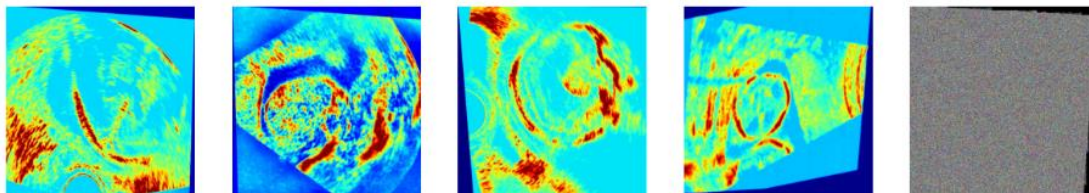
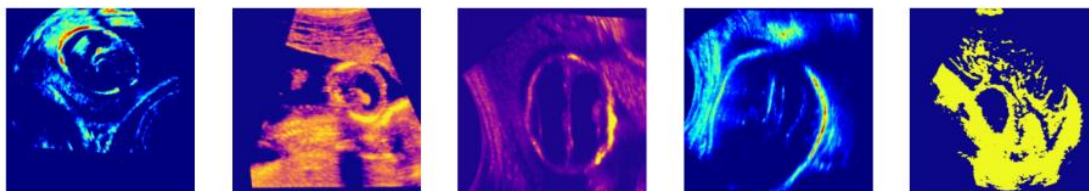


## Medical Image Classification Using Multi-Head Attention and LSTM

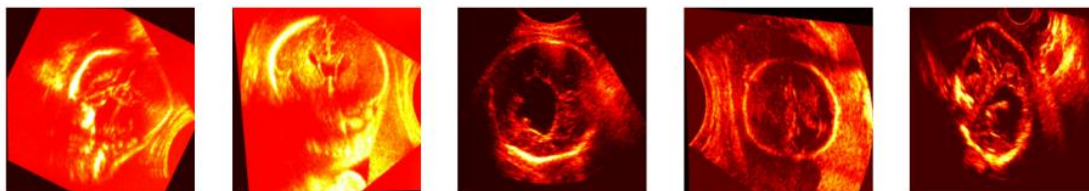
Cluster 0:



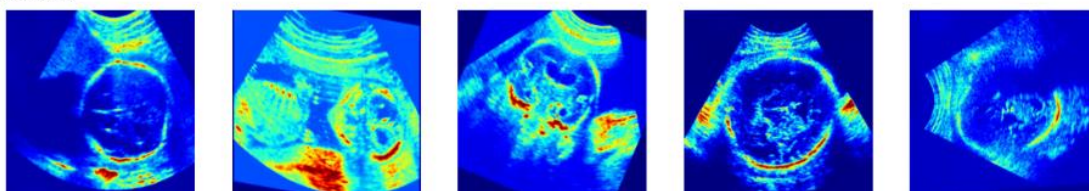
Cluster 1:



Cluster 2:



Cluster 3:



```
import numpy as np
import pandas as pd
import os
```

```
base_path = '/kaggle/input/medical-imaging-fetal-colored-new-dataset-umrict/Fetal Head Abnormalities Classification/Fetal Head Abnormalities Classification/data'
```

```
categories = [
    "3D_Rendering",
    "3D_Volume_Rendering",
    "Adaptive_Histogram_Equalization",
    "Alpha_Blending",
    "Basic_Color_Map",
    "Contrast_Stretching",
    "Edge_Detection",
    "Gamma_Correction",
    "Gaussian_Blur",
    "Heatmap_Visualization",
```

```

    "Interactive_Segmentation",
    "LUT_Color_Map",
    "Random_Color_Palette"
]

image_paths = []
labels = []

for category in categories:
    category_path = os.path.join(base_path, category)
    for image_name in os.listdir(category_path):
        image_path = os.path.join(category_path, image_name)
        image_paths.append(image_path)
        labels.append(category)

df = pd.DataFrame({
    "image_path": image_paths,
    "label": labels
})

df.head()

           image_path      label
0  /kaggle/input/medical-imaging-fetal-colored-...  3D_Rendering
1  /kaggle/input/medical-imaging-fetal-colored-...  3D_Rendering
2  /kaggle/input/medical-imaging-fetal-colored-...  3D_Rendering
3  /kaggle/input/medical-imaging-fetal-colored-...  3D_Rendering
4  /kaggle/input/medical-imaging-fetal-colored-...  3D_Rendering

df.tail()

           image_path
label
12657  /kaggle/input/medical-imaging-fetal-colored-...
Random_Color_Palette
12658  /kaggle/input/medical-imaging-fetal-colored-...
Random_Color_Palette
12659  /kaggle/input/medical-imaging-fetal-colored-...
Random_Color_Palette
12660  /kaggle/input/medical-imaging-fetal-colored-...
Random_Color_Palette
12661  /kaggle/input/medical-imaging-fetal-colored-...
Random_Color_Palette

df.shape

(12662, 2)

df.columns

Index(['image_path', 'label'], dtype='object')
```

```
df.duplicated().sum()
```

```
0
```

```
df.isnull().sum()
```

```
image_path    0
```

```
label         0
```

```
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 12662 entries, 0 to 12661
```

```
Data columns (total 2 columns):
```

