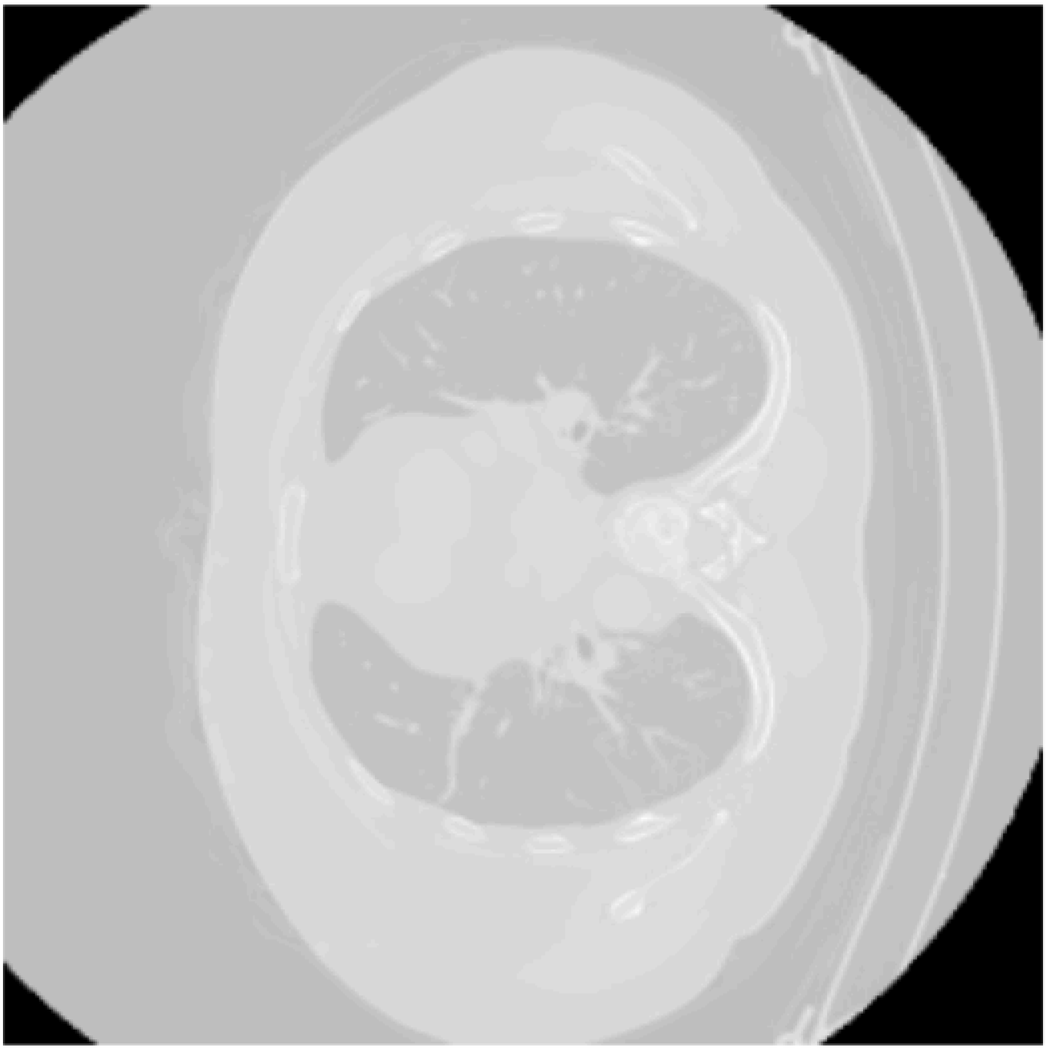
Image Preprocessing

1. ***Preprocessing dengan fastN1MeansDenoising***

```
def preprocess_ct_psnr(img_tensor, denoise_h=1):
    img = img_tensor.squeeze().numpy()
    img_u8 = (img * 255).astype(np.uint8)

    # Denoising dengan fastN1Means
    img_denoised = cv2.fastNlMeansDenoising(
        img_u8, None, h=denoise_h,
        templateWindowSize=7, searchWindowSize=21
    )

    out = img_denoised.astype(np.float32) / 255.0

    # # Enhacing image dengan Gamma
    # gamma=1.0
    # out = np.power(out, gamma)

    # # Enhancing image dengan clahe
    # out = (out * 255).clip(0,255).astype(np.uint8)
    # clahe = cv2.createCLAHE(clipLimit=2.5, tileGridSize=(8, 8))
    # out = clahe.apply(out)


    return torch.from_numpy(out).unsqueeze(0)


```

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



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

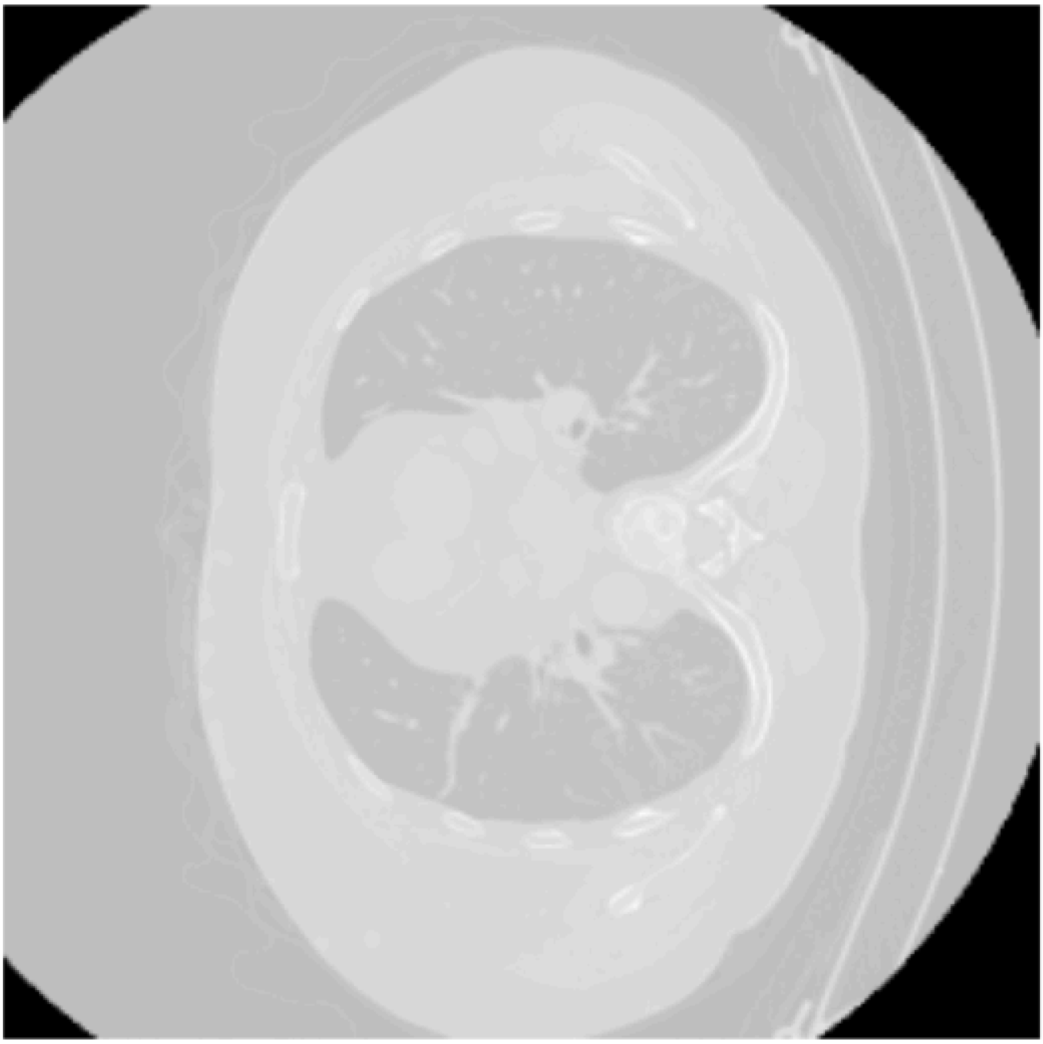
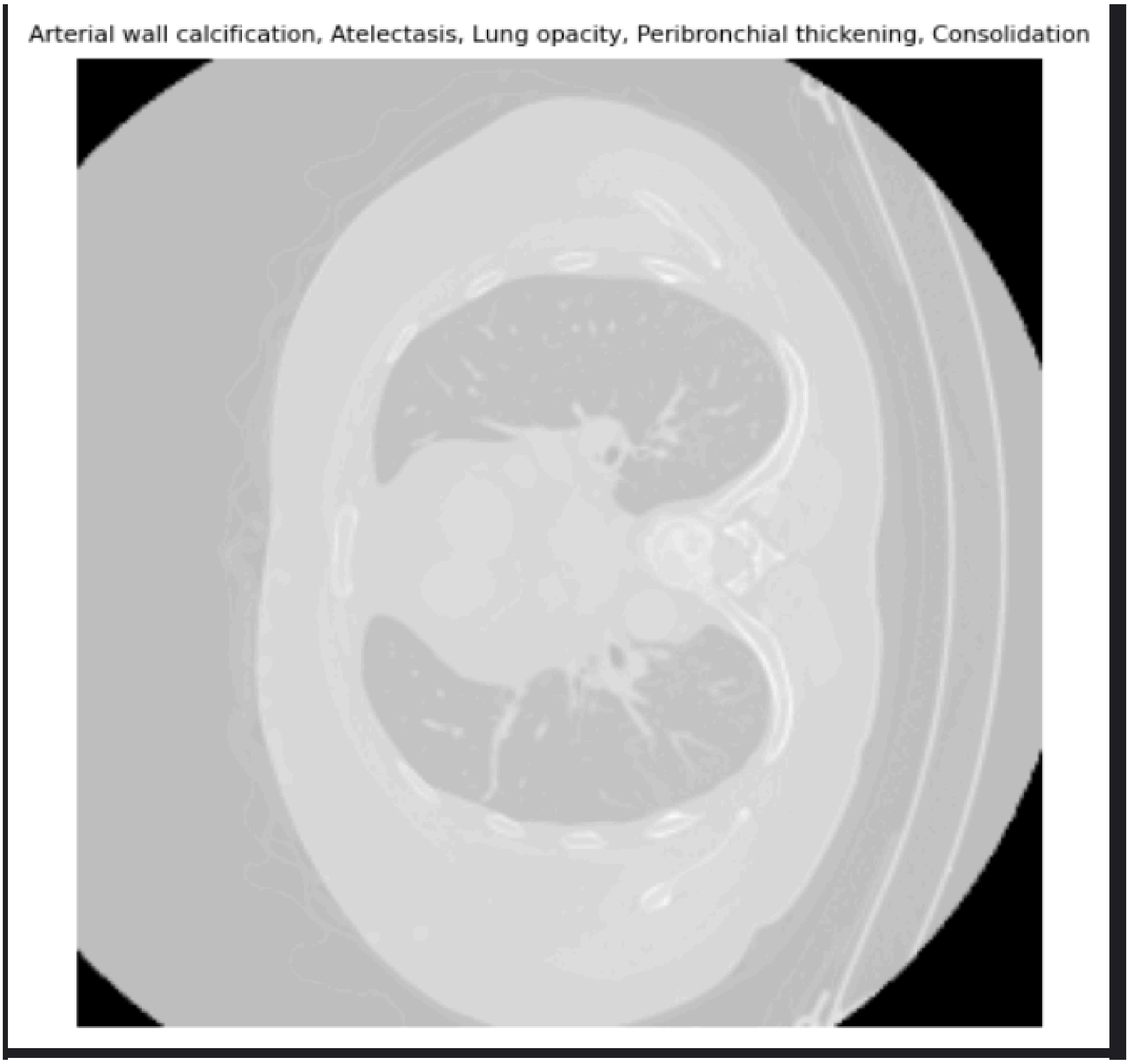


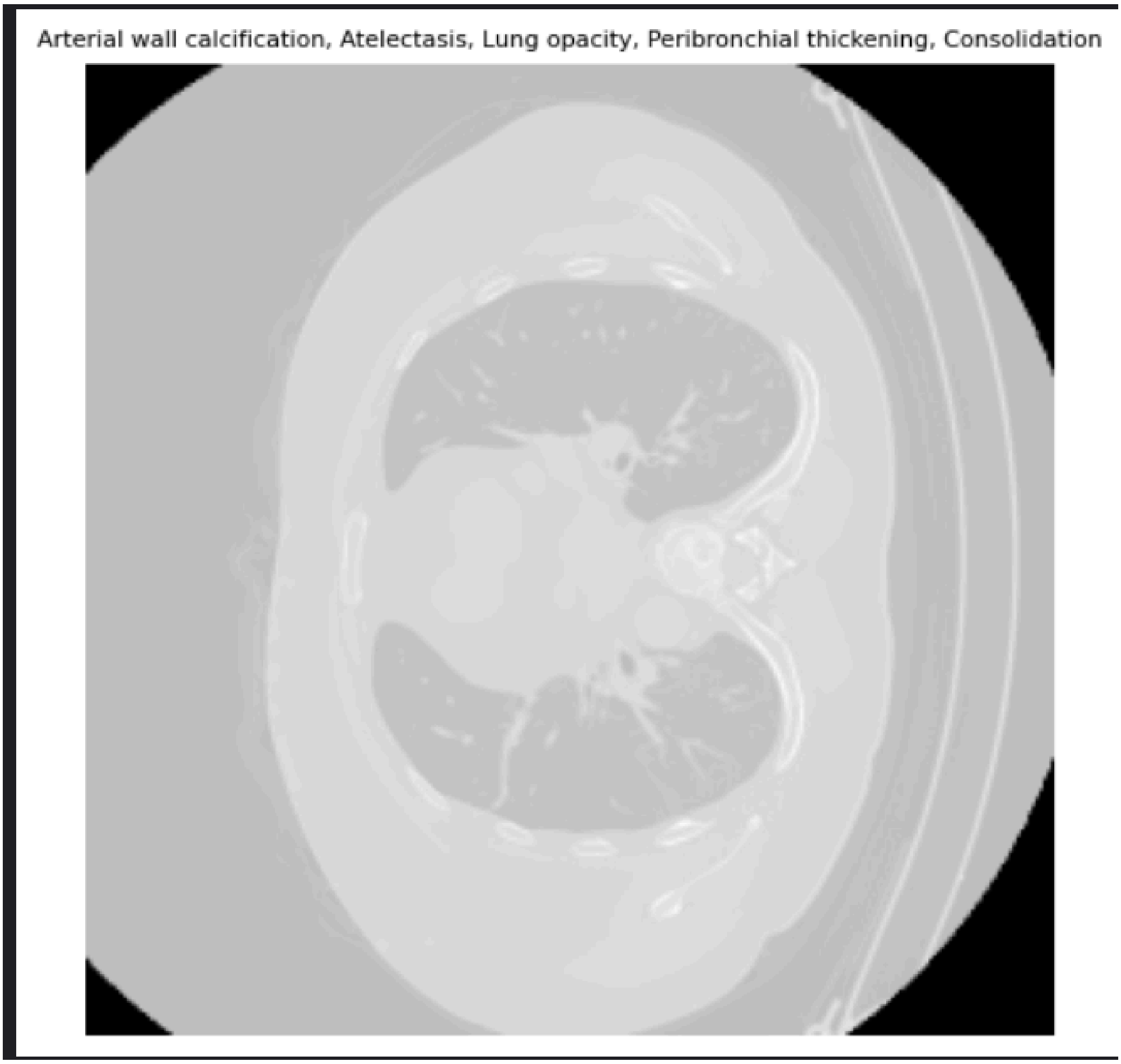
	Image	PSNR	SSIM	MSE	RMSE
0	1	50.83	0.9961	0.0	0.0
1	2	49.57	0.9930	0.0	0.0
2	3	50.21	0.9964	0.0	0.0
3	4	49.99	0.9939	0.0	0.0
4	5	49.40	0.9931	0.0	0.0
5	6	51.34	0.9967	0.0	0.0
6	7	50.40	0.9943	0.0	0.0
7	8	51.26	0.9972	0.0	0.0
8	9	49.33	0.9931	0.0	0.0
9	10	53.23	0.9973	0.0	0.0
10	11	49.73	0.9886	0.0	0.0
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 fastNlMeansDenoising h = 1 untuk menghilangkan noise dan Gamma = 1 untuk enhancing gambar

gambar train_1_a_1[.nii.gz](http://nii.gz) sebelum preprocessing



gambar train_1_a_1.nii.gz setelah preprocessing



Metric verifikasi 20 data pertama

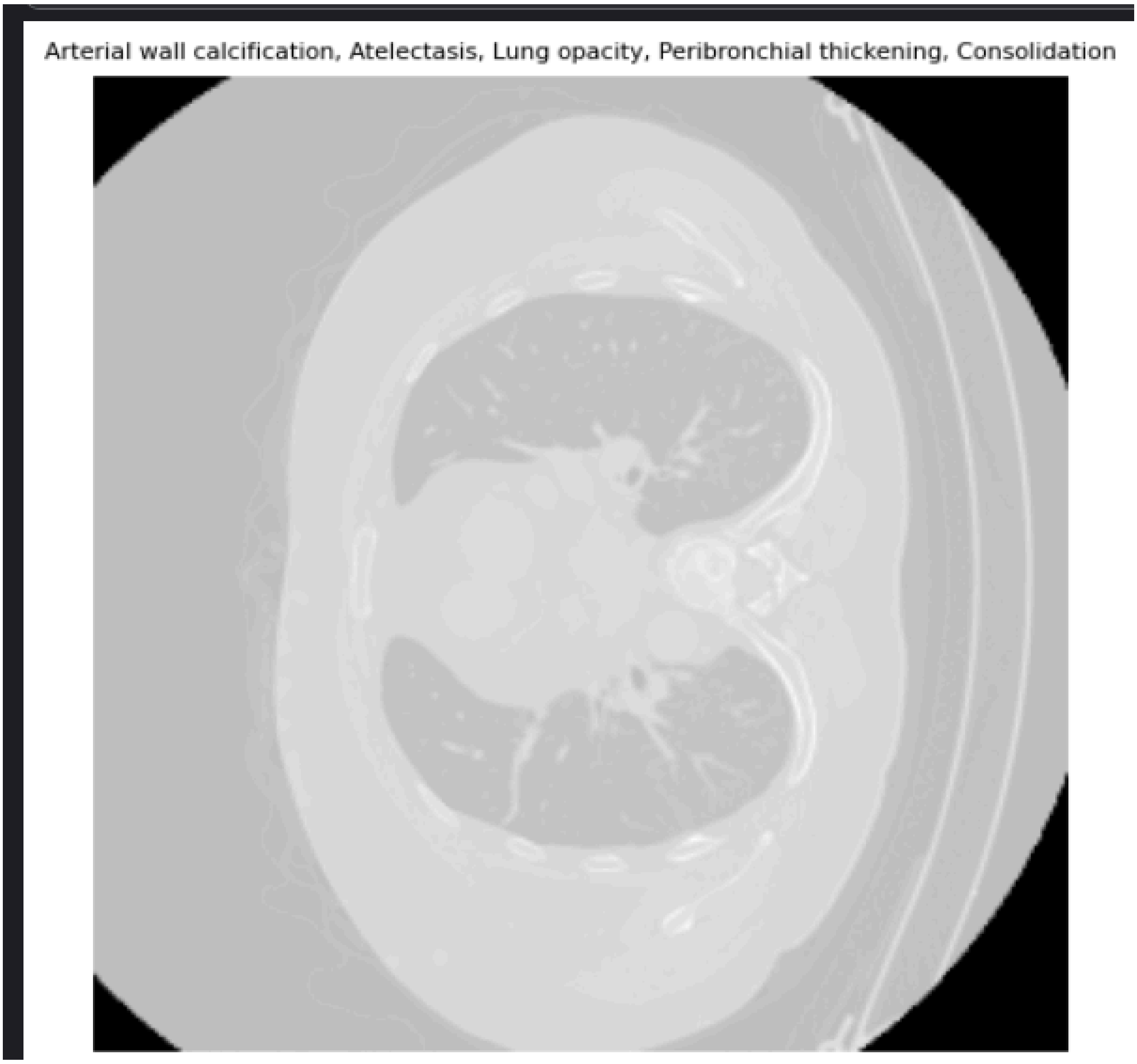
	Image	PSNR	SSIM	MSE	RMSE
0	1	50.83	0.9961	0.0	0.0
1	2	49.57	0.9930	0.0	0.0
2	3	50.21	0.9964	0.0	0.0
3	4	49.99	0.9939	0.0	0.0
4	5	49.40	0.9931	0.0	0.0
5	6	51.34	0.9967	0.0	0.0
6	7	50.40	0.9943	0.0	0.0
7	8	51.26	0.9972	0.0	0.0
8	9	49.33	0.9931	0.0	0.0
9	10	53.23	0.9973	0.0	0.0
10	11	49.73	0.9886	0.0	0.0
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

```
def preprocess_ct_full_safe(img_tensor,
                            gamma=1.0,
                            clahe_clip=1.7, clahe_tile=(8,8),
```

```
                      bilateral_d=7, bilateral_sigmaColor=55, bilateral_sigmaSpace=55,
                      unsharp_amount=0.5, unsharp_radius=1.0):
    # img_tensor: (1,H,W) atau (H,W), float 0-1
    if img_tensor.ndim == 3:
        img = img_tensor.squeeze(0).numpy()
    else:
        img = img_tensor.numpy()

    # 1) To uint8
    img_u8 = (img * 255).clip(0,255).astype(np.uint8)

    # 2) Morphological opening
    binary = cv2.adaptiveThreshold(img_u8, 255,
                                cv2.ADAPTIVE_THRESH_GAUSSIAN_C,
                                cv2.THRESH_BINARY, 11, 2)
    binary = binary.astype(np.float32) / 255.0
    kernel_open = np.ones((3, 3), np.uint8)
    img_u8 = cv2.morphologyEx(binary, cv2.MORPH_OPEN, kernel_open )

    # 3) Gamma (light)
    img_u8 = np.power(img_u8, gamma)
    img_u8 = (img_u8 * 255).clip(0,255).astype(np.uint8)

    # 4) CLAHE (local contrast but moderate)
    clahe = cv2.createCLAHE(clipLimit=clahe_clip, tileGridSize=clahe_tile)
    img_clahe = clahe.apply(img_u8)

    # 5) Bilateral filter (mild)
    img_bilat = cv2.bilateralFilter(img_clahe, d=bilateral_d,
                                    sigmaColor=bilateral_sigmaColor,
                                    sigmaSpace=bilateral_sigmaSpace)

    # 6) Unsharp mask (light sharpening to restore edges)
    blurred = cv2.GaussianBlur(img_bilat, (0,0), unsharp_radius)
    img_unsharp = cv2.addWeighted(img_bilat, 1+unsharp_amount, blurred, -unsharp_amount, 0)

    # 7) Kembali ke float 0-1
    out = (img_unsharp.astype(np.float32) / 255.0)
    return torch.from_numpy(out).unsqueeze(0)
```

