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## Lampiran

### Lampiran 1. Log Training Model

#### *EfficientNetV2B0*

```

Epoch 1/10
46/46 _____ 96s 2s/step - accuracy: 0.8682 - loss: 7.6445 -
val_accuracy: 0.9794 - val_loss: 2.3710
Epoch 2/10
46/46 _____ 76s 2s/step - accuracy: 0.9910 - loss: 1.8386 -
val_accuracy: 0.9937 - val_loss: 0.9087
Epoch 3/10
46/46 _____ 76s 2s/step - accuracy: 0.9862 - loss: 0.8107 -
val_accuracy: 0.9825 - val_loss: 0.6142
Epoch 4/10
46/46 _____ 77s 2s/step - accuracy: 0.9882 - loss: 0.5970 -
val_accuracy: 0.9889 - val_loss: 0.4540
Epoch 5/10
46/46 _____ 76s 2s/step - accuracy: 0.9777 - loss: 0.4875 -
val_accuracy: 0.9825 - val_loss: 0.4101
Epoch 6/10
46/46 _____ 76s 2s/step - accuracy: 0.9919 - loss: 0.3702 -
val_accuracy: 0.9937 - val_loss: 0.3012
Epoch 7/10
46/46 _____ 80s 2s/step - accuracy: 0.9973 - loss: 0.2778 -
val_accuracy: 0.9968 - val_loss: 0.2498
Epoch 8/10
46/46 _____ 82s 2s/step - accuracy: 0.9844 - loss: 0.3053 -
val_accuracy: 0.9921 - val_loss: 0.3242
Epoch 9/10
46/46 _____ 74s 2s/step - accuracy: 0.9894 - loss: 0.3127 -
val_accuracy: 0.9841 - val_loss: 0.2906
Epoch 10/10
46/46 _____ 73s 2s/step - accuracy: 0.9932 - loss: 0.2638 -
val_accuracy: 0.9905 - val_loss: 0.2167

```

#### *MobileNetV3*

```

Epoch 1/10
46/46 _____ 69s 1s/step - accuracy: 0.8082 - loss: 7.3196 -
val_accuracy: 0.9905 - val_loss: 3.2173
Epoch 2/10
46/46 _____ 62s 1s/step - accuracy: 0.9875 - loss: 2.8177 -
val_accuracy: 0.9889 - val_loss: 1.9202
Epoch 3/10
46/46 _____ 61s 1s/step - accuracy: 0.9929 - loss: 1.7307 -
val_accuracy: 0.9889 - val_loss: 1.3210
Epoch 4/10
46/46 _____ 61s 1s/step - accuracy: 0.9885 - loss: 1.2366 -
val_accuracy: 0.9857 - val_loss: 1.0070
Epoch 5/10
46/46 _____ 60s 1s/step - accuracy: 0.9904 - loss: 0.9431 -

```

```

val_accuracy: 0.9937 - val_loss: 0.7909
Epoch 6/10
46/46 ----- 60s 1s/step - accuracy: 0.9941 - loss: 0.7459 -
val_accuracy: 0.9921 - val_loss: 0.6939
Epoch 7/10
46/46 ----- 60s 1s/step - accuracy: 0.9950 - loss: 0.6565 -
val_accuracy: 0.9984 - val_loss: 0.5279
Epoch 8/10
46/46 ----- 60s 1s/step - accuracy: 0.9958 - loss: 0.5108 -
val_accuracy: 0.9905 - val_loss: 0.4772
Epoch 9/10
46/46 ----- 61s 1s/step - accuracy: 0.9918 - loss: 0.4655 -
val_accuracy: 0.9889 - val_loss: 0.4265
Epoch 10/10
46/46 ----- 60s 1s/step - accuracy: 0.9945 - loss: 0.3940 -
val_accuracy: 0.9810 - val_loss: 0.3969

```

### *NASNetMobile*

```

Epoch 1/10
46/46 ----- 116s 2s/step - accuracy: 0.7891 - loss: 7.5881 -
val_accuracy: 0.9159 - val_loss: 1.5261
Epoch 2/10
46/46 ----- 87s 2s/step - accuracy: 0.9070 - loss: 1.6069 -
val_accuracy: 0.9254 - val_loss: 1.2891
Epoch 3/10
46/46 ----- 88s 2s/step - accuracy: 0.8926 - loss: 1.4356 -
val_accuracy: 0.9429 - val_loss: 0.9096
Epoch 4/10
46/46 ----- 86s 2s/step - accuracy: 0.8874 - loss: 1.5890 -
val_accuracy: 0.9143 - val_loss: 1.1134
Epoch 5/10
46/46 ----- 84s 2s/step - accuracy: 0.8847 - loss: 1.9920 -
val_accuracy: 0.8889 - val_loss: 1.5435
Epoch 6/10
46/46 ----- 83s 2s/step - accuracy: 0.9158 - loss: 1.0672 -
val_accuracy: 0.9476 - val_loss: 0.7714
Epoch 7/10
46/46 ----- 83s 2s/step - accuracy: 0.9381 - loss: 0.8437 -
val_accuracy: 0.9429 - val_loss: 0.7372
Epoch 8/10
46/46 ----- 84s 2s/step - accuracy: 0.9279 - loss: 0.8153 -
val_accuracy: 0.9635 - val_loss: 0.5899
Epoch 9/10
46/46 ----- 90s 2s/step - accuracy: 0.9495 - loss: 0.6060 -
val_accuracy: 0.9619 - val_loss: 0.5588
Epoch 10/10
46/46 ----- 133s 2s/step - accuracy: 0.9491 - loss: 0.5718 -
val_accuracy: 0.9492 - val_loss: 0.5876