#	Column	Non-Null Count	Dtype
0	image_path	12662 non-null	object
1	label	12662 non-null	object

```
dtypes: object(2)
```

```
memory usage: 198.0+ KB
```

```
df['label'].unique()
```

```
array(['3D_Rendering', '3D_Volume_Rendering',  
      'Adaptive_Histogram_Equalization', 'Alpha_Blending',  
      'Basic_Color_Map', 'Contrast_Stretching', 'Edge_Detection',  
      'Gamma_Correction', 'Gaussian_Blur', 'Heatmap_Visualization',  
      'Interactive_Segmentation', 'LUT_Color_Map',  
      'Random_Color_Palette'], dtype=object)
```

```
df['label'].value_counts()
```

label	
3D_Rendering	974
3D_Volume_Rendering	974
Adaptive_Histogram_Equalization	974
Alpha_Blending	974
Basic_Color_Map	974
Contrast_Stretching	974
Edge_Detection	974
Gamma_Correction	974
Gaussian_Blur	974
Heatmap_Visualization	974
Interactive_Segmentation	974
LUT_Color_Map	974
Random_Color_Palette	974
Name: count, dtype: int64	

```
import seaborn as sns
```

```
import matplotlib.pyplot as plt
```

```

def visualize_label_distribution(df, label_column="label", figsize=(10, 6),
palette="viridis"):
    """
    Visualizes the distribution of labels in a DataFrame using count and pie
    charts.

    Args:
        df (pd.DataFrame): The DataFrame containing the Label data.
        label_column (str): The name of the column containing the labels.