gambar train_1_a_1.nii.gz sebelum preprocessing



gambar train_1_a_1.nii.gz setelah preprocessing

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

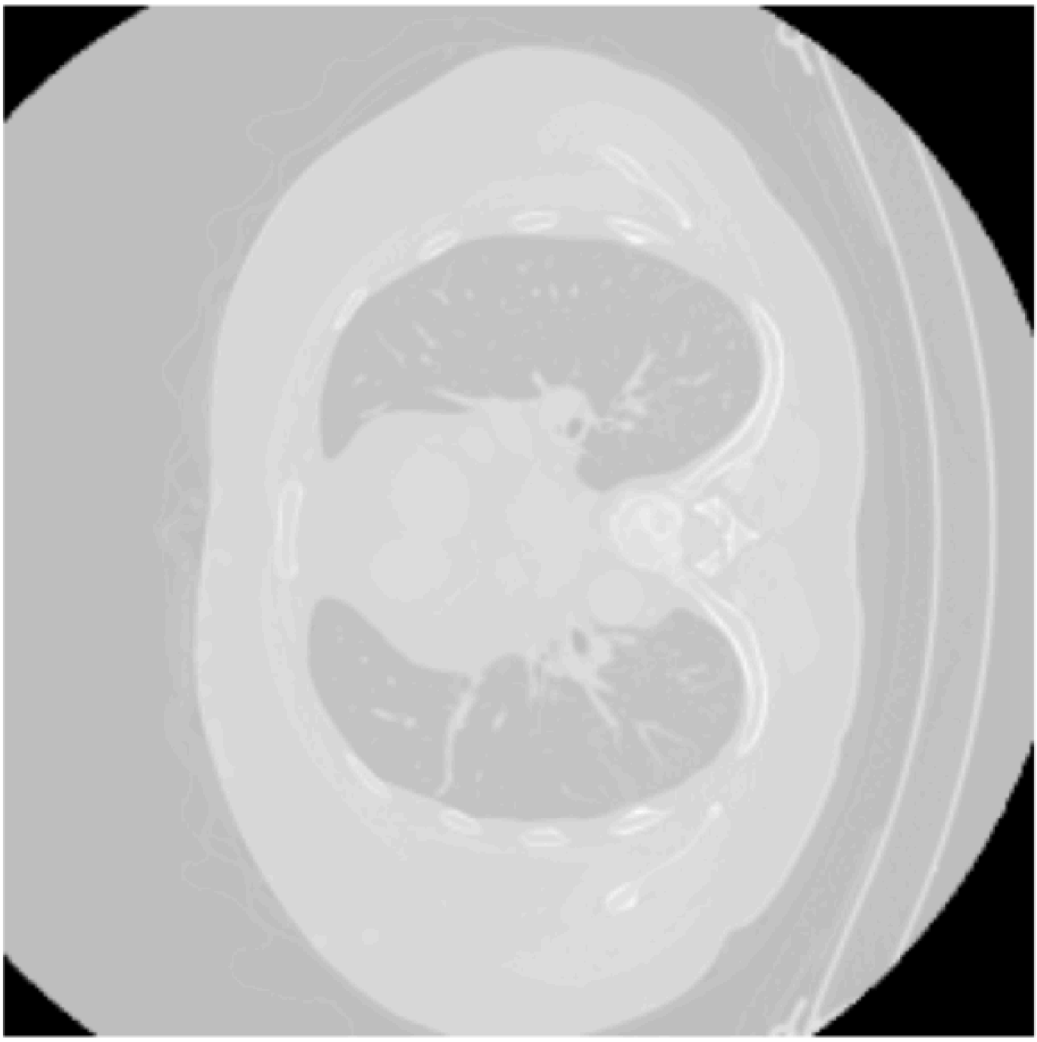
4. fastN1MeanDenoising + gamma + clache

Kode program

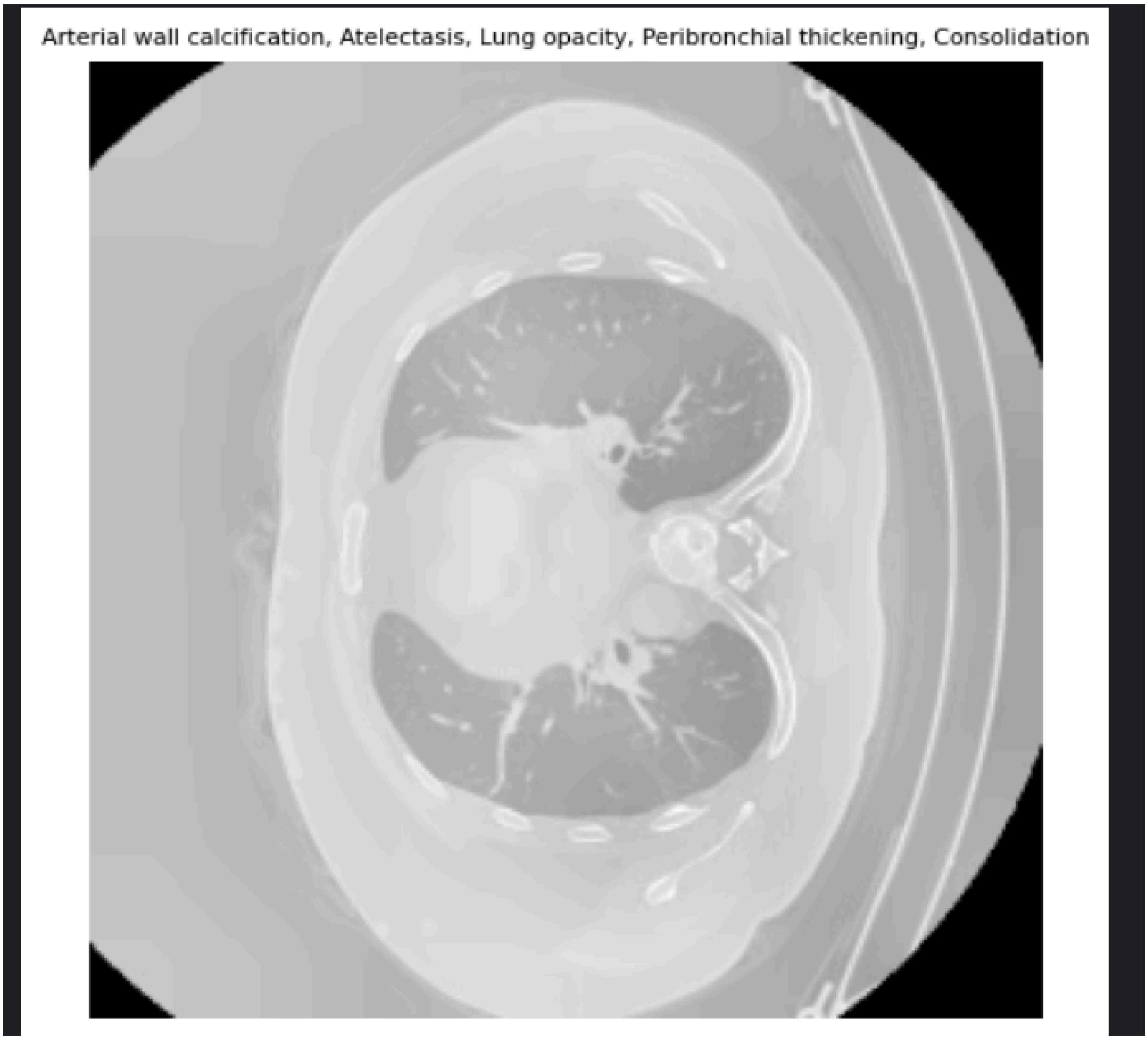
```
def preprocess_ct_psnr(img_tensor, denoise_h=1):
    img = img_tensor.squeeze().numpy()
    img_u8 = (img * 255).astype(np.uint8)

    # Denoising dengan fastN1Means
    img_denoised = cv2.fastNlMeansDenoising(
        img_u8, None, h=denoise_h,
        templateWindowSize=7, searchWindowSize=21
    )

    out = img_denoised.astype(np.float32) / 255.0

    # Enhacing image dengan Gamma
    gamma=1.0
    out = np.power(out, gamma)

    # Enhancing image dengan clahe
    out = (out * 255).clip(0,255).astype(np.uint8)
    clahe = cv2.createCLAHE(clipLimit=1.7, tileGridSize=(8, 8))
    out = clahe.apply(out)


    return torch.from_numpy(out).unsqueeze(0)
```

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



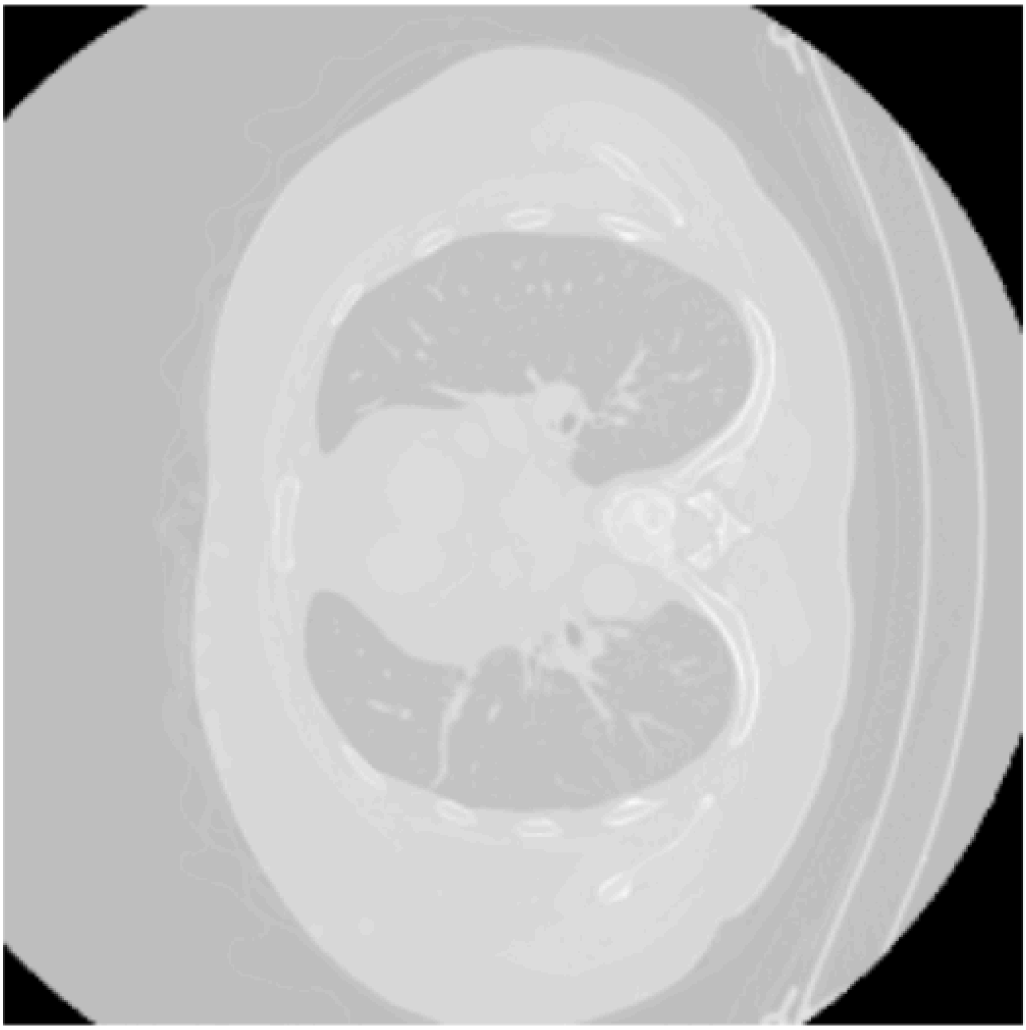
41...	Image	PSNR	SSIM	MSE	RMSE
0	1	-45.53	0.0003	35729.511719	189.020004
1	2	-45.19	0.0003	33010.660156	181.690002
2	3	-45.65	0.0006	36759.238281	191.729996
3	4	-45.29	0.0005	33817.828125	183.899994
4	5	-43.70	0.0004	23439.310547	153.100006
5	6	-45.35	0.0005	34290.480469	185.179993
6	7	-44.71	0.0003	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*

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


```

```
# Enhacing image dengan Gamma
gamma=1.0
out = np.power(img, gamma)

# Enhancing image dengan clahe
out = (out * 255).clip(0,255).astype(np.uint8)
clahe = cv2.createCLAHE(clipLimit=2.5, tileGridSize=(8, 8))
out = clahe.apply(out)

# Denoising dengan fastN1Means
img_denoised = cv2.fastNIMeansDenoising(
    out, None, h=denoise_h,
    templateWindowSize=7, searchWindowSize=21
)

out = img_denoised.astype(np.float32) / 255.0


return torch.from_numpy(out).unsqueeze(0)
```

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

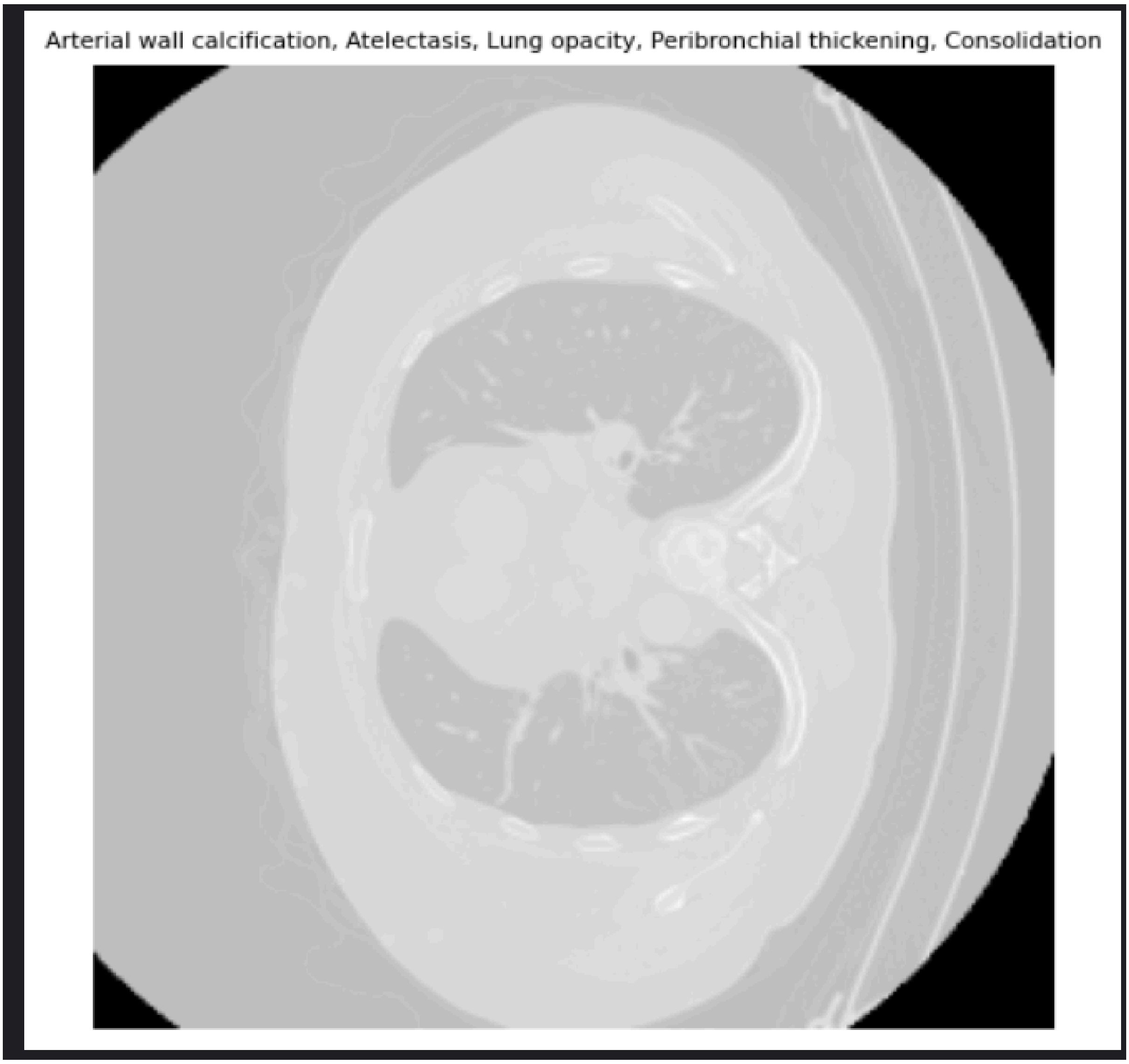

Arterial wall calcification, Atelectasis, Lung opacity, Peribronchial thickening, Consolidation

	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"""
    def __init__(self, in_chans=1, embed_dim=256):
        super().__init__()
        # two conv stages to reduce spatial size and increase channels
        self.conv1 = nn.Conv2d(in_chans, embed_dim//2, kernel_size=7, stride=4, padding=3, bias=False)
        self.bn1 = nn.BatchNorm2d(embed_dim//2)
        self.conv2 = nn.Conv2d(embed_dim//2, embed_dim, kernel_size=3, stride=2, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(embed_dim)

    def forward(self, x):
        # x: (B, C, H, W)
        x = F.gelu(self.bn1(self.conv1(x)))
        x = F.gelu(self.bn2(self.conv2(x)))  # -> (B, E, H', W')
        B, E, H2, W2 = x.shape
        tokens = x.flatten(2).transpose(1, 2)  # -> (B, N, E) where N=H'*W'
        return tokens, (H2, W2)


class FeedForward(nn.Module):
    def __init__(self, dim, hidden_dim=None, dropout=0.1):
        super().__init__()
        hidden_dim = hidden_dim or dim * 4
        self.net = nn.Sequential(
            nn.Linear(dim, hidden_dim),
            nn.GELU(),
            nn.Dropout(dropout),
            nn.Linear(hidden_dim, dim),
            nn.Dropout(dropout),
        )

    def forward(self, x):
        return self.net(x)


class TransformerEncoderBlock(nn.Module):
    def __init__(self, dim, num_heads=4, mlp_ratio=4.0, dropout=0.1):
        super().__init__()
        self.norm1 = nn.LayerNorm(dim)
        self.attn = nn.MultiheadAttention(embed_dim=dim, num_heads=num_heads, dropout=dropout, batch_first=True)
        self.drop_path = nn.Identity()  # placeholder for stochastic depth if needed
        self.norm2 = nn.LayerNorm(dim)
        self.mlp = FeedForward(dim, int(dim * mlp_ratio), dropout=dropout)

    def forward(self, x):
        # x: (B, N, E)
        # MultiheadAttention with batch_first=True expects (B, N, E)
        x_res = x
```

```
        x = self.norm1(x)
        attn_out, _ = self.attn(x, x, x, need_weights=False)
        x = x_res + attn_out  # residual
        x_res = x
        x = self.norm2(x)
        x = x_res + self.mlp(x)
        return x


class SequencePooling(nn.Module):
    """Simple sequence pooling: average pooling across tokens (N->1)"""
    def __init__(self):
        super().__init__()

    def forward(self, x):
        # x: (B, N, E) -> pooled (B, E)
        return x.mean(dim=1)


class CTXNet(nn.Module):
    def __init__(self,
                 in_chans=1,
                 num_classes=18,
                 embed_dim=256,
                 depth=6,
                 num_heads=16,
                 mlp_ratio=6.0,
                 dropout=0.1):
        super().__init__()
        self.tokenizer = ConvTokenizer(in_chans=in_chans, embed_dim=embed_dim)

        # optional learnable position embedding (small)
        self.pos_embed = None  # we'll init lazily once we know token count

        # transformer blocks
        self.blocks = nn.ModuleList([
            TransformerEncoderBlock(dim=embed_dim, num_heads=num_heads, mlp_ratio=mlp_ratio, dropout=dropout)
            for _ in range(depth)
        ])

        self.norm = nn.LayerNorm(embed_dim)
        self.pool = SequencePooling()

        # classifier head
        self.head = nn.Sequential(
            nn.Linear(embed_dim, embed_dim // 2),
            nn.GELU(),
            nn.Dropout(0.1),
            nn.Linear(embed_dim // 2, num_classes)
        )
```

```

    def forward(self, x):
        # x: (B, C, H, W)
        B = x.shape[0]
        tokens, (Hn, Wn) = self.tokenizer(x)       # tokens: (B, N, E)
        N = tokens.shape[1]

        # create pos emb if needed
        if self.pos_embed is None or self.pos_embed.shape[1] != N:
            # small learnable pos emb
            self.pos_embed = nn.Parameter(torch.zeros(1, N, tokens.shape[2]).to(tokens.device))
            nn.init.trunc_normal_(self.pos_embed, std=0.02)

        tokens = tokens + self.pos_embed

        # transformer blocks (B,N,E)
        for blk in self.blocks:
            tokens = blk(tokens)

        tokens = self.norm(tokens)
        pooled = self.pool(tokens)   # (B, E)
        logits = self.head(pooled)   # (B, num_classes)
        return logits



CTTXNet = CTXNet(in_chans=1, num_classes=18, embed_dim=128, depth=3, num_heads=16).to('cuda')
summary(CTTXNet)

