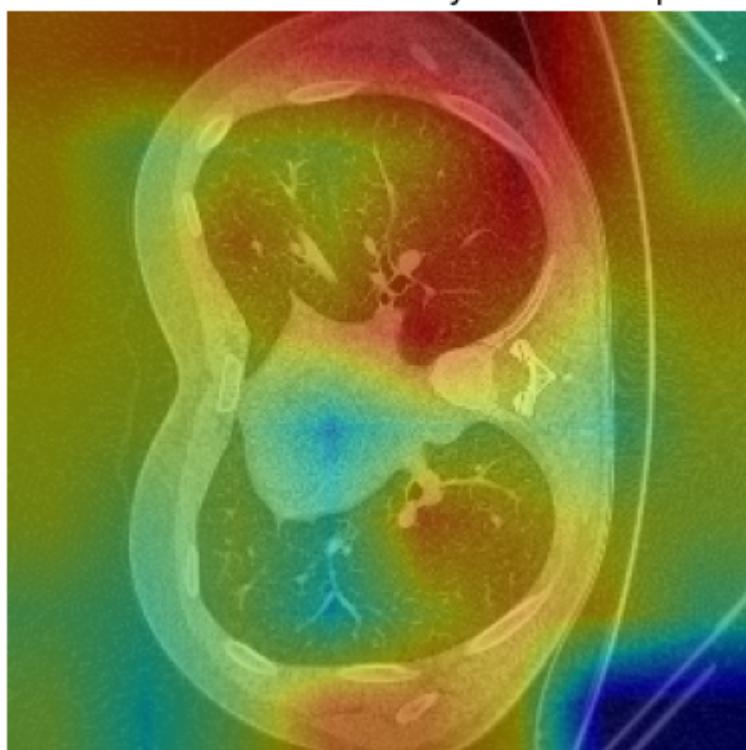


Class val dengan mcc terendah

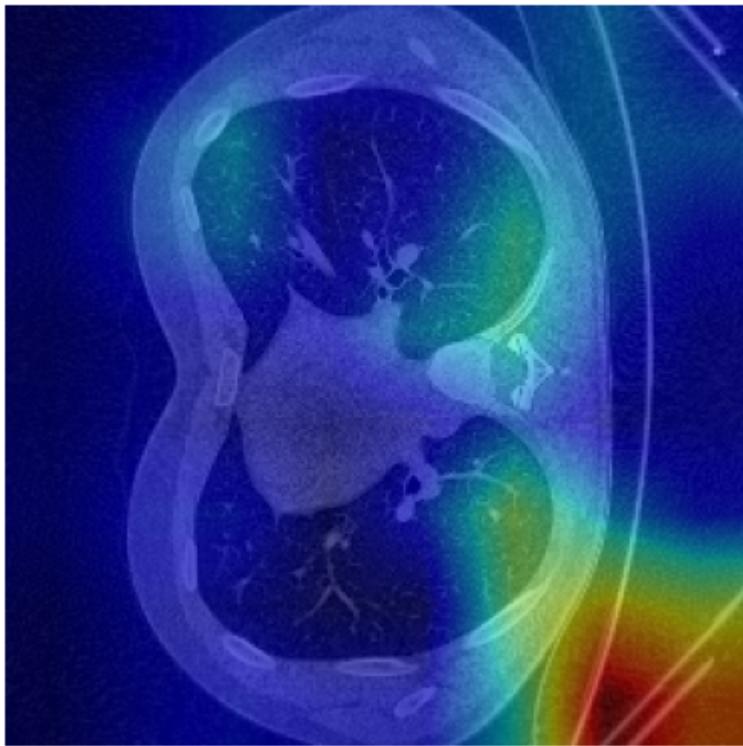
Grad-CAM class Lung opacity



Grad-CAM class Pulmonary fibrotic sequela



Grad-CAM class Atelectasis



mAP (Train): 0.2041

mAP (Validation): 0.2226

Percobaan dengan input model gambar 3D dengan model RACNET

```
/usr/local/lib/python3.11/dist-packages/torch/nn/modules/conv.py in forward(self, input)
  552
  553     def forward(self, input: Tensor) -> Tensor:
--> 554         return self._conv_forward(input, self.weight, self.bias)
  555
  556

/usr/local/lib/python3.11/dist-packages/torch/nn/modules/conv.py in _conv_forward(self, input, weight, bias)
  547             self.groups,
  548         )
--> 549         return F.conv2d(
  550             input, weight, bias, self.stride, self.padding, self.dilation, self.groups
  551         )

OutOfMemoryError: CUDA out of memory. Tried to allocate 2.34 GiB. GPU 0 has a total capacity of 14.74 GiB of which 900.12 MiB is free. Process 6971 has 13.86 GiB memory in use. Of the allocated memory 13.14 GiB is allocated by PyTorch, and 613.34 MiB is reserved by PyTorch but unallocated. If reserved but unallocated memory is large try setting PYTORCH_CUDA_ALLOC_CONF=expandable_segments=True to avoid fragmentation. See documentation for Memory Management. (https://pytorch.org/docs/stable/notes/cuda.html#environment-variables)
```