    Defaults to "label".
        figsize (tuple): The figure size for the plots. Defaults to (10, 6).
        palette (str): The color palette to use. Defaults to "viridis".
    """

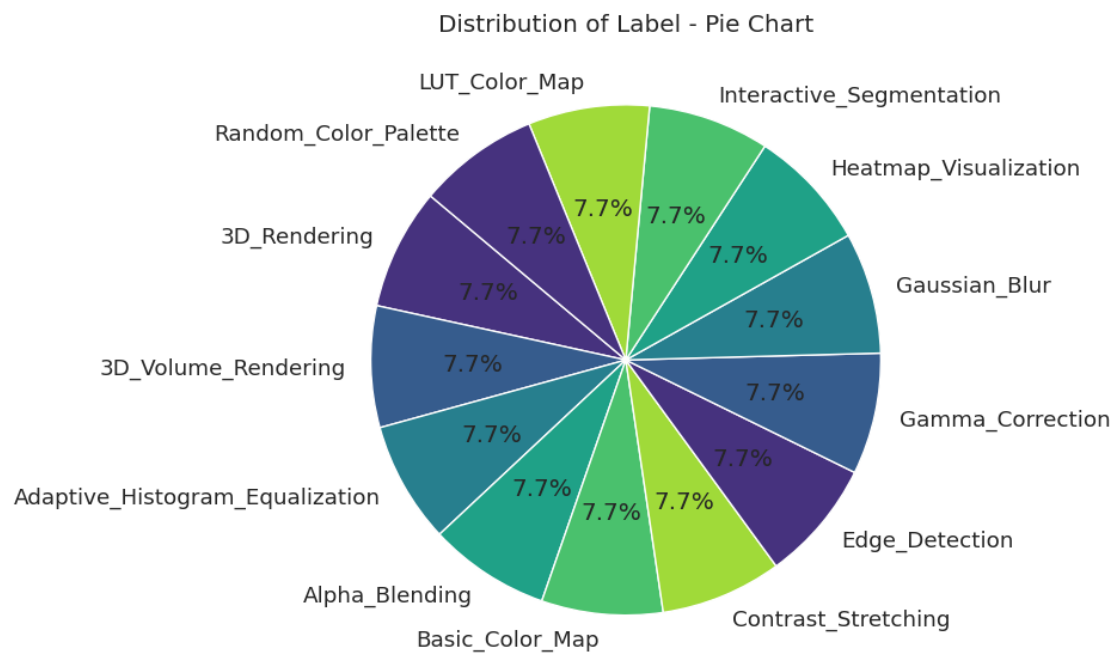
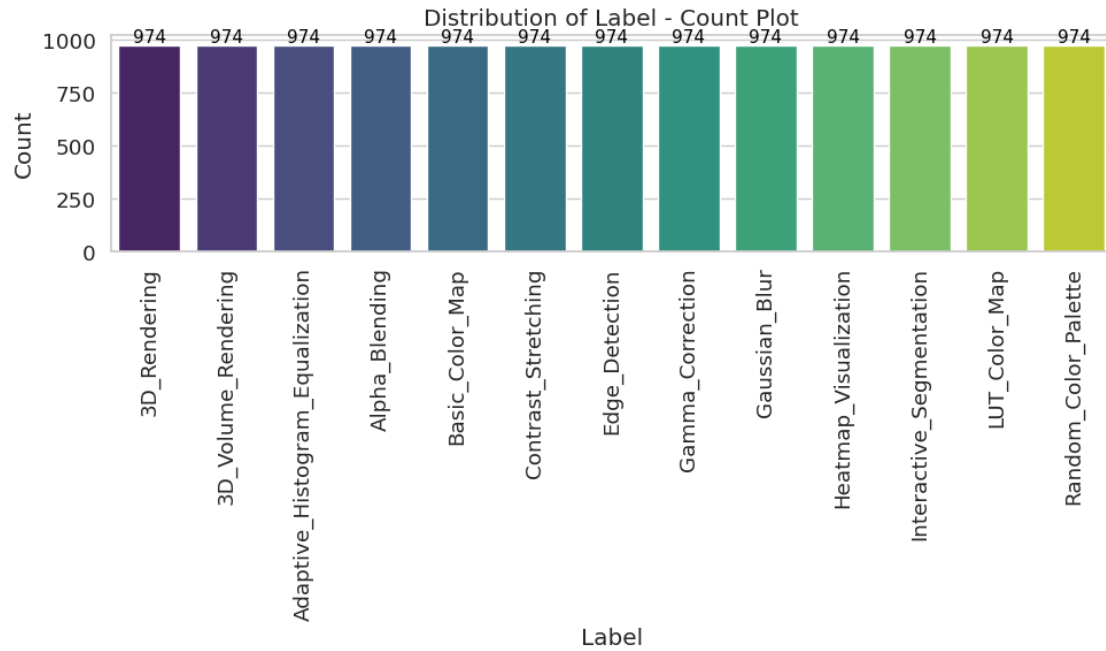
    plt.figure(figsize=figsize)
    ax = sns.countplot(data=df, x=label_column, palette=palette)
    plt.title(f"Distribution of {label_column.capitalize()} - Count Plot")
    plt.xticks(rotation = 90)
    plt.xlabel(label_column.capitalize())
    plt.ylabel("Count")

    for p in ax.patches:
        ax.annotate(f'{int(p.get_height())}',
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha='center', va='center', fontsize=11, color='black',
xytext=(0, 5),
                    textcoords='offset points')
    plt.tight_layout()
    plt.show()

    label_counts = df[label_column].value_counts()
    plt.figure(figsize=figsize)
    plt.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
startangle=140, colors=sns.color_palette(palette))
    plt.title(f"Distribution of {label_column.capitalize()} - Pie Chart")
    plt.tight_layout()
    plt.show()

visualize_label_distribution(df)

```



```
import cv2

num_images = 5

plt.figure(figsize=(20, 30))

for i, category in enumerate(categories):
    category_images = df[df['label'] ==
category]['image_path'].iloc[:num_images]
```