```

batch = 16
epoch = 5
lr = 1e-3

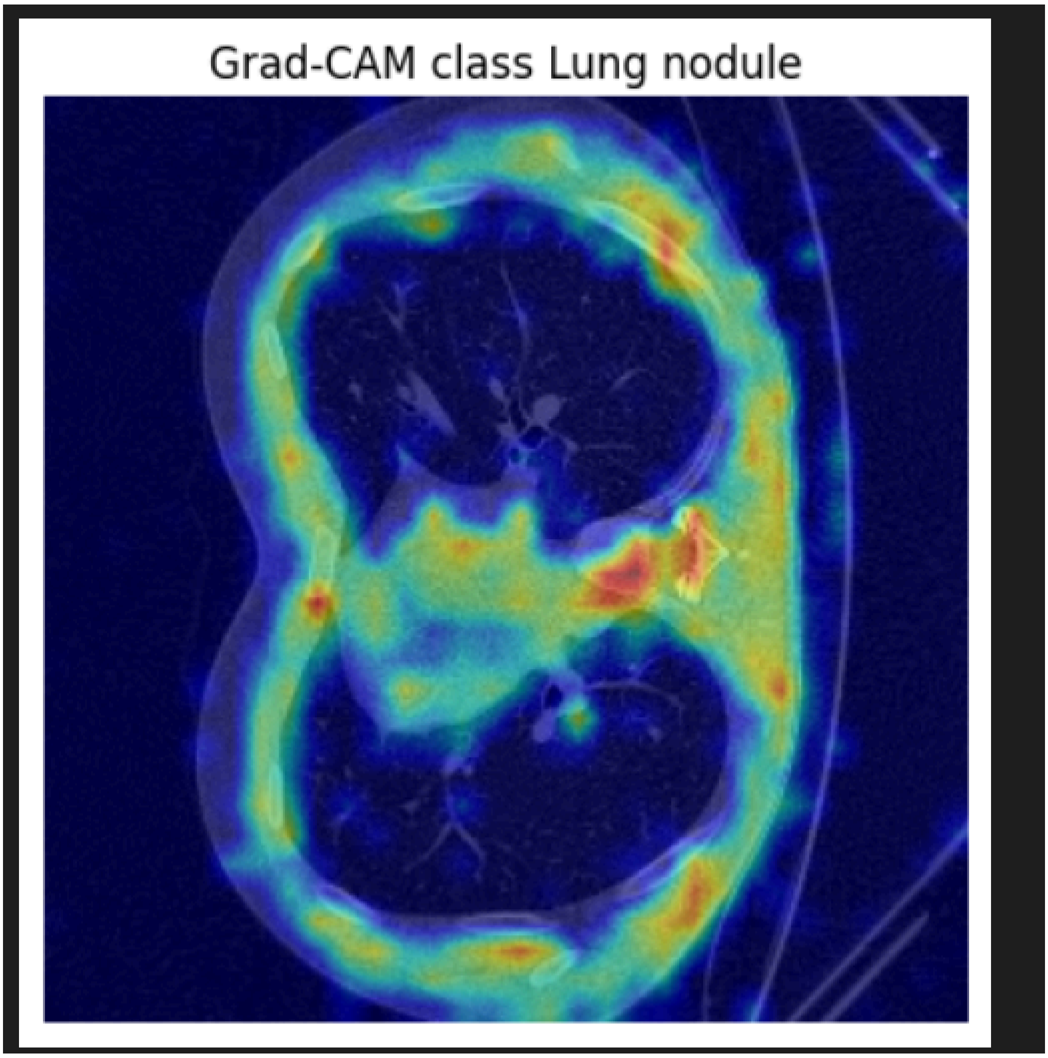
Evaluasi :

```
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

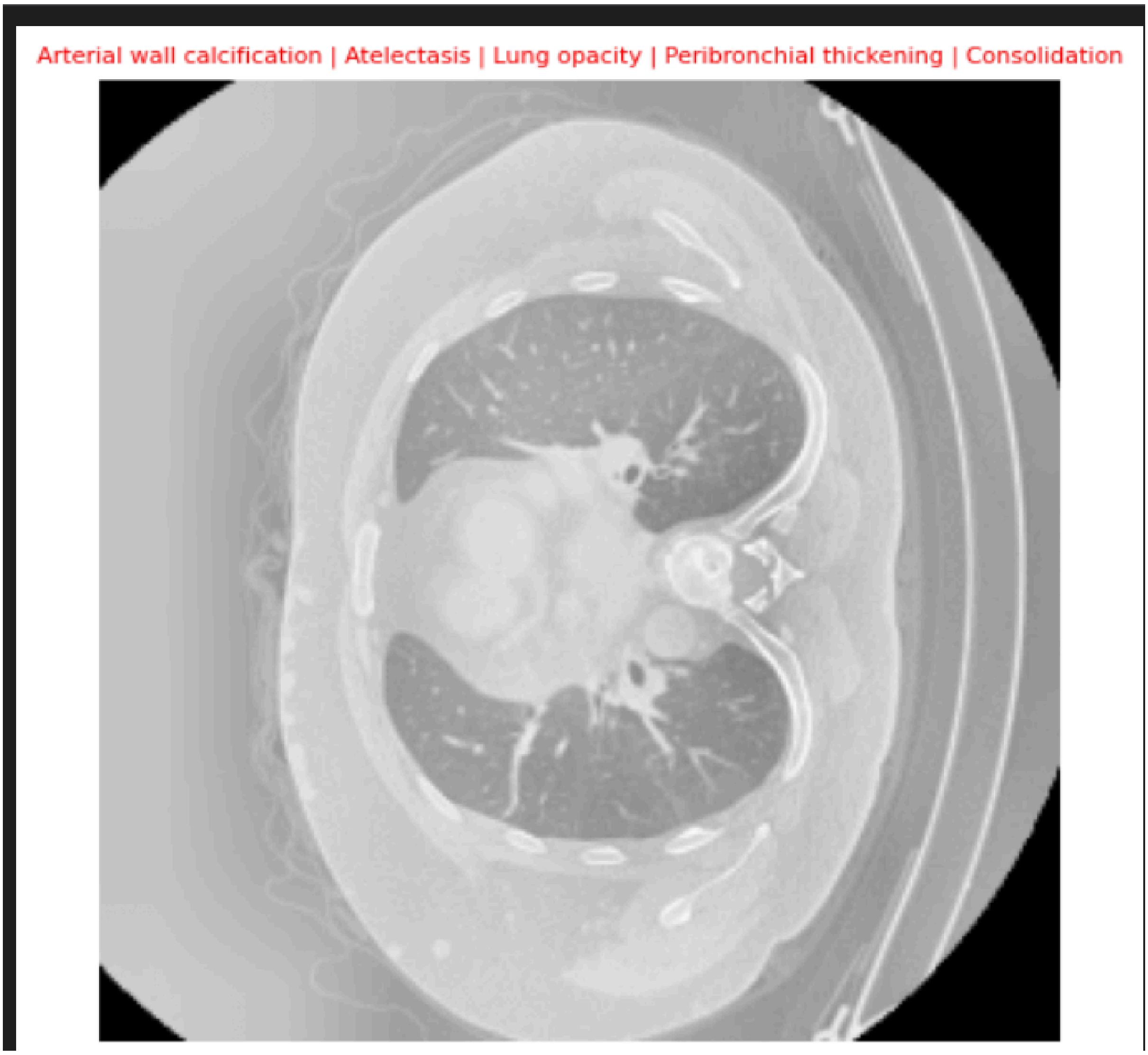

```
Predicted: ['Lung nodule'], Actual: ['Lung nodule']
```

Explainable AI GAD-CAM



Coba Preprocessing image lagi, clip_limit pada clahe naikan ke 3.0

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


    # Enhacing image dengan Gamma
    gamma=1.0
    out = np.power(img, gamma)

    # Enhancing image dengan clahe
    out = (out * 255).clip(0,255).astype(np.uint8)
    clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
    out = clahe.apply(out)

    # Denoising dengan fastN1Means
    img_denoised = cv2.fastNlMeansDenoising(
        out, None, h=denoise_h,
        templateWindowSize=7, searchWindowSize=21
    )

    out = img_denoised.astype(np.float32) / 255.0


    return torch.from_numpy(out).unsqueeze(0)

```


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

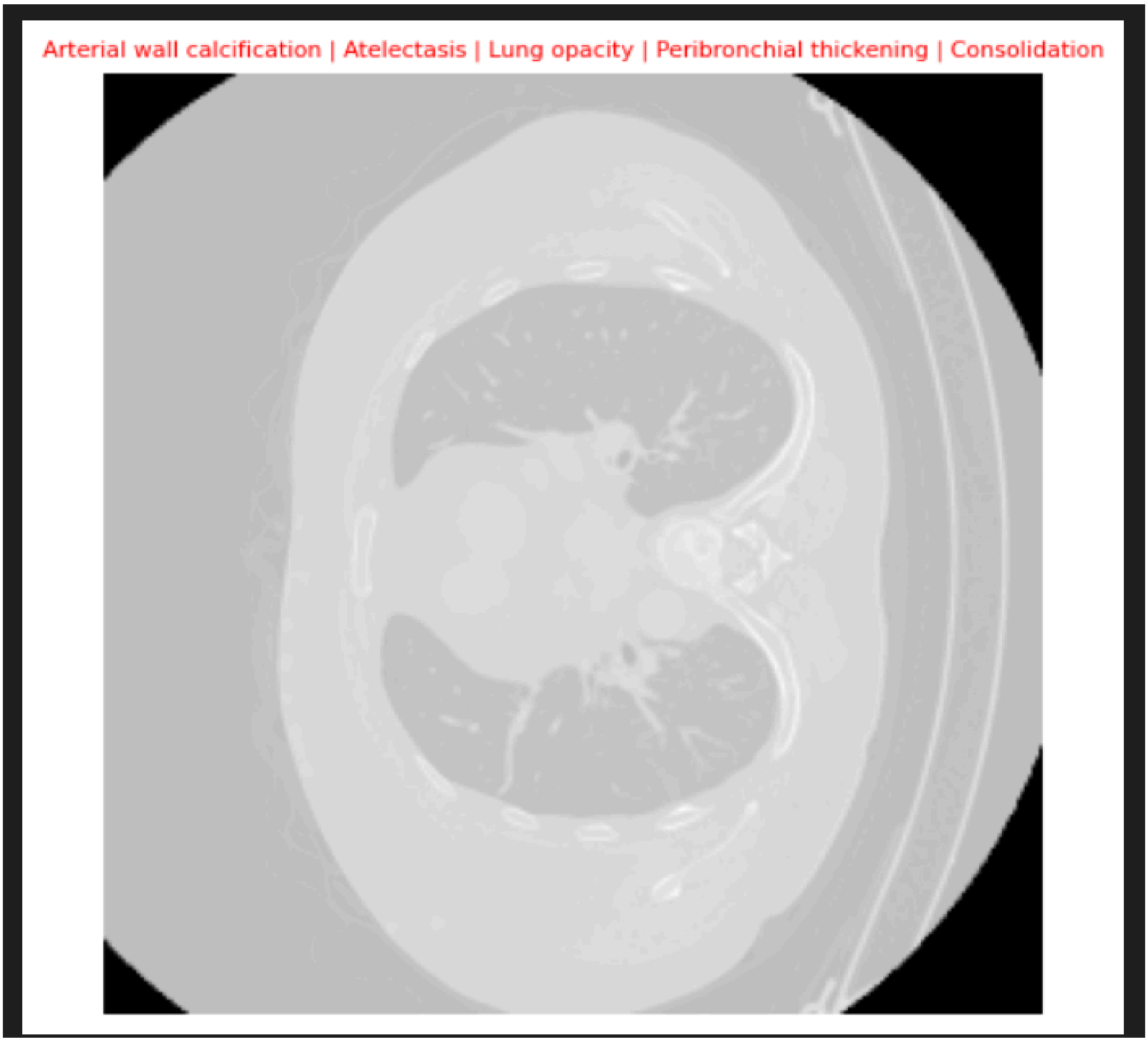
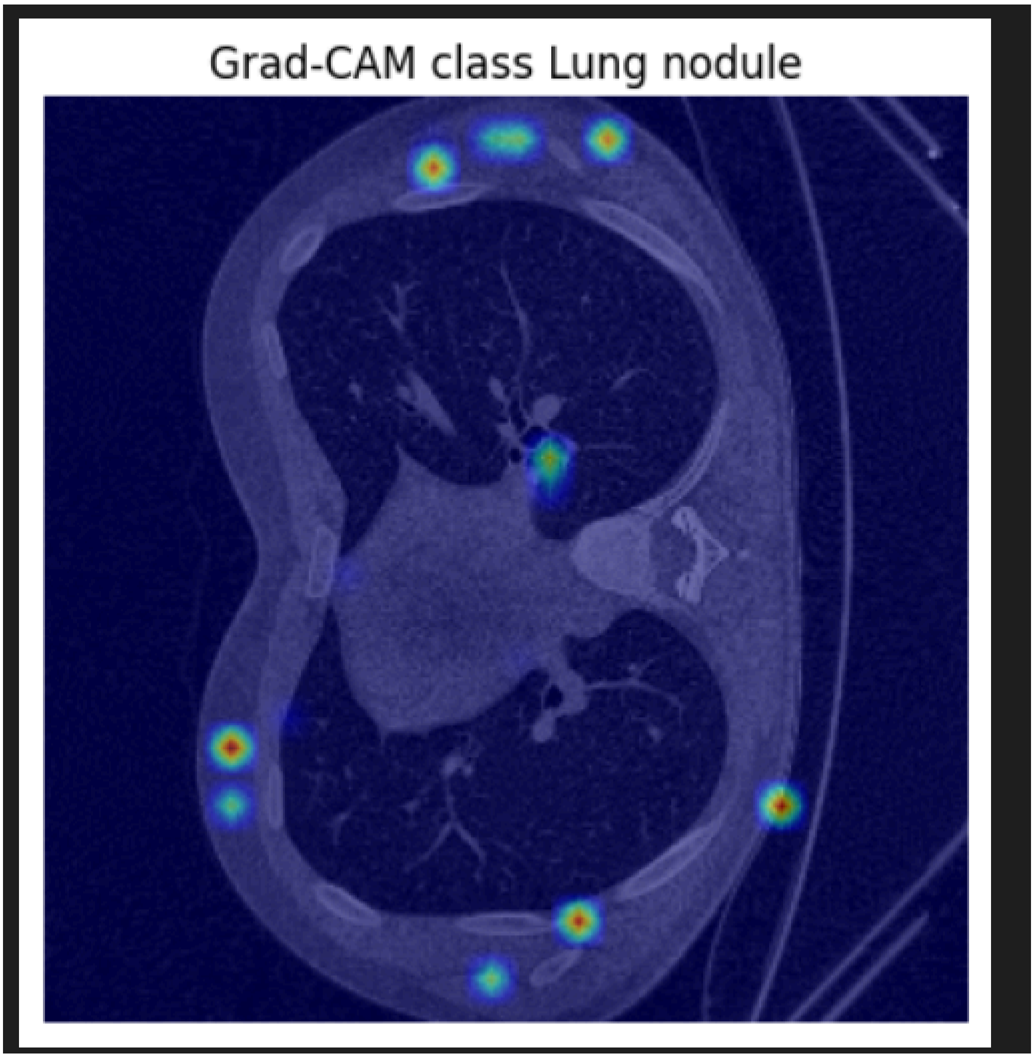


	Image	PSNR	SSIM	MSE	RMSE
0	1	22.0	0.8354	0.01	0.08
1	2	22.57	0.7942	0.01	0.07
2	3	20.98	0.8524	0.01	0.09
3	4	22.25	0.8344	0.01	0.08
4	5	25.62	0.8218	0.0	0.05
5	6	22.13	0.8568	0.01	0.08
6	7	24.36	0.7952	0.0	0.06
7	8	22.73	0.8446	0.01	0.07
8	9	19.33	0.7622	0.01	0.11
9	10	16.79	0.5084	0.02	0.14
10	11	20.55	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