```

## DenseNet121

Epoch 1/10

46/46 ————— 241s 5s/step - accuracy: 0.8102 - loss: 27.3806 -  
val\_accuracy: 0.9746 - val\_loss: 4.4586

Epoch 2/10

46/46 ————— 219s 5s/step - accuracy: 0.9627 - loss: 4.4634 -  
val\_accuracy: 0.9778 - val\_loss: 3.2087

Epoch 3/10

46/46 ————— 219s 5s/step - accuracy: 0.9590 - loss: 3.7641 -  
val\_accuracy: 0.9810 - val\_loss: 2.6573

Epoch 4/10

46/46 ————— 196s 4s/step - accuracy: 0.9618 - loss: 3.6503 -  
val\_accuracy: 0.9810 - val\_loss: 2.6091

Epoch 5/10

46/46 ————— 196s 4s/step - accuracy: 0.9834 - loss: 2.5750 -  
val\_accuracy: 0.9746 - val\_loss: 2.5057

Epoch 6/10

46/46 ————— 197s 4s/step - accuracy: 0.9817 - loss: 1.9752 -  
val\_accuracy: 0.9921 - val\_loss: 1.6391

Epoch 7/10

46/46 ————— 198s 4s/step - accuracy: 0.9793 - loss: 1.8167 -  
val\_accuracy: 0.9810 - val\_loss: 1.8012

Epoch 8/10

46/46 ————— 198s 4s/step - accuracy: 0.9858 - loss: 1.6830 -  
val\_accuracy: 0.9698 - val\_loss: 1.9331

Epoch 9/10

46/46 ————— 203s 4s/step - accuracy: 0.9768 - loss: 1.7394 -  
val\_accuracy: 0.9889 - val\_loss: 1.4039

Epoch 10/10

46/46 ————— 195s 4s/step - accuracy: 0.9845 - loss: 1.4578 -  
val\_accuracy: 0.9825 - val\_loss: 1.3594



## Lampiran 2. Source code implementasi model

```

import streamlit as st
from PIL import Image, ImageChops
import numpy as np
from tensorflow.keras.applications import mobilenet_v3
from tensorflow.keras.models import load_model
from huggingface_hub import hf_hub_download

preprocess_input = mobilenet_v3.preprocess_input

# Set page configuration
st.set_page_config(
    page_title="Klasifikasi Tuberkulosis",
    page_icon="🏠",
    layout="centered",
)

# Load your trained model
@st.cache_resource
def load_my_model():
    # Download the MobileNetV3 model from the Hugging Face Hub
    model_path = hf_hub_download(repo_id="reaim70/MobileNetV3.keras",
    filename="MobileNetV3.keras")
    model = load_model(model_path)
    return model

model = load_my_model()

# Fungsi prediksi menggunakan model yang dimuat
def predict(image):
    # Preprocess the image to match the input shape the model expects
    img = image.resize((224, 224)) # Ganti ukuran sesuai dengan input model Anda
    img_array = np.array(img)

    # Ensure the image has 3 channels (RGB)
    if img_array.shape[-1] == 3: # Already RGB
        img_array = preprocess_input(img_array)
    else: # Grayscale or other format
        img_array = np.stack((img_array,) * 3, axis=-1) # Convert to RGB
        img_array = preprocess_input(img_array)

    img_array = np.expand_dims(img_array, axis=0) # Add batch dimension
    prediction = model.predict(img_array)

    # Assuming model output is probability, choose the class with highest
    probability
    if prediction[0][0] > prediction[0][1]:
        return "Normal"
    else:
        return "Tuberkulosis"

def is_chest_xray(image):

```

```

# Check image dimensions and aspect ratio
width, height = image.size
aspect_ratio = width / height

# Typical chest X-ray aspect ratio is approximately 0.7 - 1.3
if not (0.7 < aspect_ratio < 1.3):
    return False

# Convert the image to grayscale and check if it's nearly grayscale
grayscale_image = image.convert("L")
diff = ImageChops.difference(image.convert("RGB"),
grayscale_image.convert("RGB"))

# Check the difference (whether the image is close to grayscale)
diff_stat = diff.getbbox()

# If there is no bounding box (None), the image is already grayscale
if diff_stat is None:
    return True

return False

# Title of the web app
st.title("Klasifikasi Tuberkulosis")

# Center the icon representation
st.markdown(
    """
    <div style='text-align: center; margin-bottom: 20px;'>
        <i class="fas fa-lungs" style='font-size: 100px; color: grey;'></i>
    </div>
    """, unsafe_allow_html=True
)

# Container for upload and results
with st.container():
    # File uploader
    uploaded_file = st.file_uploader("Upload Gambar Rontgen Dada", type=["jpg",
"jpeg", "png"])

    if uploaded_file is not None:
        image = Image.open(uploaded_file)

        # Columns for image preview and detection button
        col1, col2 = st.columns([1, 1])
        with col1:
            st.image(image, caption='Gambar yang diupload',
use_column_width=True)

        with col2:
            if st.button("Klasifikasi"):
                # Display loading message
                with st.spinner('Mengklasifikasi...'):

```

```
# Check if the uploaded image is likely a chest X-ray
if not is_chest_xray(image):
    st.warning("Bukan Citra Rontgen Dada")
else:
    # Prediction using the Loaded model
    result = predict(image)

    # Display result below the button
    st.subheader("Hasil Klasifikasi")
    if result == "Normal":
        st.success("Terklasifikasi Normal")
    else:
        st.error("Terklasifikasi Tuberkulosis")
```

## Lampiran 1. Riwayat Hidup



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