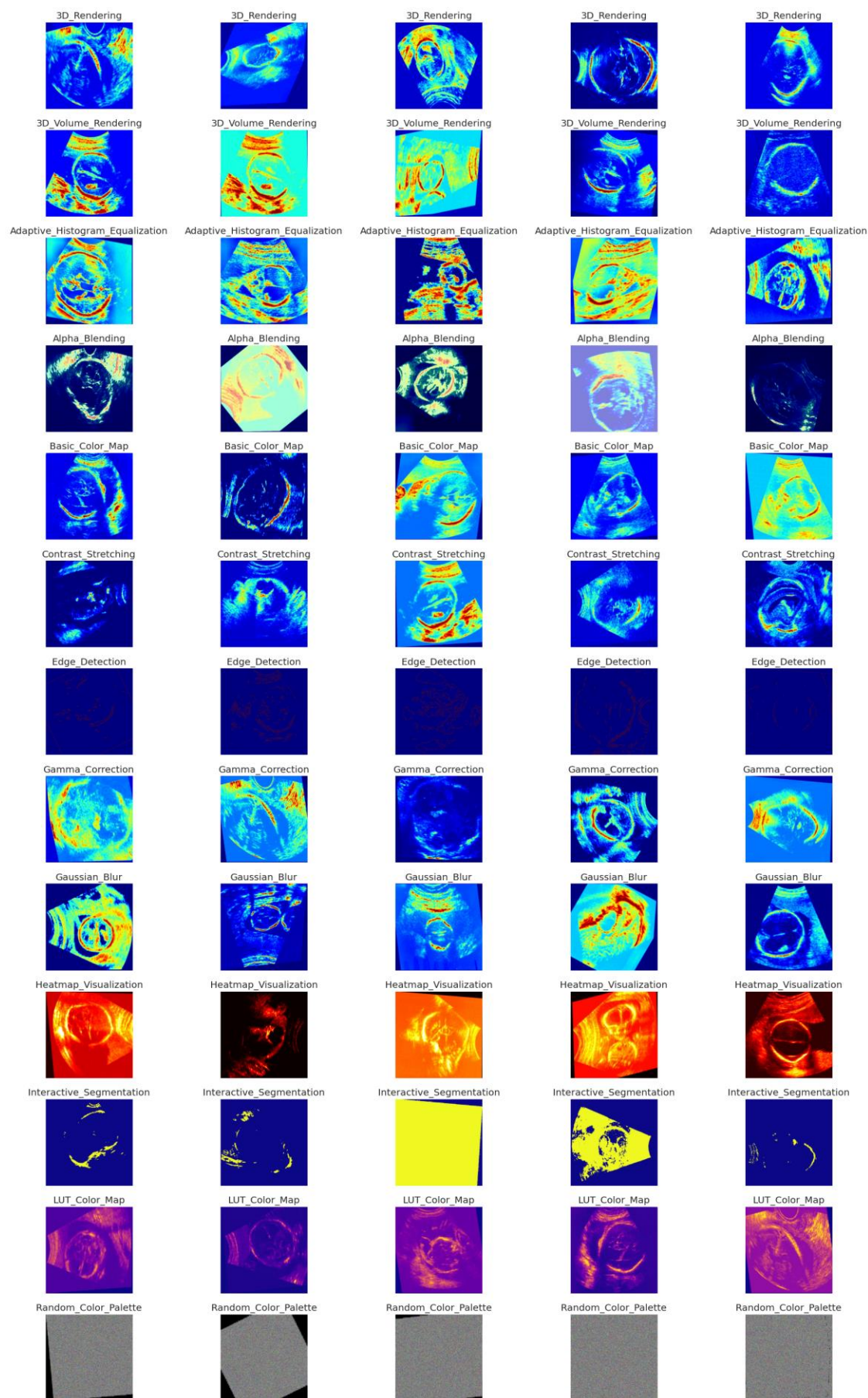
```
for j, img_path in enumerate(category_images):

    img = cv2.imread(img_path)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    plt.subplot(len(categories), num_images, i * num_images + j + 1)
    plt.imshow(img)
    plt.axis('off')
    plt.title(category)

plt.tight_layout()
plt.show()
```





```

from PIL import Image

def preprocess_image(img_path, target_size=(64, 64)):
    img = Image.open(img_path).resize(target_size)
    img_array = np.array(img) / 255.0
    return img_array.flatten()