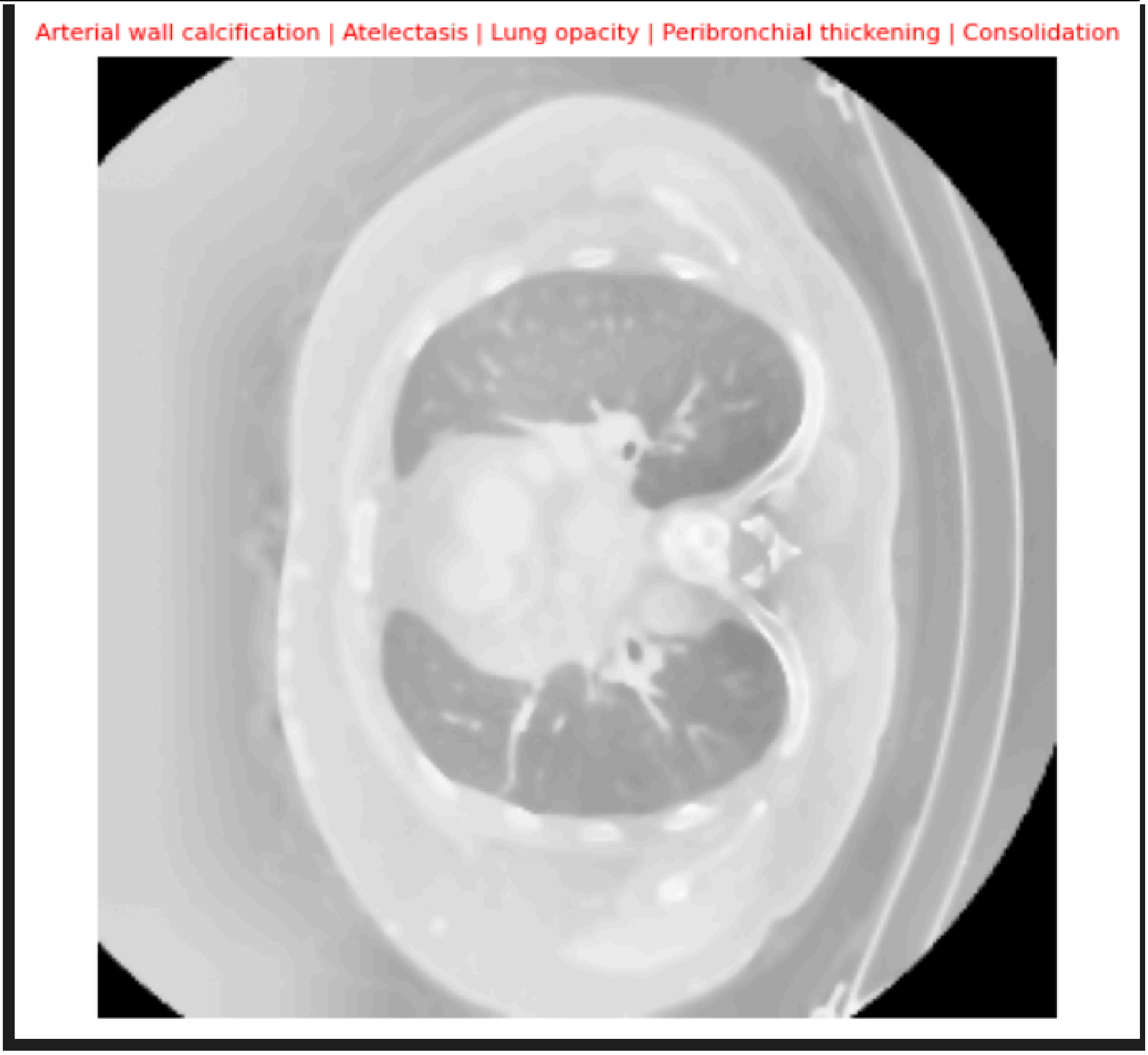
```
Epoch 1
-------------------------------
loss: 0.679748  [   16/  100]
Test Error:
 Accuracy: 83.7%, Avg loss: 0.518273

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

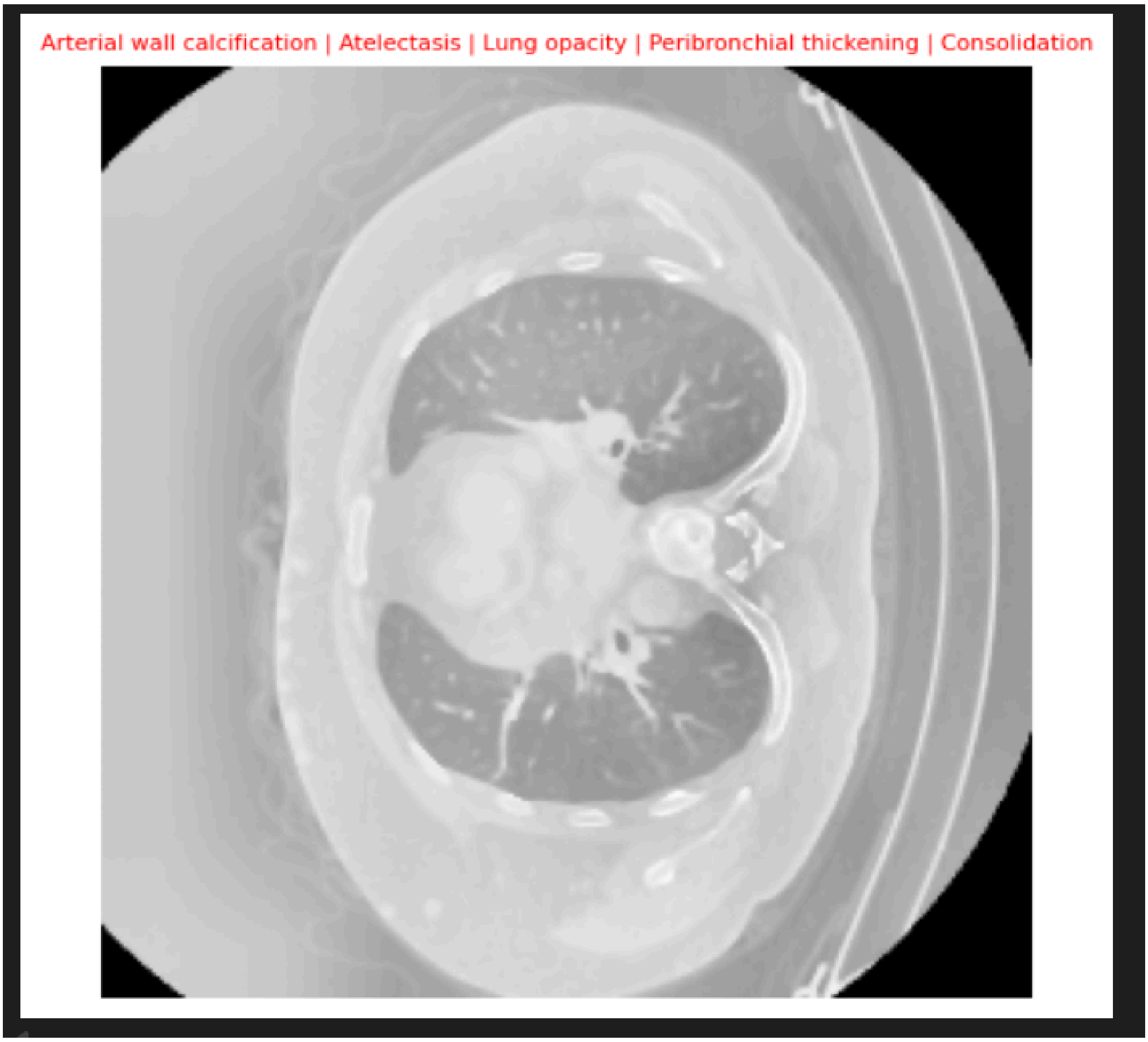
```
def preprocess_ct_psnr(img_tensor, denoise_h=1):
    img = img_tensor.squeeze().numpy()

    # Enhacing image dengan Gamma
    gamma=1.0
    out = np.power(img, gamma)


    # Enhancing image dengan clahe
    out = (out * 255).clip(0,255).astype(np.uint8)
    clahe = cv2.createCLAHE(clipLimit=3.0, tileGridSize=(8, 8))
    out = clahe.apply(out)

    # Denoising dengan fastN1Means
```

```
img_denoised = cv2.fastNlMeansDenoising(
    out, None, h=denoise_h,
    templateWindowSize=7, searchWindowSize=21
)

# Smooth sisa noise pake bilateral filter
img_bila = cv2.bilateralFilter(out, d=5, sigmaColor=30, sigmaSpace=30)

out = img_bila.astype(np.float32) / 255.0

return torch.from_numpy(out).unsqueeze(0)

```



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

hasil masih ngeblur**, coba turunkan d ke 3**



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
-------------------------------
```

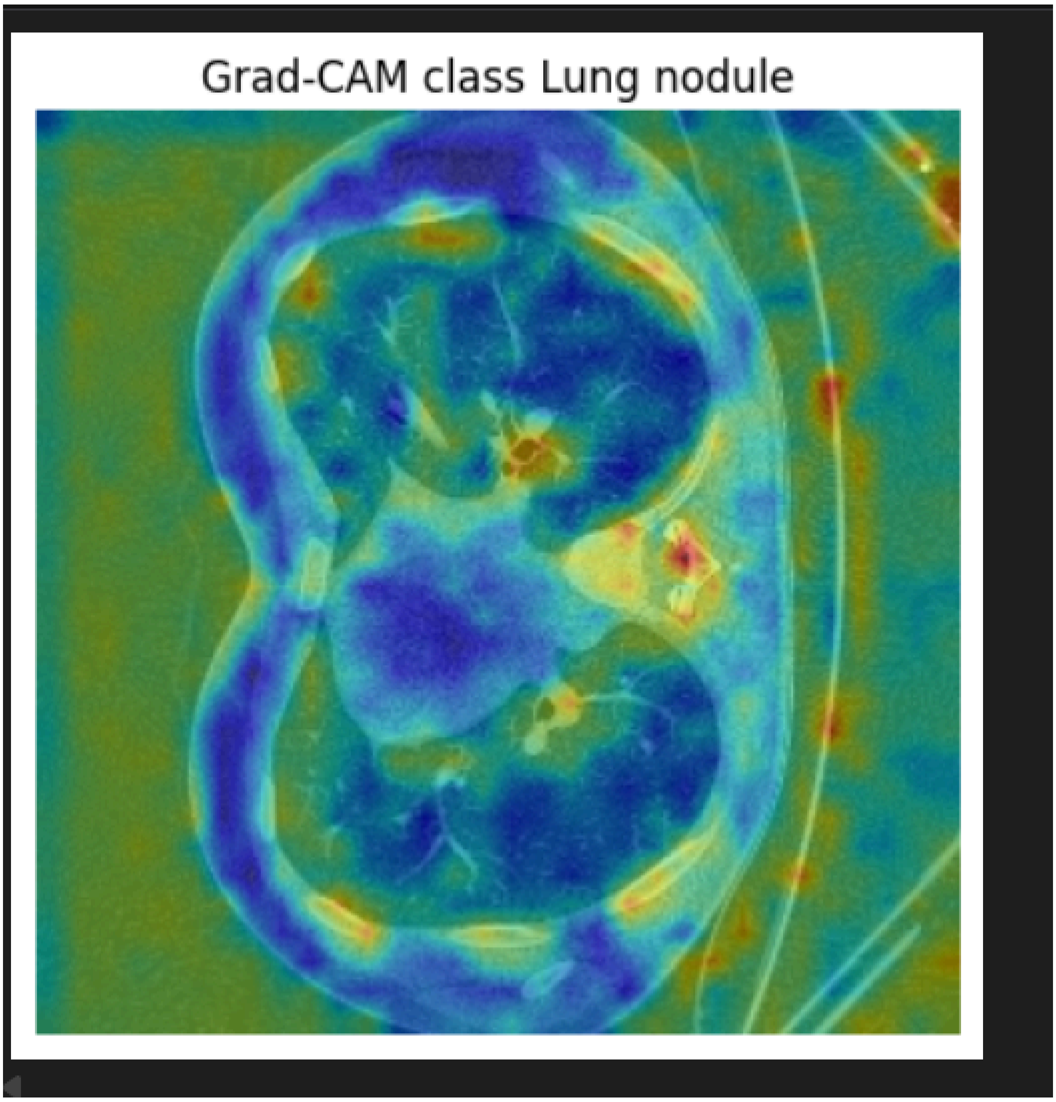
loss: 0.610267 [16/ 100]
Test Error:
 Accuracy: 83.7%, Avg loss: 0.438313

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

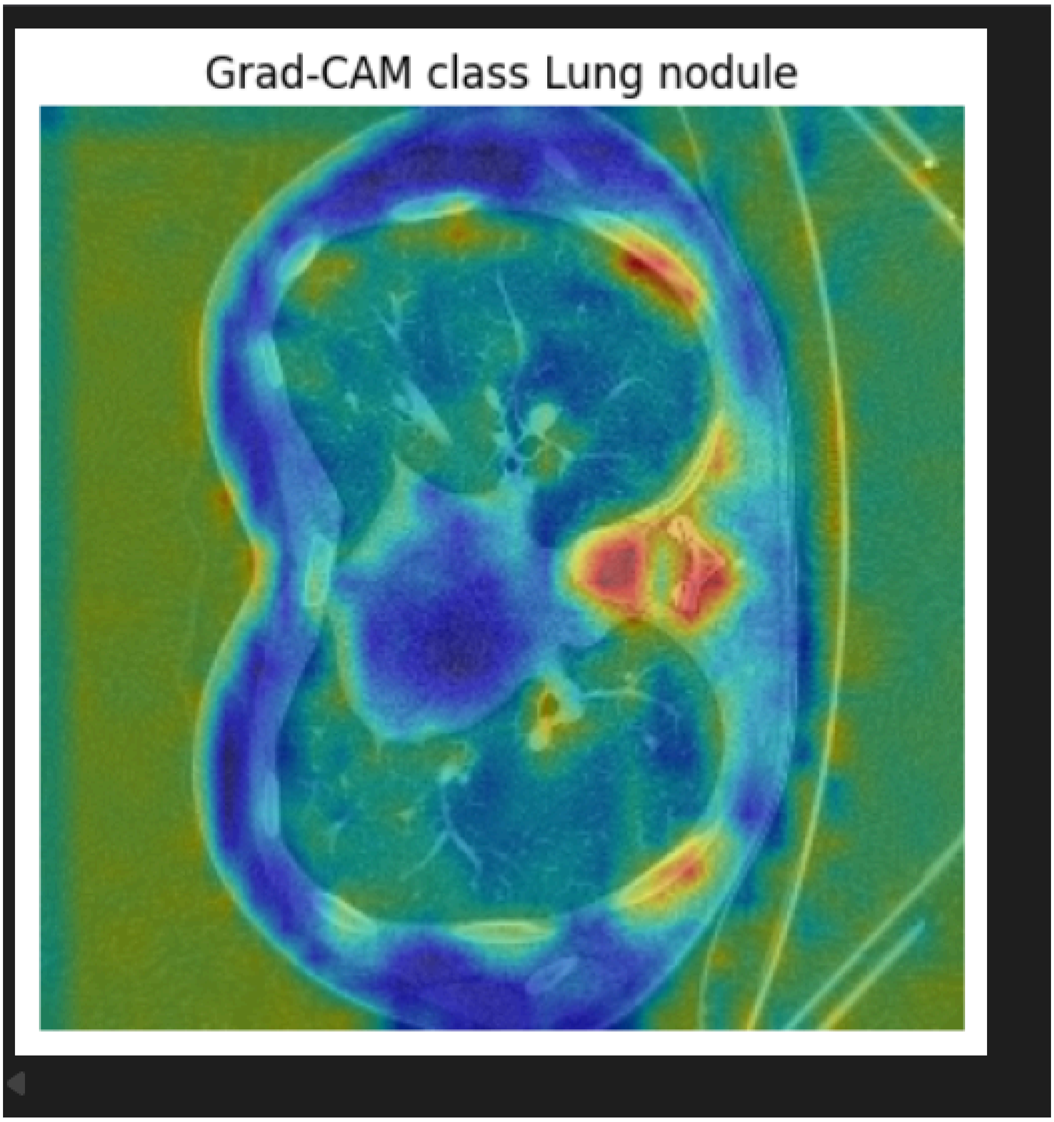
Epoch 2
----
loss: 0.551225 [32/ 500]
Test Error:
 Accuracy: 80.1%, Avg loss: 0.478153

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

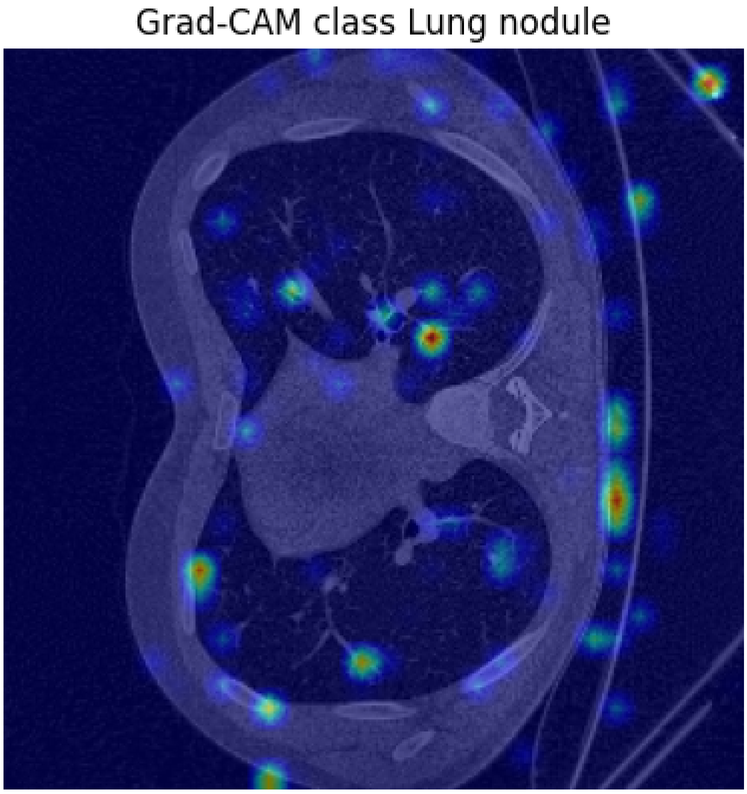
Epoch 5
...
Test Error:
 Accuracy: 80.1%, Avg loss: 0.473683

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



tapi hasilnya lebih bagus

Metric evaluasi data Training

Label	**ACC**	**Precission**	**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
Cardiomegal	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 calcificatio	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 opacit	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	Precission	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
Cardiomegal	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 calcificatio	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

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

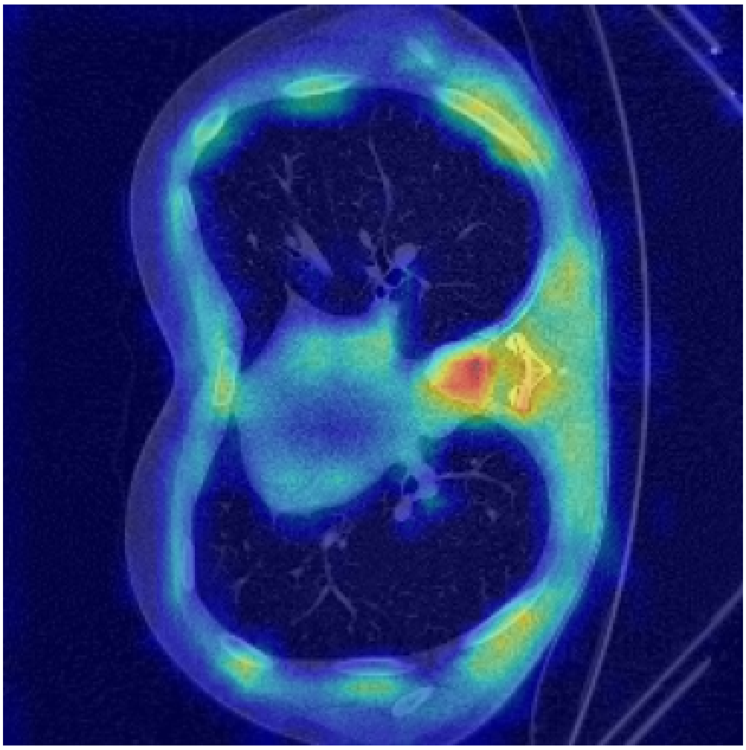
----

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 mendeteksi long nodule, tapi tidak dengan class lain, Pericardial effusion contohnya

Metric evaluasi Training

Label	ACC	Precission	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
Cardiomegal	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 calcificatio	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 evaliasi data val

Label	**ACC**	**Precission**	**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
Cardiomegal	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 calcificatio	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	0.78	0.0	0.0	0.99	0.0	0.0	0.00	0.0	0.77	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	0.50	0.48	0.19	0.80	0.27	0.19	0.80	0.51	0.51	-0.004
Lung opacity	0.61	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.61	0.0
Pulmonary fibrotic sequela	0.72	0.0	0.0	0.99	0.0	0.0	0.99	0.0	0.72	0.0
Pleural 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**	**Precission**	**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
Cardiomegal	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 calcification										
Hiatal hernia	0.22	0.17	0.95	0.07	0.29	0.99	0.04	0.82	0.88	0.04
Lymphadenopathy	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
Peribronchial 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

olidation										
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

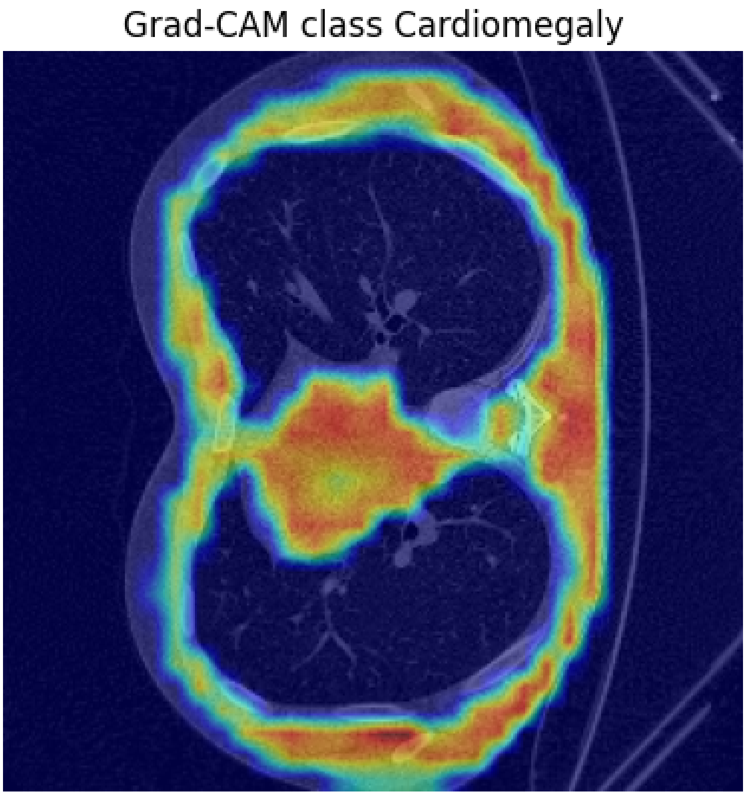
Evaluasi Validasi

Label	**ACC**	**Precission**	**Recall**	**Specificity**	**f1**	**FPR**	**FNR**	**FDR**	**NPV**	**MCC**
Medical material	0.61	0.16	0.46153846118343195	0.6436781608455543	0.23999999605600006	0.35632183903950326	0.5384615380473372	0.8378378376113952	0.8888888887477954	0.07328996632911351
Arterial wall calcification	0.54	0.4057971013904642	0.8749999997265625	0.3970588234710208	0.554455441105774	0.6029411763819205	0.1249999999609375	0.5942028984646083	0.8709677416545265	0.2744017450483129
Cardiomegal	0.5399999999946	0.2068965516884661	0.9999999991666666	0.4772727272184918	0.3428571399183674	0.5227272726678719	0.0	0.79310344813912	0.9999999997619048	0.3142388924126067
Pericardial effusion	0.12999999998700001	0.10309278349452652	0.9999999989999999	0.03333333332962963	0.18691588612105864	0.9666666665592594	0.0	0.8969072164023808	0.9999999966666667	0.0586210381760538
Coronary artery wall calcificatio	0.5699999999943	0.3793103447621879	0.7586206893935791	0.4929577464094426	0.5057471218760735	0.5070422534497124	0.24137931026159334	0.6206896550653983	0.8333333331349206	0.231293242455363
Hiatal hernia	0.21999999997800002	0.14285714284144427	0.9999999992307692	0.10344827585017836	0.24999999776442305	0.8965517240348791	0.0	0.8571428570486657	0.9999999988888888	0.1215661347709655
Lymp	0.459	0.301	0.879	0.319	0.0.44	0.679	0.119	0.698	0.888	0.195