X = np.array([preprocess_image(img_path) for img_path in df['image_path']])
print(X.shape)

(12662, 12288)

from sklearn.decomposition import PCA

pca = PCA(n_components=100)
X_reduced = pca.fit_transform(X)
print(X_reduced.shape)

(12662, 100)

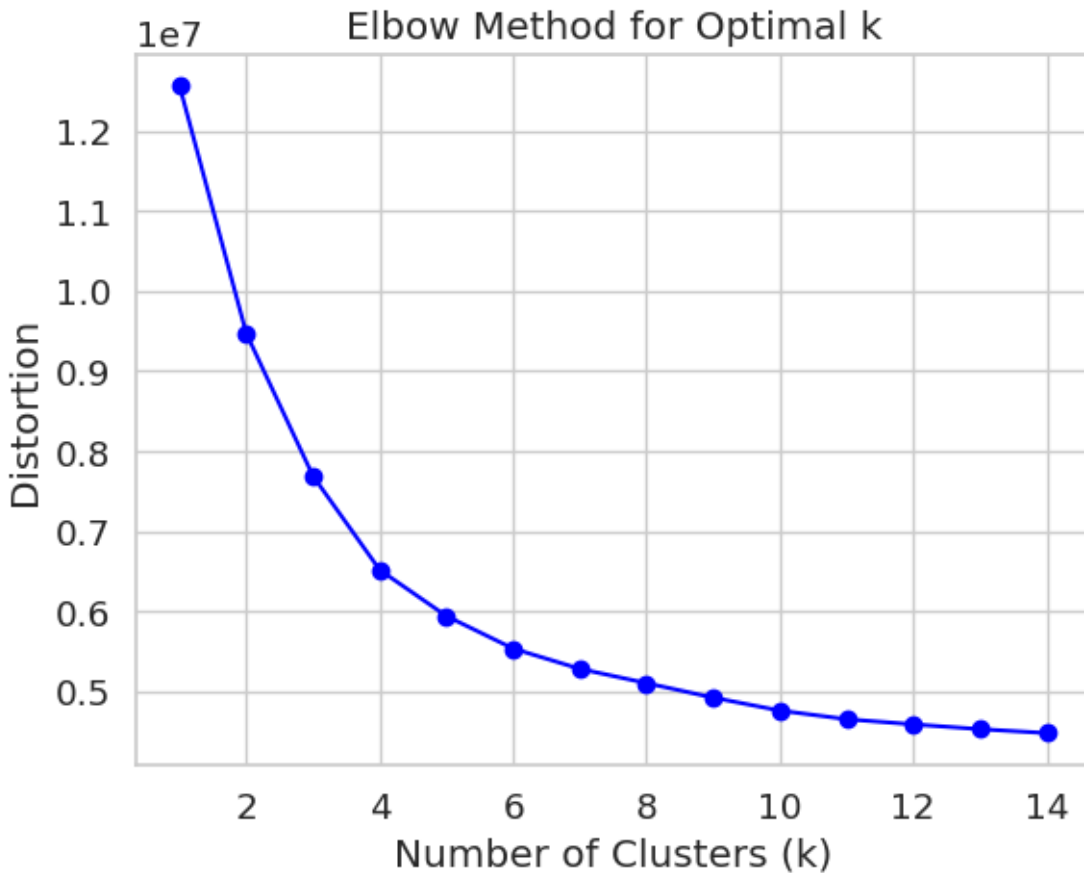
from sklearn.cluster import KMeans

distortions = []
K = range(1, 15)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_reduced)
    distortions.append(kmeans.inertia_)

plt.plot(K, distortions, 'bo-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Distortion')
plt.title('Elbow Method for Optimal k')
plt.show()

```





```
k = 4
kmeans = KMeans(n_clusters=k, random_state=42)
df['cluster'] = kmeans.fit_predict(X_reduced)

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
    warnings.warn(
```

```
df
```

```

                                image_path \
0      /kaggle/input/medical-imaging-fetal-colored-...
1      /kaggle/input/medical-imaging-fetal-colored-...
2      /kaggle/input/medical-imaging-fetal-colored-...
3      /kaggle/input/medical-imaging-fetal-colored-...
4      /kaggle/input/medical-imaging-fetal-colored-...
...
12657  /kaggle/input/medical-imaging-fetal-colored-...
12658  /kaggle/input/medical-imaging-fetal-colored-...
12659  /kaggle/input/medical-imaging-fetal-colored-...
12660  /kaggle/input/medical-imaging-fetal-colored-...
12661  /kaggle/input/medical-imaging-fetal-colored-...
```

	label	cluster
0	3D_Rendering	3
1	3D_Rendering	3
2	3D_Rendering	3
3	3D_Rendering	1
4	3D_Rendering	3
...	...	...
12657	Random_Color_Palette	0
12658	Random_Color_Palette	0
12659	Random_Color_Palette	0
12660	Random_Color_Palette	0
12661	Random_Color_Palette	1

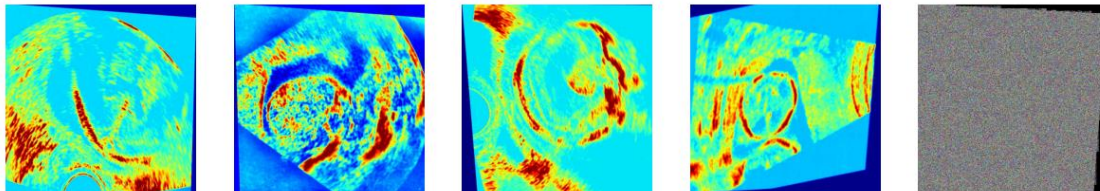
[12662 rows x 3 columns]

```

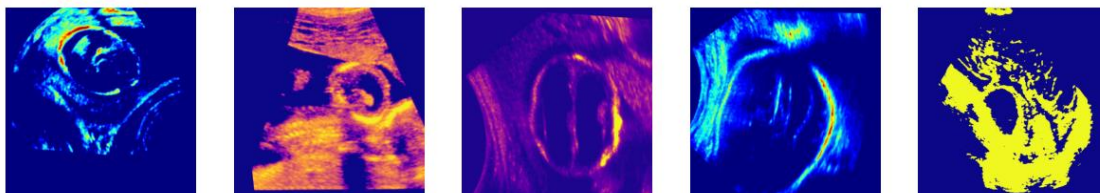
for cluster in range(k):
    print(f"Cluster {cluster}:")
    cluster_samples = df[df['cluster'] == cluster]['image_path'].sample(5,
random_state=42)
    plt.figure(figsize=(15, 3))
    for i, img_path in enumerate(cluster_samples):
        plt.subplot(1, 5, i + 1)
        img = Image.open(img_path)
        plt.imshow(img)
        plt.axis('off')
    plt.show()

```

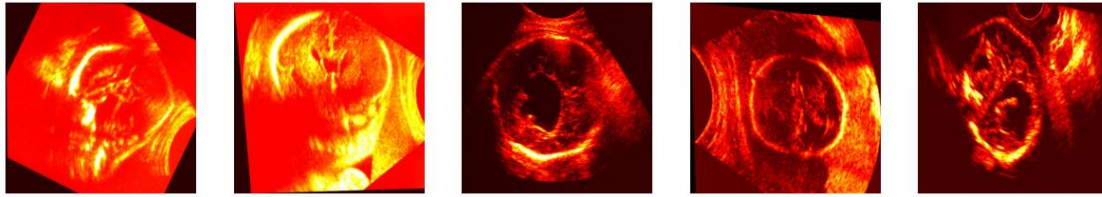
Cluster 0:



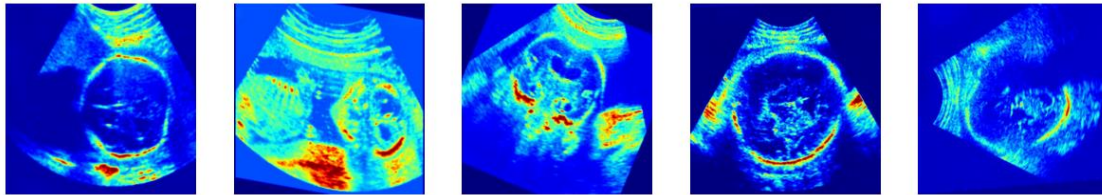
Cluster 1:



Cluster 2:



Cluster 3:



```
df['cluster'].unique()
array([3, 1, 0, 2], dtype=int32)
df['cluster'].value_counts()
cluster
3      4685
1      4379
0      2626
2       972
Name: count, dtype: int64

df = df[['image_path', 'cluster']]
from imblearn.over_sampling import RandomOverSampler

ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(df[['image_path']],
df['cluster'])

df_resampled = pd.DataFrame(X_resampled, columns=['image_path'])
df_resampled['category_encoded'] = y_resampled

print("\nClass distribution after oversampling:")
print(df_resampled['category_encoded'].value_counts())
```

```
Class distribution after oversampling:
category_encoded
3      4685
1      4685
0      4685
2      4685
Name: count, dtype: int64
```

```

df_resampled['category_encoded'] =
df_resampled['category_encoded'].astype(str)

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Activation, Dropout, BatchNormalization
from tensorflow.keras import regularizers

import warnings
warnings.filterwarnings("ignore")

print ('check')

check

train_df_new, temp_df_new = train_test_split(
    df_resampled,
    train_size=0.8,
    shuffle=True,
    random_state=42,
    stratify=df_resampled['category_encoded']
)

valid_df_new, test_df_new = train_test_split(
    temp_df_new,
    test_size=0.5,
    shuffle=True,
    random_state=42,
    stratify=temp_df_new['category_encoded']
)

batch_size = 16
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)

tr_gen = ImageDataGenerator(rescale=1./255)
ts_gen = ImageDataGenerator(rescale=1./255)

train_gen_new = tr_gen.flow_from_dataframe(
    train_df_new,
    x_col='image_path',
    y_col='category_encoded',