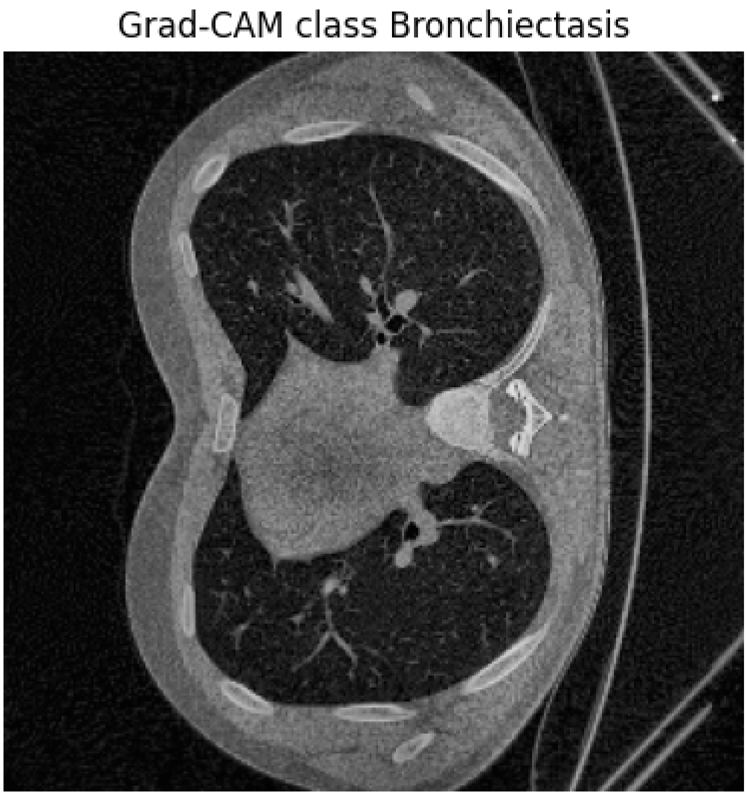
hadenopathy	999999954000004	36986297241514	999999648	99999995733336	897958794460646	9999999093334	999999952	6301368905987	8888885596707	06857866021737
Emphysema	0.339999999966	0.17105263155644046	0.8124999994921874	0.2499999999702381	0.2826086927173913	0.7499999999107143	0.1874999998828125	0.8289473683119807	0.8749999996354166	0.0536496922049344
Atelectasis	0.43999999995600003	0.35632183903950326	0.9999999996774194	0.1884057970741441	0.5254237248506177	0.8115942027809284	0.0	0.6436781608455543	0.9999999992307692	0.25910055985390706
Lung nodule	0.469999999953	0.40740740725651575	0.2291666666189236	0.6923076921745562	0.2933333286471112	0.3076923076331361	0.770833333172743	0.5925925923731138	0.493150684863952	-0.0883670727358293
Lung opacity	0.639999999936	0.5362318839802563	0.9024390241701368	0.4576271185665039	0.6727272679289257	0.5423728812640046	0.09756097558596073	0.46376811587481626	0.8709677416545265	0.38290834252661204
Pulmonary fibrotic sequela	0.509999999949	0.3061224489171179	0.4999999998333333	0.5142857142122449	0.37974683063611603	0.485714285644898	0.4999999998333333	0.6938775508788005	0.7058823528027681	0.01309569281468872
Pleural effusion	0.6299999999370001	0.23255813948080042	0.7142857137755102	0.6162790696957815	0.35087718915358573	0.38372093018793946	0.28571428551020406	0.7674418602866414	0.9298245612403816	0.2316851364884415
Mosaic attenuation pattern	0.43999999995600003	0.15384615382248523	0.9090909082644627	0.3820224718671885	0.26315789219182834	0.617977528020452	0.09090909082644627	0.8461538460236687	0.9714285711510204	0.1909689734713449
Peribronchial thickening	0.7399999999260001	0.22222222213991769	0.5454545449586776	0.764044943734377	0.31578946940443214	0.23595505615326348	0.45454545413223135	0.7777777774897119	0.9315068491874648	0.21812626876989355
Consolidation	0.5599999999440001	0.13157894733379502	0.3124999998046875	0.6071428570705782	0.1851851809465022	0.3928571428103742	0.6874999995703125	0.8684210524030471	0.822580645028616	-0.06069270278805855
Bronc	0.619	0.060	0.222	0.659	0.095	0.340	0.777	0.939	0.895	-0.07

hiectasis	999999938	606060587 69513	2222219753086	3406592682044	23809182539694	6593406219056	7777769135802	3939391092745	5223879260416	20834247340762
Interlobular septal thickening	0.909999999909	0.33333333222222222	0.124999999843 74999	0.97826086945888 48	0.18181817752066123	0.02173913043241966	0.87499999890624 99	0.66666666444444444	0.92783505145073 87	0.16422081026965651

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



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



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

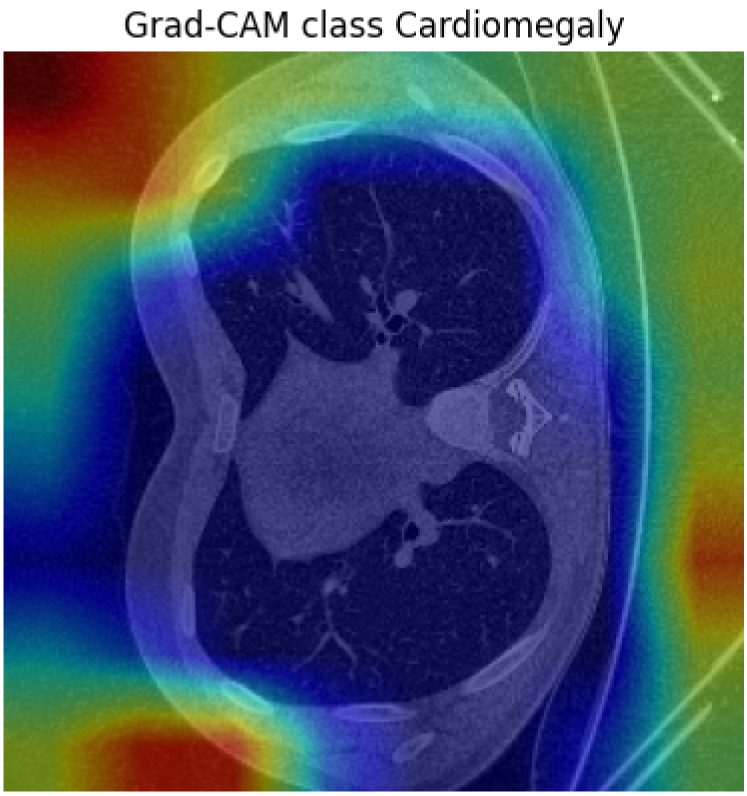
Label	ACC	Precission	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.92199999998156	0.6440677965010054	0.6785714284502551	0.9527027026812455	0.6608695601058603	0.04729729729623204	0.3214285713711735	0.35593220332950304	0.9591836734476376	0.6171037576569398
Arterial wall calcification	0.86399999998272	0.8733333332751111	0.8599999999754285	0.7939393889325986	0.139999999996	0.1266666666582222	0.27222222220709874	0.9406249999706054	0.7277777777373456	0.7001157311738089
Cardiomegal	0.899999999982	0.5624999999296876	0.749999999875	0.920454545433626	0.6428571378673471	0.0795454545436467	0.24999999995833333	0.4374999999453125	0.9642857142627551	0.594294435968718
Pericardial effusion	0.96199999998076	0.6666666664444444	0.6896551721759809	0.9787685774739114	0.6779660964665325	0.021231422504857083	0.31034482747919145	0.3333333332222222	0.9808510638089181	0.6578877028419604
Coronary artery wall calcificatio	0.8199999999836	0.6391752576990115	0.8611111110513117	0.8033707864942873	0.7337278057168867	0.19662921347762277	0.13888888887924383	0.3608247422494442	0.9346405228452732	0.6174870029297219
Hiatal hernia	0.79599999998408	0.44516129029386053	0.8117647057868512	0.7927710843182465	0.5749999953774306	0.20722891565765714	0.18823529409550174	0.5548387096416233	0.9536231883781559	0.4909984622943456
Lymphadenopathy	0.73199999998536	0.29	0.87	0.22	0.44	0.77	0.12	0.7	0.82	0.109
Emphysema	0.8699999999826	0.6774193547294485	0.4827586206341657	0.9515738498558941	0.5637583843268322	0.048426150119892826	0.5172413792508919	0.32258064510926115	0.8972602739521174	0.4996018644551454
Atelectasis	0.6699999999866	0.4457364340912505	0.8394160583328892	0.5822784764523634	0.3939393939285416	0.16058394159411796	0.5542635658699898	0.6060606060439102	0.9090909090533433	0.3975767866787894
Lung	0.709	0.708	0.618	0.786	0.660	0.213	0.381	0.291	0.710	0.412

nodule	9999999858	542713532234	4210526044552	7647058534277	4215406595769	23529410980752	5789473516851	45728641751467	9634551258815	2837920328778
Lung opacity	0.731999999998536	0.645348837171782	0.6032608695324314	0.8069620252909189	0.6235955005886252	0.1930379746774355	0.3967391304132207.34	0.3546511627700784	0.7774390243665414	0.4164579936874762
Pulmonary fibrotic sequela	0.733999999998532	0.6168224298488951	0.4177215189609037	0.8801169590385931	0.4981132026947669	0.11988304093216716	0.5822784809758051	0.38317757005764697	0.7659033078685521	0.33762471955699686
Pleural effusion	0.883999999998232	0.5425531914316433	0.7727272726101929	0.9009216589654165	0.6374999950734377	0.09907834101154198	0.22727272723829203	0.4574468084619738	0.9630541871683976	0.5836110609945767
Mosaic attenuation pattern	0.917999999998164	0.45161290315296565	0.7999999997714285	0.9268817204101746	0.5773195828972262	0.07311827956832004	0.19999999994285714	0.548387096685744	0.9840182648177165	0.5627186978560278
Peribronchial thickening	0.9199999999816	0.5737704917092179	0.7142857141399417	0.9423503325733403	0.6363636313074381	0.0576496674044867	0.2857142856559767	0.4262295081268476	0.9681093393856922	0.5965046774756931
Consolidation	0.85199999999829599	0.5652173912551985	0.7303370785696252	0.878345498762084	0.6372548969795273	0.12165450121358505	0.26966292131801545	0.434782608657845	0.9376623376379828	0.5532577424377602
Bronchiectasis	0.893999999998212	0.5238095237263795	0.5892857141804847	0.9324324324114317	0.5546218436635831	0.06756756756604577	0.41071428564094387	0.4761904761148904	0.9473684210309526	0.49580448179493986
Interlobular septal thickening	0.917999999998164	0.6249999998697917	0.566037735742257	0.9597315436026905	0.5940594008352122	0.04026845637493807	0.43396226406906374	0.374999999921875	0.9491150442267895	0.5494106416414718

Evaluasi Validasi

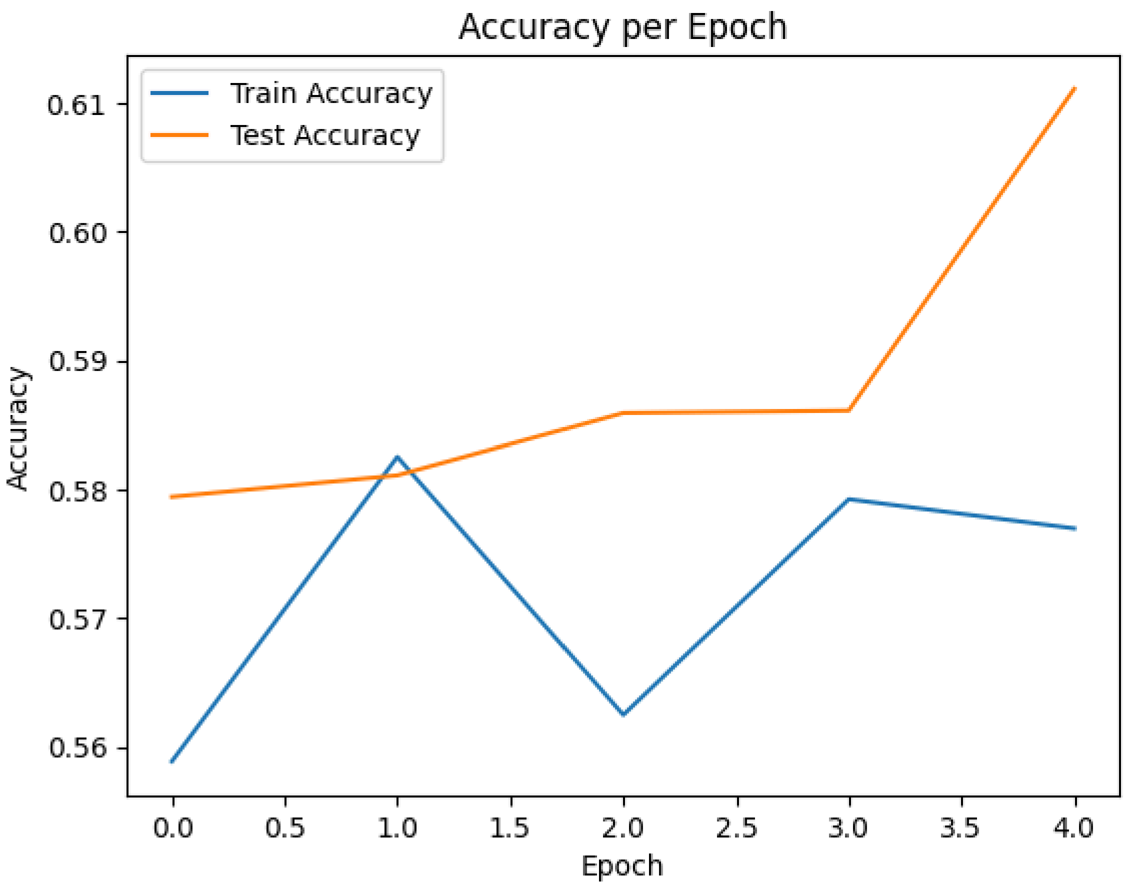
Label	ACC	Precision	Recall	Specificity	f1	FPR	FNR	FDR	NPV	MCC
Medical material	0.79999999992	0.29411764688581316	0.3846153843195266	0.86206896541815 3	0.33333332820000006	0.13793103446669045	0.6153846149112425	0.7058823525259516	0.9036144577224562	0.22085609748246096
Arterial wall calcification	0.7399999999260001	0.56818181805268 6	0.7812499997558594	0.7205882351881489	0.6578947317936289	0.2794117646647924	0.21874999993164063	0.43181818172000413	0.87499999984375	0.47159896262693355
Cardiomegal	0.869999999913	0.47368421027700083	0.7499999999375	0.8863636362629133	0.5806451561706556	0.11363636362345042	0.24999999979166665	0.5263157891966759	0.9629629628440787	0.5271303284099097
Pericardial effusion	0.719999999928	0.21874999993164063	0.6999999992999999	0.7222222221419754	0.33333332954648526	0.2777777777469136	0.29999999969999996	0.7812499997558594	0.9558823528006056	0.27153942647563833
Coronary artery wall calcificatio	0.7699999999230001	0.5937499998144531	0.6551724135671819	0.8169014083356477	0.6229508144799786	0.18309859152350727	0.34482758608799047	0.4062499998730469	0.8529411763451558	0.45920715482127816
Hiatal hernia	0.45999999995400004	0.17460317457545982	0.8461538455029586	0.4022988505284714	0.2894736812984765	0.5977011493565861	0.15384615372781063	0.8253968252658 1	0.9459459456902849	0.17306286166790671
Lymphadenopathy	0.5199999999480001	0.3380281689664749	0.9599999999616	0.3733333332835556	0.4999999960438368	0.6266666665831112	0.0399999999984	0.6619718308926801	0.9655172410463734	0.31809087296630295
Emphysema	0.869999999913	0.9999999966666667	0.1874999998828125	0.9999999998809525	0.3157894706925208	0.0	0.8124999994921874	0.0	0.8659793813540227	0.40295301713799636
Atelectasis	0.6299999999370001	0.44827586199167657	0.8387096771488033	0.5362318839802563	0.5842696582502209	0.46376811587481626	0.16129032252861603	0.5517241378359097	0.8809523807426304	0.35134221425963025
Lung nodule	0.579999999942	0.79999999992	0.16666666663194443	0.9615384613535503	0.27586206601664687	0.03846153845414201	0.833333333159722 2	0.1999999998	0.5555555554938272	0.21350420507344903

Lung opacity	0.68999999931	0.6136363634969008	0.658536585205235	0.7118644066590061	0.6352941125038062	0.28813559317150245	0.3414634145508626	0.3863636362758264	0.7499999998660715	0.36700309245440427
Pulmonary fibrotic sequela	0.52999999947	0.3731343283025173	0.8333333330555556	0.3999999999428572	0.515463913146987	0.5999999999142858	0.1666666666111111	0.626865671548229	0.8484848482277318	0.22740083830843708
Pleural effusion	0.8499999999150001	0.481481481303155	0.9285714279081632	0.8372093022282315	0.6341463366567519	0.16279069765548945	0.07142857137755101	0.5185185183264746	0.986301369727904	0.5985140715168469
Mosaic attenuation pattern	0.7399999999260001	0.2580645160457856	0.7272727266115702	0.7415730336245424	0.3809523769047619	0.25842696626309813	0.2727272724793388	0.7419354836316336	0.9565217389918085	0.3171874148561068
Peribronchial thickening	0.7699999999230001	0.26923076912721894	0.6363636357851239	0.7865168538442117	0.37837837399561725	0.21348314604342888	0.3636363633057851	0.7307692304881657	0.9459459458181155	0.30165217521884213
Consolidation	0.64999999935	0.22857142850612244	0.49999999996875	0.6785714284906463	0.31372548576701276	0.3214285713903062	0.49999999996875	0.7714285712081632	0.8769230767881657	0.13725270326150305
Bronchiectasis	0.89999999991	0.3333333322222222	0.1111111109876543	0.9780219779145032	0.16666666263888896	0.02197802197560681	0.8888888879012344	0.6666666644444444	0.917525773101286	0.14953209388661085
Interlobular septal thickening	0.7099999999290001	0.1818181817630854	0.7499999990624999	0.706521739053639	0.2926829235455086	0.29347826083766543	0.24999999968749997	0.8181818179338842	0.970149253586545	0.2633940735253188



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	0.7858333333267848	0.2807017543736534	0.4076433120759463	0.8427612655719774	0.332467527620307	0.15723873441843492
1	0.6099999999949167	0.39965694681990294	0.6638176637987516	0.5877502944571525	0.498929331486251	0.4122497055310689
2	0.7791666666601736	0.28618421051690185	0.6444444443967078	0.7962441314479227	0.3963553487981072	0.20375586854268776
3	0.8249999999931251	0.18781725887371487	0.4252873562729555	0.8562443845385783	0.2605633760134398	0.14375561545243706
4	0.6249999999947917	0.3840579710075352	0.6583850931472551	0.612756264229923	0.485125853458729	0.3872437357586874
5	0.5933333333283889	0.19361277444723327	0.5359116021803364	0.603532875362085	0.28445747409830496	0.3964671246281014
6	0.4891666666259034	0.3065789473643871	0.730407523488075	0.4018161180431122	0.43188136746762923	0.5981838819455371
7	0.5949999999950417	0.219088937088523	0.4449339206852452	0.630010277485817	0.2936046467326512	0.36998972250390555
8	0.5791666666618404	0.3636363636303531	0.6470588235103806	0.5523255813889264	0.46560846099179765	0.4476744185994456
9	0.4666666666277784	0.46260869564815127	0.9602888086469262	0.04334365325010304	0.6244131411442561	0.956656346734417
10	0.6433333333279723	0.5024390243657346	0.24009324008764352	0.8677042801443877	0.32492113126058575	0.13229571984264207
11	0.49583333332920143	0.2949852507331123	0.6116207950883297	0.45246277204521806	0.3980099458507265	0.5475372279433272
12	0.7499999999937501	0.2776025236505488	0.5534591194620466	0.7800192122883765	0.3697478946950251	0.2199807877020175
13	0.8941666666592154	0.2911392404694761	0.24468085103779993	0.9493670885990112	0.2658959487640751	0.05063291139194727
14	0.6774999999943542	0.16172506738108558	0.44117647055579584	0.7077067669106419	0.23668638659741922	0.2922932330799597
15	0.7099999999940834	0.2671232876620848	0.36792452828453187	0.78340080970867	0.30952380463750323	0.2165991902812085
16	0.8216666666598195	0.1653543306956414	0.16279069766179916	0.9010270774892529	0.16406249498748796	0.09897292250141015
17	0.5758333333285348	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	0.559999999888	0.00906229694421424

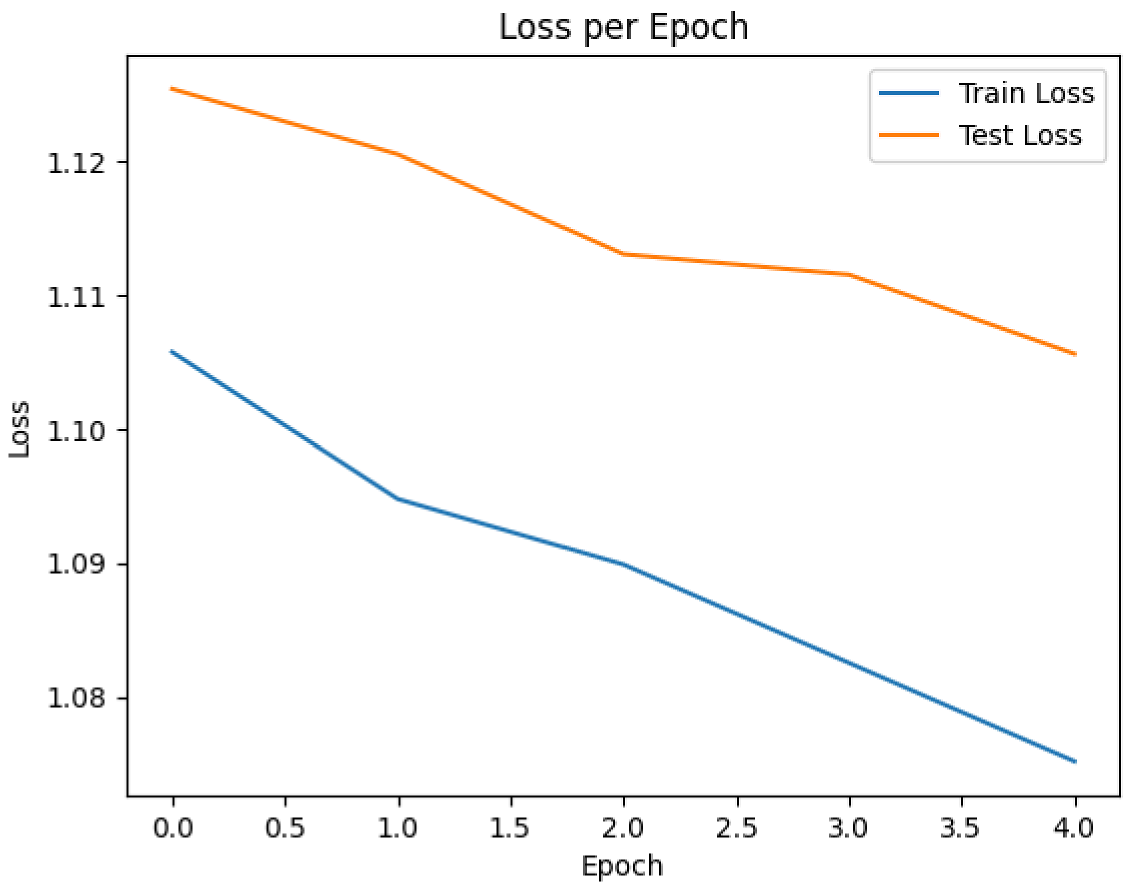
# FNR	# FDR	# NPV	# MCC
0.7599067598890464	0.4975609755854848	0.6723618090384688	0.1372701583804053
0.3883792048810893	0.7050147492521384	0.7567049808284156	0.05755427374977732
0.4465408804750603	0.7223974763179054	0.919592298970333	0.2564375177156557
0.7553191488558172	0.7088607594039418	0.9366636931227774	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

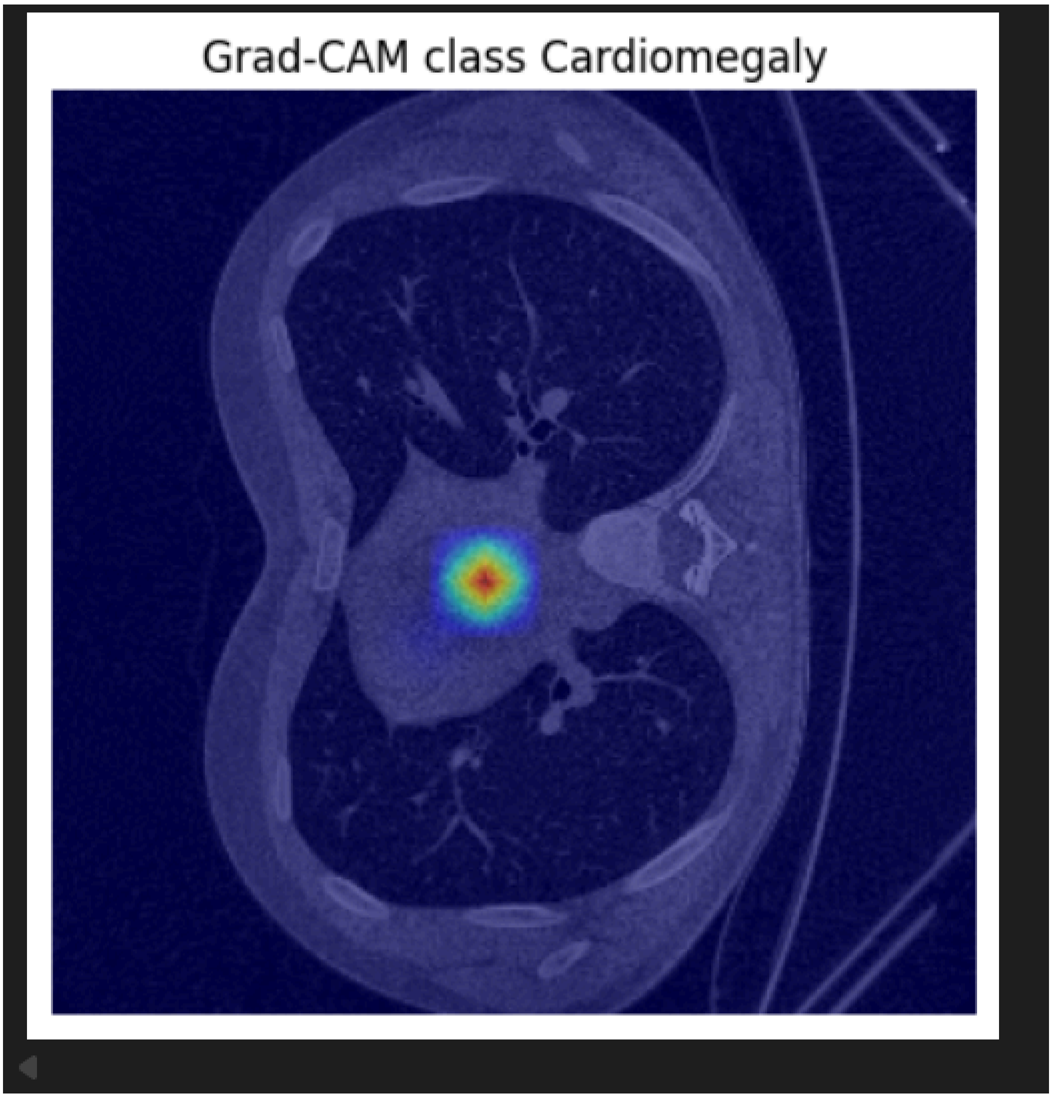
	# ACC	# Precision	# Recall	# Specificity	# F1	# FPR
0	0.6033333333132223	0.1574803149482299	0.6249999998046875	0.6007462686343005	0.25157232379731814	0.39925373132838604
1	0.5933333333135555	0.40140845067595715	0.6063829786588955	0.5873786407481855	0.4830508426235278	0.4126213592032708
2	0.7633333333078889	0.3116883116478327	0.571428571292517	0.7945736433800552	0.4033613399025493	0.20542635658118502
3	0.8233333333058889	0.20930232553272038	0.3214285713137755	0.8749999999678308	0.25352112191231907	0.12499999999540441
4	0.6466666666451111	0.38541666662651913	0.44047619042375286	0.7268518518182012	0.4111111060876544	0.27314814813550237
5	0.3033333333232222	0.1217391304294896	0.7999999997714285	0.2377358490476326	0.2113207524084016	0.7622641509146315
6	0.5033333333165555	0.3350253806936535	0.7857142856207484	0.39351851850030006	0.46975088545484495	0.6064814814534036
7	0.5833333333138889	0.18749999998325895	0.3818181817487603	0.6285714285457725	0.2514970015403924	0.37142857141341107
8	0.5633333333145556	0.32894736839941136	0.632911392324948	0.5384615384371737	0.4329004283622871	0.46153846151757744
9	0.47333333331755556	0.45804195802594255	0.9776119402255513	0.06626506023697198	0.6238095194346939	0.933734939702787
10	0.5933333333135555	0.49999999989130434	0.1885245901484816	0.870786516805012	0.27380951980017015	0.12921348313880823
11	0.37333333332088886	0.29674796746761184	0.8295454544511881	0.18396226414226594	0.4371257445957188	0.8160377358105643
12	0.8633333333045555	0.9999999966666667	0.06818181816632231	0.9999999999609375	0.12765957321865096	0.0
13	0.5433333333152222	0.13157894735976453	0.79999999968	0.5199999999810909	0.2259886981135689	0.47999999998254544
14	0.7599999999746666	0.26562499995849614	0.40476190466553286	0.8178294573326422	0.32075471213599155	0.18217054262859803
15	0.539999999982	0.21854304634314284	0.6226415093164828	0.5222672064565883	0.32352940788687046	0.4777327935029258
16	0.5166666666494444	0.11029411763894896	0.3846153845167653	0.5363984674123985	0.1714285679451429	0.46360153254928727
17	0.5833333333138889	0.12307692306745562	0.5925925923731138	0.5824175823962484	0.20382165317700518	0.4175824175671215

# FNR	# FDR	# NPV	# MCC
0.3749999998828125	0.84251968497303	0.930635838096495	0.1410386215657749
0.39361702123472164	0.5985915492536202	0.7658227847616568	0.1800083193195915
0.4285714284693877	0.6883116882222973	0.9192825111695389	0.2907504647362502
0.6785714283290816	0.7906976742347215	0.9260700388744719	0.1630674712137648
0.5595238094571996	0.6145833332693142	0.769607843099529	0.16105883315842878
0.19999999994285714	0.8782608695270321	0.8999999998714286	0.02864165750631024
0.2142857142602041	0.664974619255585	0.8252427183664813	0.16948540008218163
0.6181818180694215	0.8124999999274554	0.819148936126641	0.008311429258190126
0.36708860754846984	0.6710526315347991	0.8040540539997261	0.1509729895676248
0.022388059699821786	0.5419580419390924	0.7857142851530612	0.1034180489024629

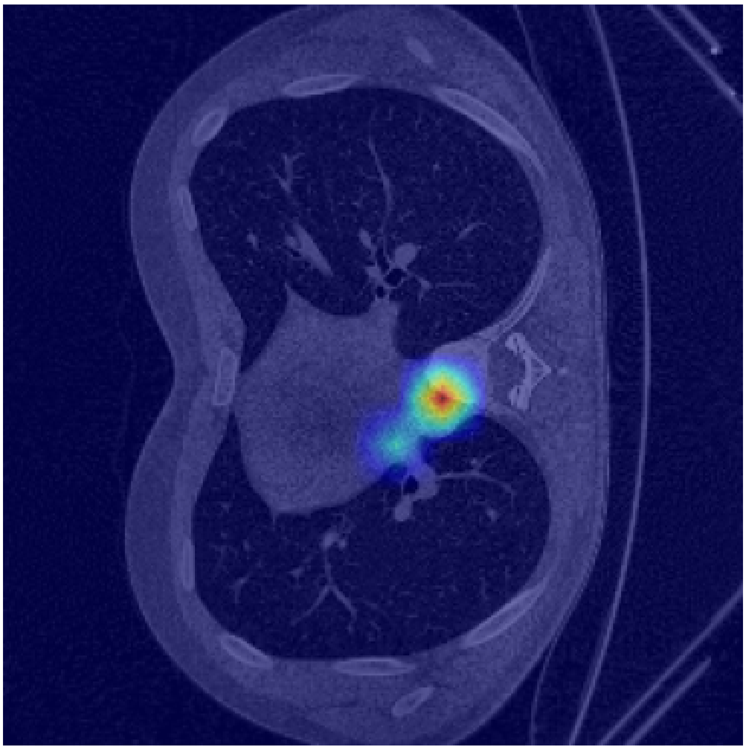
# FNR	# FDR	# NPV	# MCC
0.8114754097695512	0.49999999989130434	0.6102362204484159	0.08085933631737356
0.17045454543517563	0.7032520324917377	0.7222222220884773	0.016007622750131578
0.931818181606405	0.0	0.8619528619238399	0.24242424242424232
0.19999999992	0.8684210525744459	0.9662162161509313	0.17690238084063178
0.5952380950963718	0.734374999885254	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