```

```

        target_size=img_size,
        class_mode='sparse',
        color_mode='rgb',
        shuffle=True,
        batch_size=batch_size
    )

    valid_gen_new = ts_gen.flow_from_dataframe(
        valid_df_new,
        x_col='image_path',
        y_col='category_encoded',
        target_size=img_size,
        class_mode='sparse',
        color_mode='rgb',
        shuffle=True,
        batch_size=batch_size
    )

    test_gen_new = ts_gen.flow_from_dataframe(
        test_df_new,
        x_col='image_path',
        y_col='category_encoded',
        target_size=img_size,
        class_mode='sparse',
        color_mode='rgb',
        shuffle=False,
        batch_size=batch_size
    )

```

Found 14992 validated image filenames belonging to 4 classes.

Found 1874 validated image filenames belonging to 4 classes.

Found 1874 validated image filenames belonging to 4 classes.

```
import tensorflow as tf
```

```
print("Num GPUs Available: ", len(tf.config.list_physical_devices('GPU')))
```

Num GPUs Available: 2

```

gpus = tf.config.list_physical_devices('GPU')
if gpus:
    try:
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        print("GPU is set for TensorFlow")
    except RuntimeError as e:
        print(e)

```

GPU is set for TensorFlow

```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
```

```

early_stopping = EarlyStopping(monitor='val_loss', patience=5,
restore_best_weights=True)

from tensorflow.keras import layers, models

from tensorflow.keras.applications import MobileNet
from tensorflow.keras.models import Model
from tensorflow.keras.layers import (
    GlobalAveragePooling2D, Dense, Dropout,
    BatchNormalization, GaussianNoise, Input,
    MultiHeadAttention, Reshape, LSTM
)
from tensorflow.keras.optimizers import Adam

def create_mobilenet_lstm_model(input_shape, num_classes=4,
learning_rate=0.0001):
    inputs = Input(shape=input_shape, name="Input_Layer")

    base_model = MobileNet(weights='imagenet', input_tensor=inputs,
include_top=False)
    base_model.trainable = False

    x = base_model.output

    height, width, channels = x.shape[1], x.shape[2], x.shape[3]
    x = Reshape((height * width, channels), name="Reshape_to_Sequence")(x)

    attention_output = MultiHeadAttention(
        num_heads=8, key_dim=channels, name="Multi_Head_Attention"
    )(x, x)

    attention_output = Reshape((height, width, channels),
name="Reshape_to_Spatial")(attention_output)

    x = GaussianNoise(0.25, name="Gaussian_Noise_1")(attention_output)
    x = GlobalAveragePooling2D(name="Global_Avg_Pooling")(x)

    x = Reshape((1, -1), name="Reshape_for_LSTM")(x)

    x = LSTM(128, return_sequences=False, name="LSTM_Layer")(x)

    outputs = Dense(num_classes, activation='softmax',
name="Output_Layer")(x)

    model = Model(inputs=inputs, outputs=outputs, name="MobileNet_with_LSTM")

    model.compile(
        optimizer=Adam(learning_rate=learning_rate),
        loss='sparse_categorical_crossentropy',

```

```

        metrics=['accuracy']
    )

    return model

input_shape = (224, 224, 3)
cnn_model = create_mobilenet_lstm_model(input_shape, num_classes=4,
learning_rate=0.0001)

cnn_model.summary()

Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/mobilenet/mobilenet_1_0_224_tf_no_top.h5
17225924/17225924 — 0s 0us/step

```

Model: "MobileNet\_with\_LSTM"