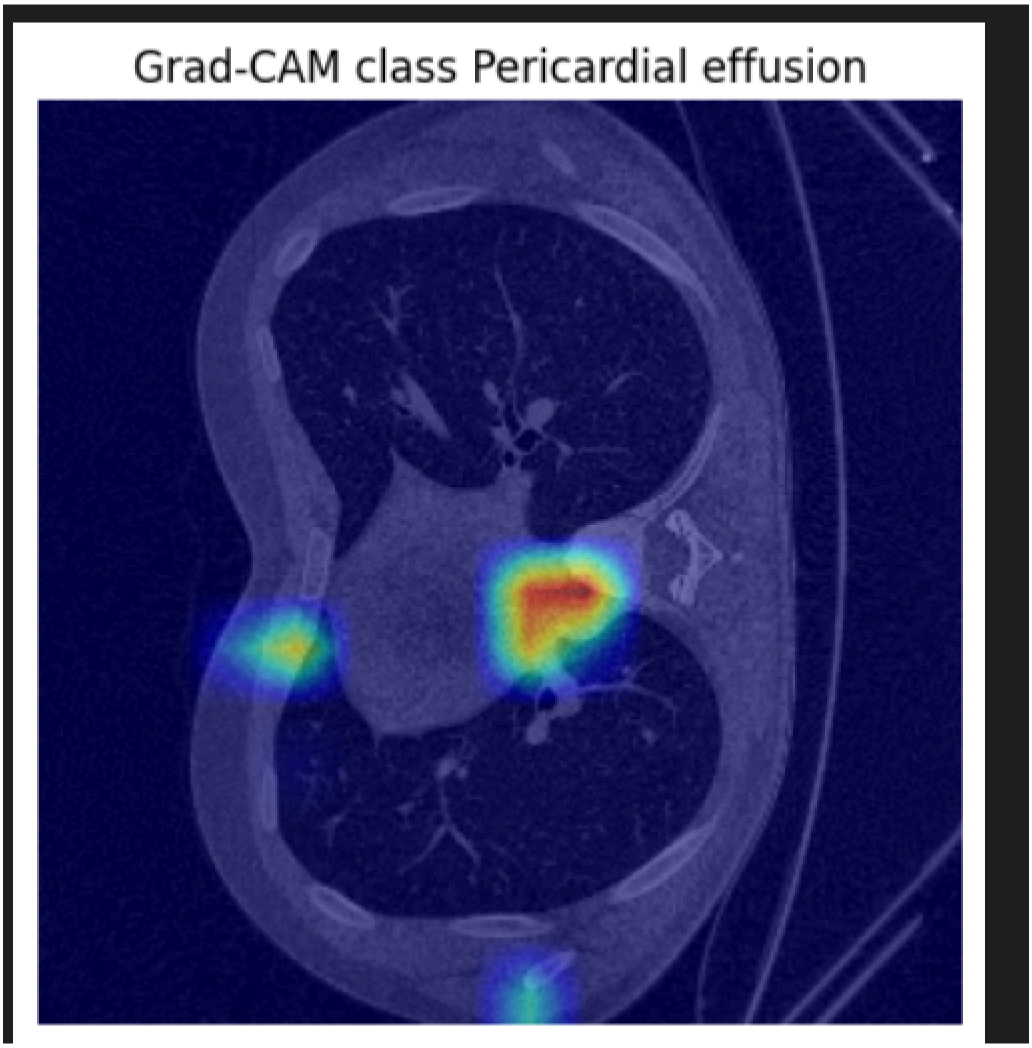


class dengan MCC ter tinggi

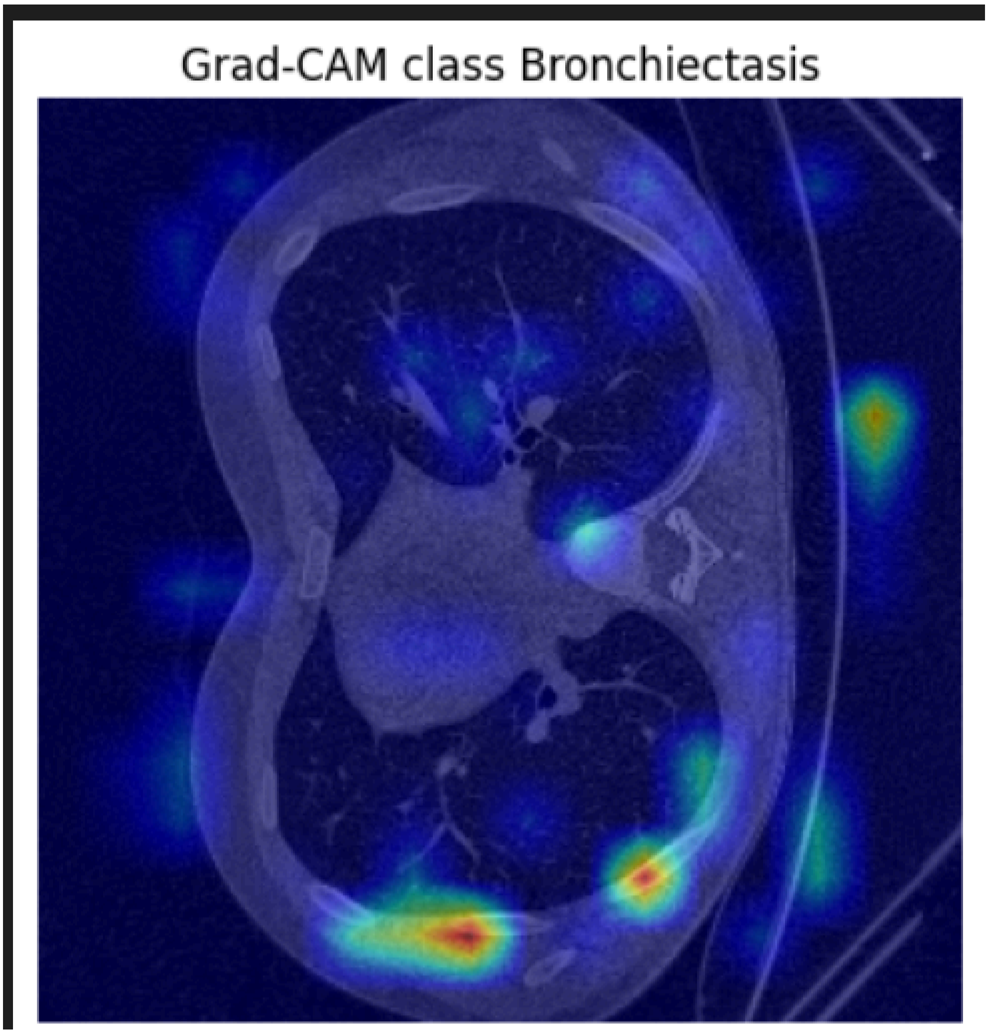

Grad-CAM class Cardiomegaly

Grad-CAM class Pleural effusion

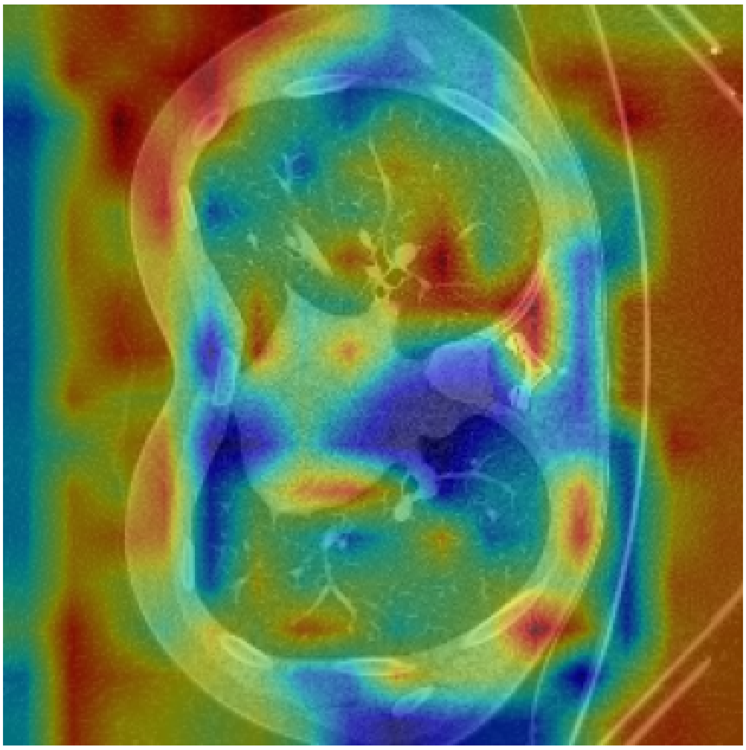




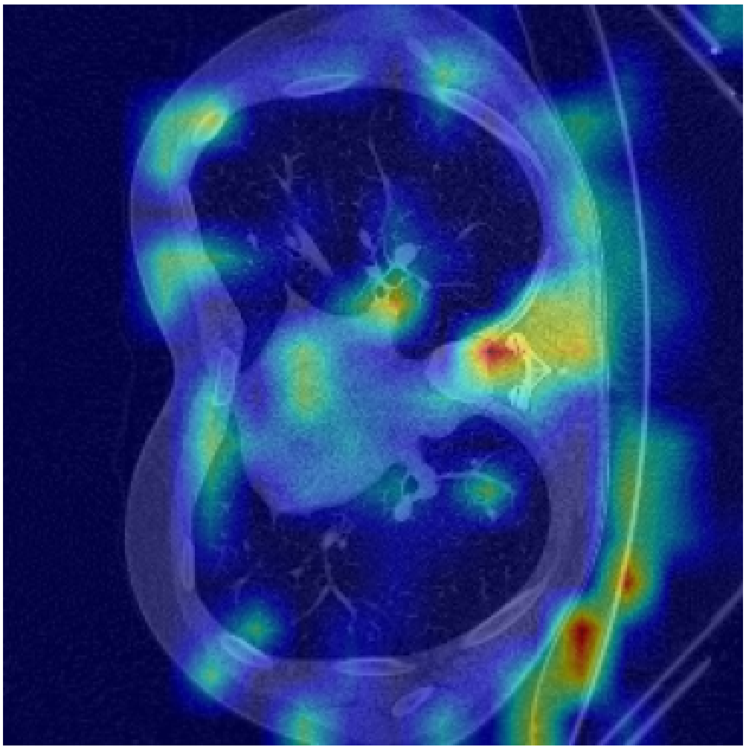
kelas dengan MCC terendah


Grad-CAM class Bronchiectasis

Grad-CAM class Pulmonary fibrotic sequela

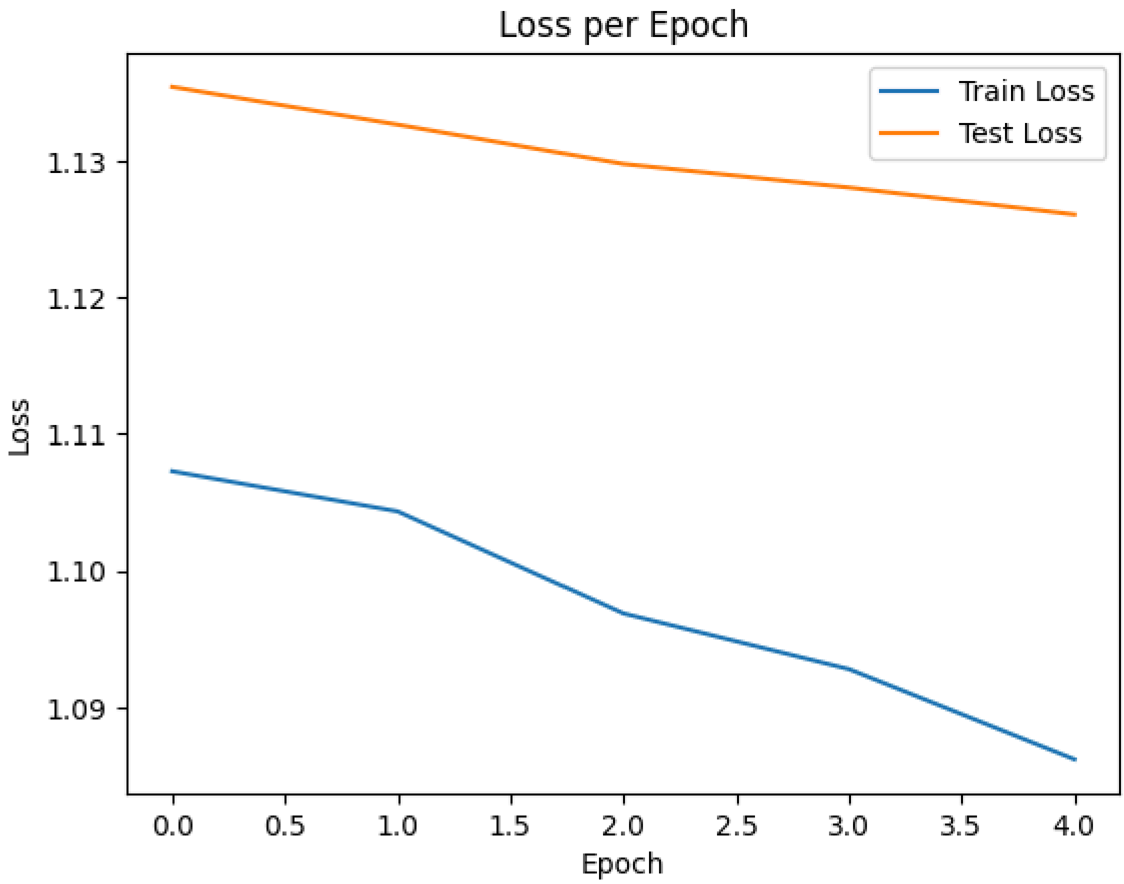


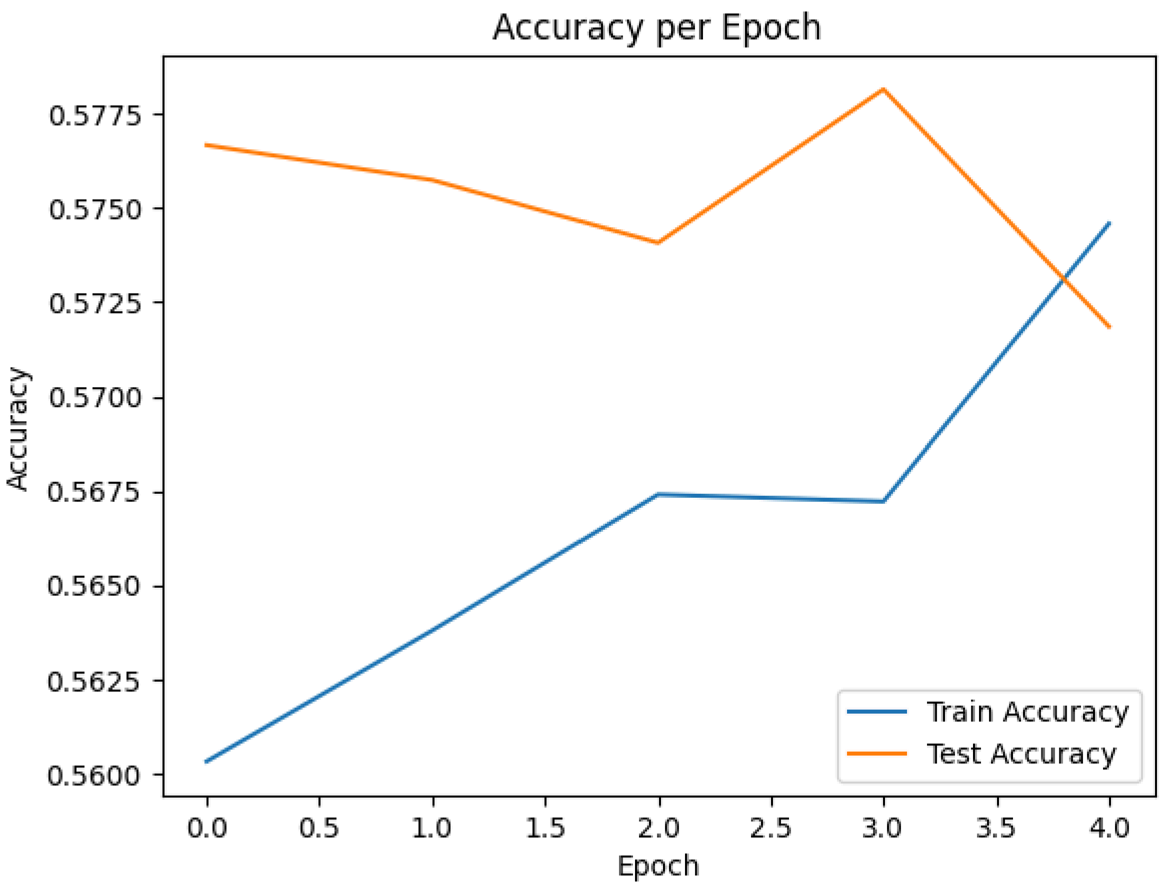
Grad-CAM class Lung opacity



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	0.709166666660757	0.24603174602523725	0.5923566878603594	0.7267497602998395	0.34766354724206483	0.2732502396905729
1	0.6449999999946251	0.43068391866117034	0.6638176637987516	0.6372202591208808	0.5224215198788182	0.36277974086734066
2	0.8533333333262223	0.3815028901513582	0.48888888885267484	0.8995305164234787	0.42857142361970824	0.10046948356713176
3	0.9066666666591112	0.3188405796639362	0.2528735631893249	0.957771787951862	0.2820512770816898	0.04222821203915339
4	0.6691666666610904	0.4020887728354546	0.47826086955036456	0.7391799544334945	0.4368794276491525	0.26082004555511595
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	0.6624548736342517	0.4380804953492557	0.5716510854277181	0.5619195046352644
10	0.5374999999955209	0.40337423312264764	0.6130536130393227	0.4954604409793066	0.4865864891908253	0.5045395590077232
11	0.5216666666623195	0.32075471697647673	0.6758409785726043	0.4639175257678818	0.4350393657049221	0.5360824742206635
12	0.8674999999927709	0.4999999998958333	0.1509433962169218	0.9769452449473878	0.23188405438633344	0.0230547550430062
13	0.7983333333266807	0.22388059700657162	0.6382978722725215	0.8119349005351544	0.3314917088440524	0.18806509945580413
14	0.6166666666615278	0.18235294117289505	0.6838235293614835	0.6080827067612022	0.28792569326141343	0.39191729322939933
15	0.7383333333271807	0.29599999998816	0.34905660375711994	0.8218623481698192	0.3203463153662788	0.17813765182005933
16	0.39166666666340283	0.14011976047736383	0.9069767441157381	0.32959850606601687	0.24273858688837574	0.6704014939246462
17	0.5483333333287639	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
0.511111111073251	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	0.152993380817257
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	0.1592829273785341
0.15596330273798503	0.8508914100348316	0.97084048025779	0.2086162435713583

Metric test

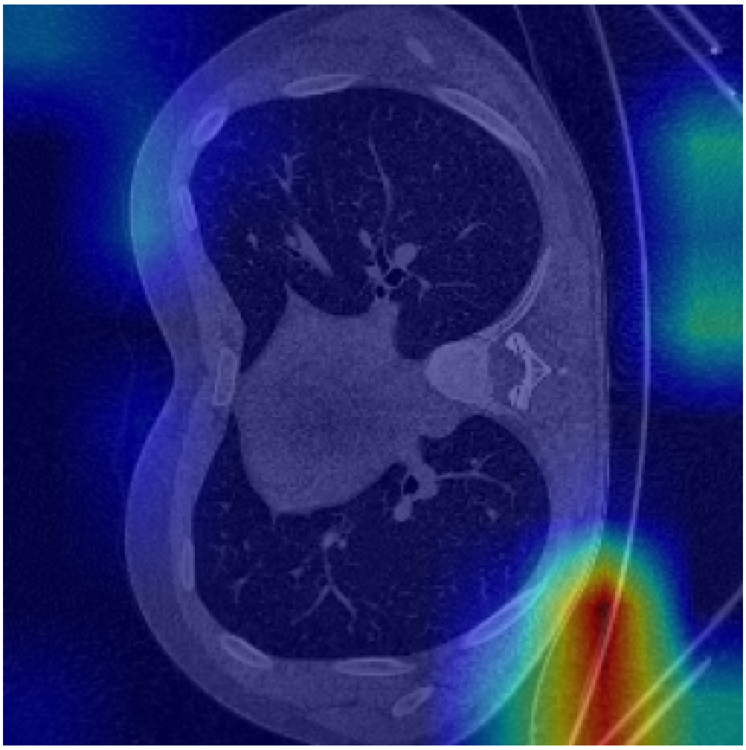
	# ACC	# Precision	# Recall	# Specificity	# F1
0	0.5433333333152222	0.14285714284742468	0.6562499997949218	0.5298507462488862	0.23463686854592555
1	0.6099999999796667	0.40799999996736	0.5425531914316433	0.6407766989980205	0.46575341971518525
2	0.8333333333055555	0.4090909089979339	0.4285714284693877	0.8992248061666966	0.41860464606814496
3	0.7466666666417777	0.17567567565193573	0.46428571411989794	0.7757352940891273	0.25490195675124955
4	0.5333333333155555	0.33908045975062756	0.7023809522973357	0.46759259257094477	0.45736433665825377
5	0.40333333331988885	0.13265306121772177	0.742857142644898	0.35849056602420787	0.225108222517569
6	0.5833333333138889	0.3586206896304399	0.6190476189739229	0.5694444444180813	0.45414846693083655
7	0.7166666666427778	0.26562499995849614	0.30909090903471076	0.8081632652731362	0.2857142806948663
8	0.659999999978	0.3678160919117453	0.4050632910879667	0.7511312216854692	0.3855421636398607
9	0.48999999998366667	0.43790849670340465	0.4999999999626865	0.48192771081434166	0.46689894969320983
10	0.5633333333145556	0.46399999996288005	0.4754098360266058	0.6235955055829441	0.4696356224930749
11	0.38999999998699997	0.30612244896709706	0.8522727271758782	0.19811320753782485	0.4504504465348231
12	0.8166666666394444	0.37777777769382714	0.3863636362758264	0.8906249999652099	0.382022466824895
13	0.3133333333228889	0.10480349344520508	0.959999999616	0.2545454545361983	0.18897637616312232
14	0.749999999975	0.24615384611597635	0.380952380861678	0.8100775193484466	0.29906541573587214
15	0.7166666666427778	0.25757575753673095	0.3207547169206123	0.8016194331659263	0.2857142807259375
16	0.743333333085556	0.1481481481207133	0.20512820507560814	0.8237547892404692	0.17204300584576265
17	0.873333333042222	0.26086956510396975	0.22222222213991769	0.9377289376945886	0.23999999493600008

# FPR	# FNR	# FDR	# NPV	# MCC
0.4701492537138004	0.3437499998925781	0.8571428570845481	0.9281045751027382	0.1149174863984101
0.35922330095343574	0.4574468084619738	0.5919999999526401	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	0.4999999999626865	0.5620915032312358	0.5442176870378083	-0.017972778710452376

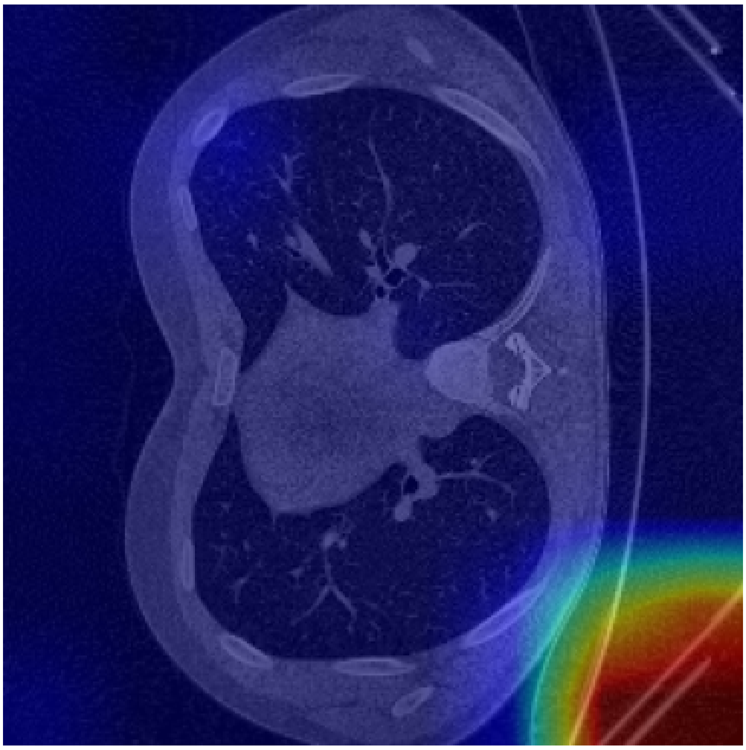
# FPR	# FNR	# FDR	# NPV	# MCC
0.37640449436087614	0.5245901638914271	0.53599999995712	0.6342857142494693	0.09864487176467432
0.8018867924150053	0.14772727271048555	0.6938775509920866	0.7636363634975206	0.05928627991011872
0.10937499999572754	0.6136363634969008	0.6222222220839506	0.8941176470237601	0.27443021509848686
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	0.8461538461176857	0.11266686338435034
0.17624521072121666	0.7948717946679815	0.8518518516941015	0.8739837398018705	0.025283101011410482
0.06227106226878128	0.7777777774897119	0.7391304344612476	0.9241877255984048	0.17204687828828036

Grid cam class val mcc terbesar

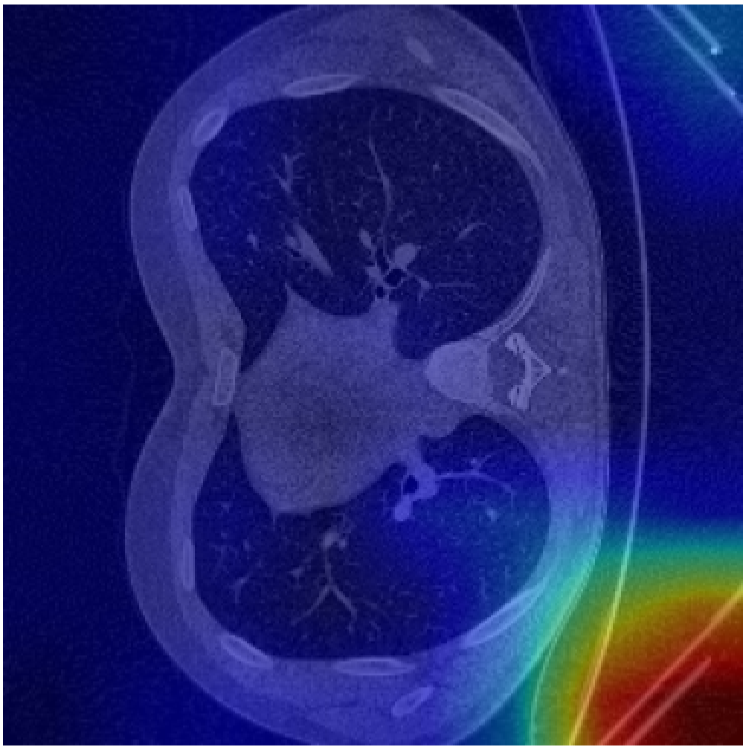
Grad-CAM class Cardiomegaly



Grad-CAM class Arterial wall calcification

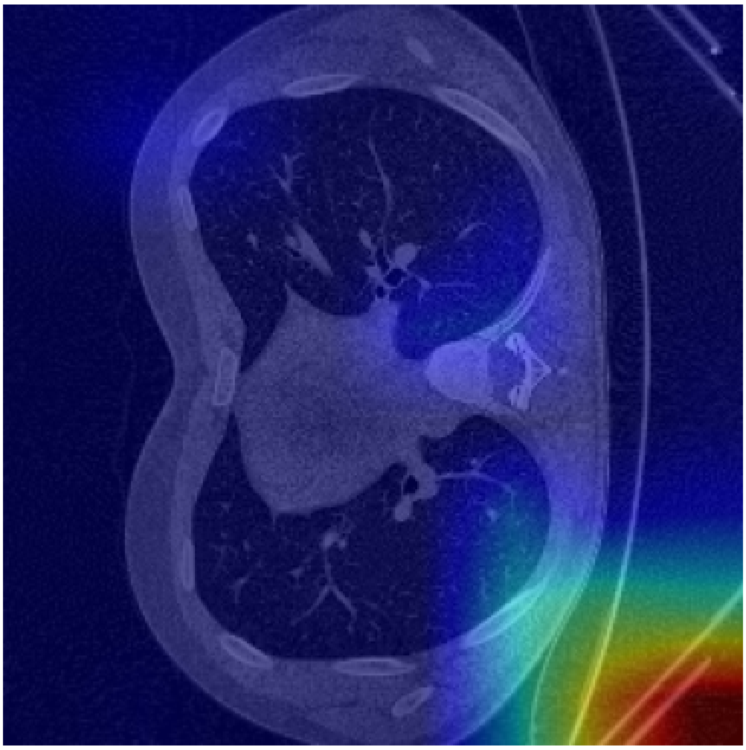


Grad-CAM class Mosaic attenuation pattern

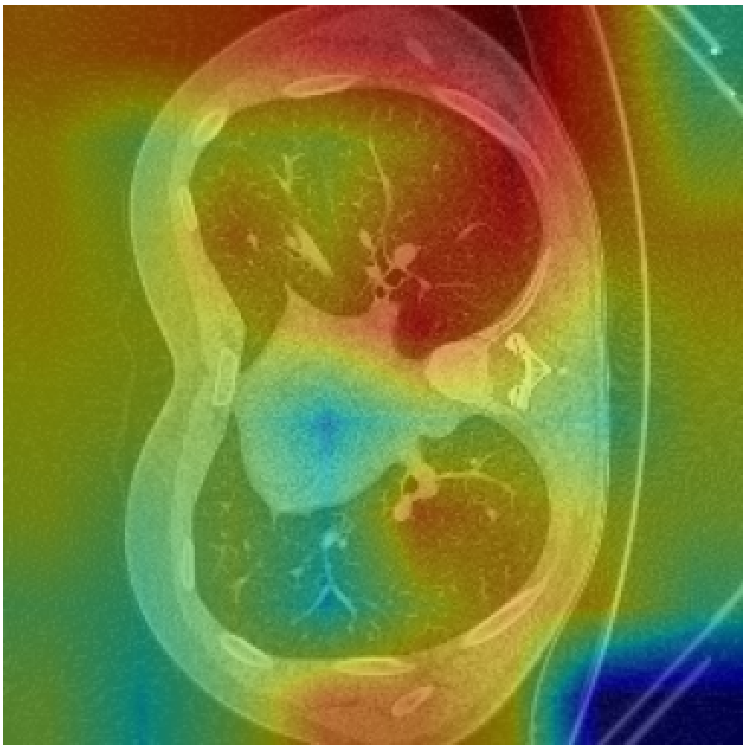


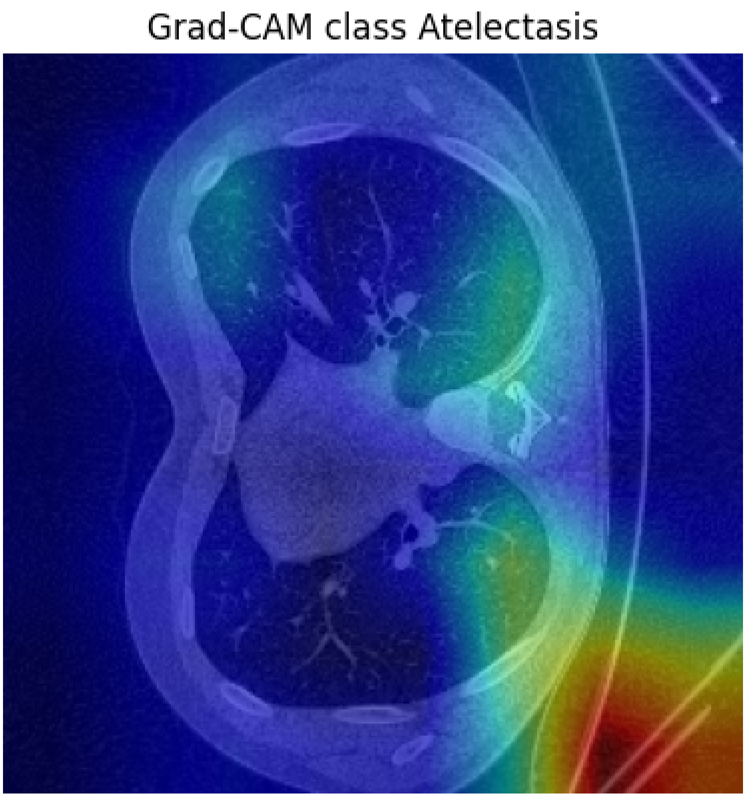
Class val dengan mcc terendah

Grad-CAM class Lung opacity



Grad-CAM class Pulmonary fibrotic sequela



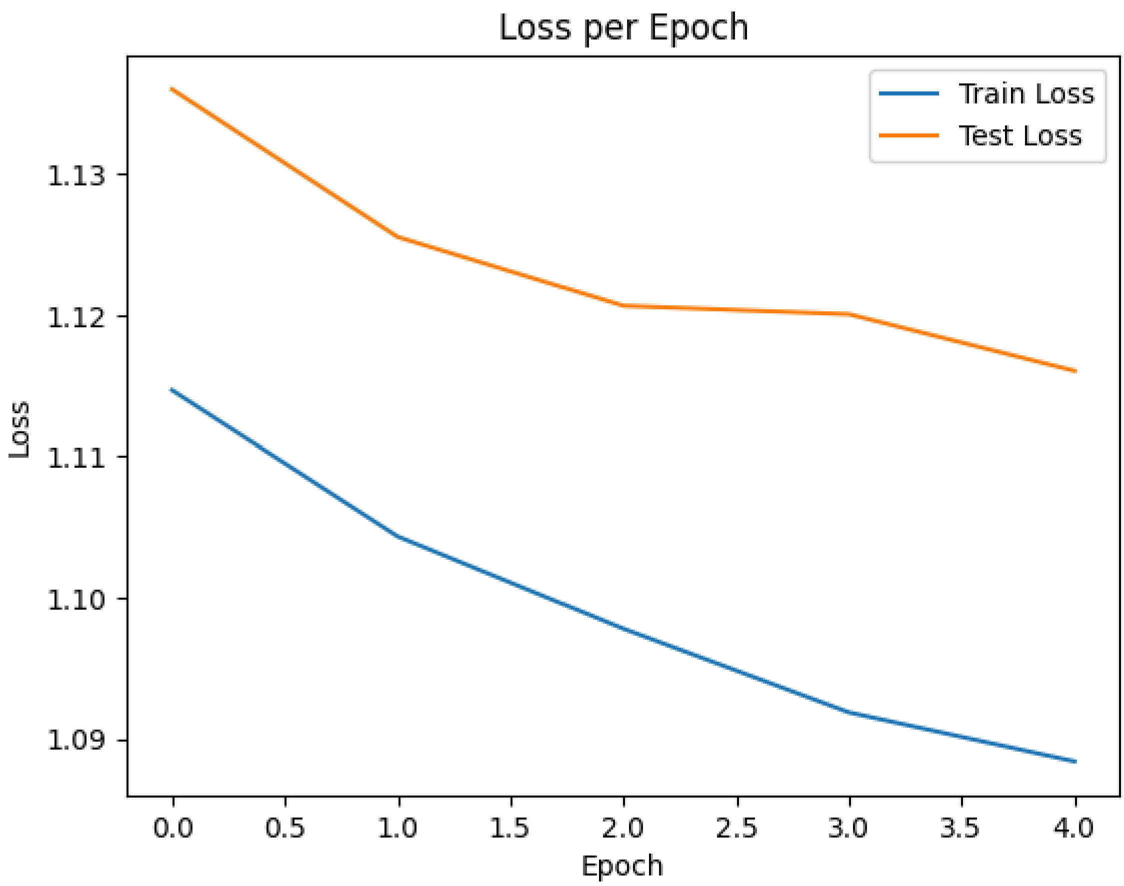


mAP (Train): 0.2041
mAP (Validation): 0.2226

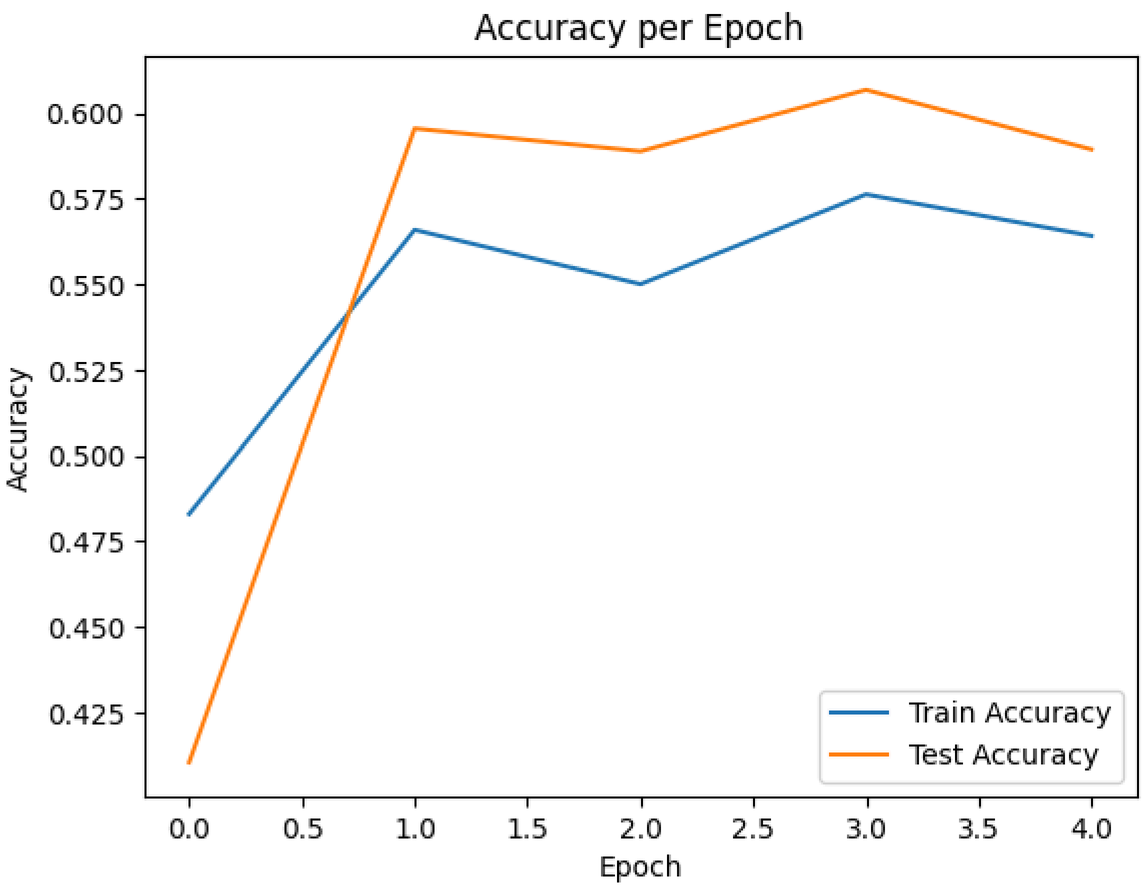
Percobaan dengan input model gambar 3D dengan model RACNET

```
/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. P
rocess 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 PyTorc
h but unallocated. If reserved but unallocated memory is large try setting PYTORCH_CUDA_ALLOC_CONF=expandable_segments:True to avoid fra
gmentation.  See documentation for Memory Management  (https://pytorch.org/docs/stable/notes/cuda.html#environment-variables)
```

Gamma = 1.2


Loss per Epoch
Train Loss
Test Loss
1.13
1.12
1.11
1.10
1.09
Loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch

\


Accuracy per Epoch
0.600
0.575
0.550
0.525
0.500
0.475
0.450
0.425
Accuracy
Train Accuracy
Test Accuracy
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Epoch

⋯	# ACC	# Precision	# Recall	# Specificity	# F1
0	0.6924999999942292	0.21957671957091066	0.5286624203484929	0.7171620325913983	0.3102803696733689
1	0.5791666666618404	0.3629893238369575	0.5811965811800229	0.5783274440450138	0.4468784180392985
2	0.7358333333272015	0.23699421964632963	0.6074074073624143	0.752112676049276	0.34095633690431837
3	0.8274999999931042	0.17741935482917098	0.37931034478398734	0.8625336927146224	0.24175823739805985
4	0.6283333333280973	0.37449392711792523	0.5745341614728405	0.6480637813138034	0.4534313677600562
5	0.4508333333295764	0.1761517615152283	0.7182320441592137	0.4033366045102715	0.28291621010588935
6	0.4874999999959375	0.30160857908442884	0.705329153582905	0.40862656072180903	0.42253520706343106
7	0.7616666666603195	0.26399999997888	0.14537444933280289	0.9054470709053911	0.18749999540918788
8	0.5516666666620695	0.35311572699772825	0.6999999999794118	0.4930232558082065	0.4694280034227716
9	0.518333333329014	0.47993311035986735	0.5180505415068943	0.5185758513851614	0.49826388388753257

	# ACC	# Precision	# Recall	# Specificity	# F1
10	0.5516666666620695	0.4119547657445565	0.5944055943917388	0.527885862509366	0.4866412165291031
11	0.28999999999758336	0.2754491017940509	0.9847094800922107	0.02978235967892574	0.4304812800006167
12	0.7066666666607778	0.2384823848173853	0.5534591194620466	0.7300672430285297	0.3333333291164204
13	0.528333333289306	0.11935483870775233	0.7872340424694433	0.5063291139194727	0.20728291087305512
14	0.5924999999950625	0.14770459081541507	0.5441176470188148	0.5986842105206891	0.232339086116287 8
15	0.37916666666350696	0.20089786756227948	0.84433962260 1682	0.2793522267178203 4	0.32456935318989094
16	0.814166666659882	0.1642857142739796	0.17829457362958956	0.8907563025126914	0.17100371246776594
17	0.9016666666591528	0.3333333332098765	0.08256880733187442	0.9835013748764116	0.1323529379746973

# FPR	# FNR	# FDR	# NPV	# MCC
0.28283796739901407	0.47133757958781286	0.7804232804026343	0.9099756690886864	0.17845768428034728
0.4216725559432076	0.4188034187914871	0.6370106761452489	0.7695924764769656	0.14543033543147774
0.24788732394133442	0.39259259256351164	0.7630057803247686	0.9379391100592747	0.25078286485077267
0.13746630727639295	0.6206896551010702	0.8225806451170655	0.946745562120840 7	0.17328746302549125
0.3519362186748071	0.42546583849610353	0.6255060728618318	0.8059490084871679	0.20041513481984496
0.596663395479915	0.28176795578553765	0.8238482384712216	0.8896103895911339	0.08941261571556795
0.5913734392668403	0.294670846385747	0.6983914209021663	0.7929515418327544	0.10380590604025468
0.09455292908433142	0.8546255506231443	0.7359999999411201	0.8195348837133067	0.0651565022459828
0.5069767441801515	0.29999999999117644	0.6468842729874349	0.8060836501747892	0.17529741044682387
0.4814241485993588	0.48194945847505505	0.5200668896234103	0.5564784053063708	0.03651879625415082

Python

# FPR	# FNR	# FDR	# NPV	# MCC
0.4721141374776639	0.4055944055849512	0.5880452342392885	0.7005163511067036	0.11727854340693254
0.9702176403096195	0.01529051987720824	0.7245508981973948	0.8387096771488033	0.040673956536585246
0.26993275696186425	0.4465408804750603	0.7615176151555144	0.914560770145432 5	0.20830691069199464
0.49367088607148585	0.21276595742417384	0.8806451612761186	0.9655172413626635	0.15784586066068548
0.4013157894699125	0.45588235290765566	0.8522954091646249	0.9113018597866767	0.09179450287335952
0.7206477732720582	0.1556603773511481	0.7991021324264972	0.8932038834662394	0.10788706881174008
0.1092436974779716	0.821705426292891	0.8357142856545918	0.8999999999915095	0.06662570747304748
0.01649862511442256	0.9174311925763825	0.666666666419753	0.9147485080910934	0.1280266084457049

mAP (Train): 0.2644

⋯	# ACC	# Precision	# Recall	# Specificity	# F1
0	0.7466666666417777	0.17647058820934258	0.3749999998828125	0.7910447760898863	0.2399999956000001
1	0.59999999998	0.40845070419658797	0.6170212765301042	0.592233009679988 7	0.491525418889396 1
2	0.6066666666464444	0.22463768114314217	0.7380952379195012	0.5852713178067724	0.34444444082839504
3	0.8966666666367777	0.333333329629629	0.10714285710459183	0.9779411764346345	0.16216215839298767
4	0.5899999999803334	0.34146341460638513	0.4999999999404762	0.6249999999710648	0.4057970965875517
5	0.809999999973	0.176470588183391	0.17142857137959183	0.8943396226077608	0.17391303842890163
6	0.4933333333168889	0.3229166666498481	0.7380952380073696	0.3981481481297153 3	0.4492753580518799
7	0.2533333333248889	0.1835205992440629	0.8909090907471074	0.1102040816281549 3	0.3043478232354076
8	0.30999999998966665	0.2730496453803883	0.9746835441804199	0.07239819004197293	0.4265927943413571
9	0.5799999999806666	0.6111111109413581	0.16417910446535977	0.9156626505472492	0.2588235260429066

	# ACC	# Precision	# Recall	# Specificity	# F1
10	0.5666666666477778	0.4740259739951931	0.598360655688659	0.5449438201941043	0.5289855022752575
11	0.3166666666561111	0.3003412969180771	0.9999999998863637	0.033018867922970804	0.4619422536411295
12	0.8466666666384445	0.4285714282653061	0.1363636363264462	0.9687499999621582	0.20689654799048754
13	0.419999999986	0.11398963729979328	0.87999999999648	0.3781818181680661	0.20183486033625117
14	0.7966666666401111	0.22857142850612244	0.190476190430839	0.8953488371745989	0.20779220277955823
15	0.6933333333102222	0.2253521126443166 2	0.3018867923958704	0.7773279351912012	0.258064511192768
16	0.48999999998366667	0.11999999999199999	0.46153846142011834	0.4942528735442815	0.19047618718065007
17	0.8866666666371111	0.26666666648888887	0.14814814809327845	0.9597069596718055	0.1904761857936509

# FPR	# FNR	# FDR	# NPV	# MCC
0.20895522387280016	0.6249999998046875	0.8235294116435987	0.9137931034088882	0.1224247298437256
0.4077669902714676	0.3829787233635129	0.5915492957329894	0.7721518986853068	0.194401308604207
0.41472868215446784	0.26190476184240363	0.775362318784394	0.9320987653745617	0.22512957362855393
0.022058823528600078	0.8928571425382653	0.6666666659259258	0.9140893470476258	0.1450921074936019
0.3749999999826389	0.4999999999404762	0.6585365853123142	0.7627118643636885	0.11411358324106621
0.10566037735450338	0.8285714283346939	0.8235294115224914	0.8909774435755271	0.06660281711746142
0.6018518518239884	0.2619047618735828	0.6770833332980686	0.7962962962225653	0.12744401813416534
0.8897959183310287	0.10909090907107438	0.8164794007184839	0.8181818179338842	0.001376620623384883
0.9276018099127782	0.025316455692997918	0.7269503545841507	0.8888888883950616	0.08731750713228086
0.0843373493925098	0.8358208954600134	0.3888888887808642	0.5757575757357667	0.12214714048677087

# FPR	# FNR	# FDR	# NPV	# MCC
0.4550561797497159	0.40163934422937386	0.5259740259398717	0.6643835615983299	0.14083574112193434
0.9669811320298594	0.0	0.6996587030477932	0.9999999985714286	0.09958378189021537
0.031249999998779296	0.8636363634400827	0.5714285710204081	0.8671328671025478	0.1763024498123226
0.6218181817955702	0.119999999952	0.8860103626483932	0.9719626167315923	0.1489674771472825
0.10465116278664142	0.8095238093310657	0.7714285712081632	0.8716981131746528	0.09276656832713102
0.22267206476831286	0.6981132074154504	0.7746478872148383	0.8384279475616406	0.07107967435038343
0.5057471264174043	0.5384615383234714	0.8799999999413333	0.8599999999426666	-0.02973505167250263
0.04029304029156436	0.8518518515363511	0.7333333328444444	0.919298245581779	0.14162367623847627

Grad-CAM class Atelectasis