Layer (type) Connected to	Output Shape	Param #
Input_Layer (InputLayer)	(None, 224, 224, 3)	0 -
conv1 (Conv2D) Input_Layer[0][0]	(None, 112, 112, 32)	864
conv1_bn conv1[0][0] (BatchNormalization)	(None, 112, 112, 32)	128
conv1_relu (ReLU) conv1_bn[0][0]	(None, 112, 112, 32)	0
conv_dw_1 conv1_relu[0][0] (DepthwiseConv2D)	(None, 112, 112, 32)	288
conv_dw_1_bn conv_dw_1[0][0] (BatchNormalization)	(None, 112, 112, 32)	128



conv_dw_1_relu (ReLU) conv_dw_1_bn[0][0]	(None, 112, 112, 32)	0	
conv_pw_1 (Conv2D) conv_dw_1_relu[0][0]	(None, 112, 112, 64)	2,048	
conv_pw_1_bn conv_pw_1[0][0] (BatchNormalization)	(None, 112, 112, 64)	256	
conv_pw_1_relu (ReLU) conv_pw_1_bn[0][0]	(None, 112, 112, 64)	0	
conv_pad_2 conv_pw_1_relu[0][0] (ZeroPadding2D)	(None, 113, 113, 64)	0	
conv_dw_2 conv_pad_2[0][0] (DepthwiseConv2D)	(None, 56, 56, 64)	576	
conv_dw_2_bn conv_dw_2[0][0] (BatchNormalization)	(None, 56, 56, 64)	256	
conv_dw_2_relu (ReLU) conv_dw_2_bn[0][0]	(None, 56, 56, 64)	0	
conv_pw_2 (Conv2D) conv_dw_2_relu[0][0]	(None, 56, 56, 128)	8,192	
conv_pw_2_bn conv_pw_2[0][0] (BatchNormalization)	(None, 56, 56, 128)	512	

conv_pw_2_relu (ReLU) conv_pw_2_bn[0][0]	(None, 56, 56, 128)	0	
conv_dw_3 conv_pw_2_relu[0][0] (DepthwiseConv2D)	(None, 56, 56, 128)	1,152	
conv_dw_3_bn conv_dw_3[0][0] (BatchNormalization)	(None, 56, 56, 128)	512	
conv_dw_3_relu (ReLU) conv_dw_3_bn[0][0]	(None, 56, 56, 128)	0	
conv_pw_3 (Conv2D) conv_dw_3_relu[0][0]	(None, 56, 56, 128)	16,384	
conv_pw_3_bn conv_pw_3[0][0] (BatchNormalization)	(None, 56, 56, 128)	512	
conv_pw_3_relu (ReLU) conv_pw_3_bn[0][0]	(None, 56, 56, 128)	0	
conv_pad_4 conv_pw_3_relu[0][0] (ZeroPadding2D)	(None, 57, 57, 128)	0	
conv_dw_4 conv_pad_4[0][0] (DepthwiseConv2D)	(None, 28, 28, 128)	1,152	
conv_dw_4_bn	(None, 28, 28, 128)	512	

conv_dw_4[0][0] (BatchNormalization)			
conv_dw_4_relu (ReLU) conv_dw_4_bn[0][0]	(None, 28, 28, 128)	0	
conv_pw_4 (Conv2D) conv_dw_4_relu[0][0]	(None, 28, 28, 256)	32,768	
conv_pw_4_bn conv_pw_4[0][0] (BatchNormalization)	(None, 28, 28, 256)	1,024	
conv_pw_4_relu (ReLU) conv_pw_4_bn[0][0]	(None, 28, 28, 256)	0	
conv_dw_5 conv_pw_4_relu[0][0] (DepthwiseConv2D)	(None, 28, 28, 256)	2,304	
conv_dw_5_bn conv_dw_5[0][0] (BatchNormalization)	(None, 28, 28, 256)	1,024	
conv_dw_5_relu (ReLU) conv_dw_5_bn[0][0]	(None, 28, 28, 256)	0	
conv_pw_5 (Conv2D) conv_dw_5_relu[0][0]	(None, 28, 28, 256)	65,536	
conv_pw_5_bn conv_pw_5[0][0] (BatchNormalization)	(None, 28, 28, 256)	1,024	
conv_pw_5_relu (ReLU)	(None, 28, 28, 256)	0	

conv_pw_5_bn[0][0]			
conv_pad_6	(None, 29, 29, 256)	0	
conv_pw_5_relu[0][0] (ZeroPadding2D)			
conv_dw_6	(None, 14, 14, 256)	2,304	
conv_pad_6[0][0] (DepthwiseConv2D)			
conv_dw_6_bn	(None, 14, 14, 256)	1,024	
conv_dw_6[0][0] (BatchNormalization)			
conv_dw_6_relu (ReLU)	(None, 14, 14, 256)	0	
conv_dw_6_bn[0][0]			
conv_pw_6 (Conv2D)	(None, 14, 14, 512)	131,072	
conv_dw_6_relu[0][0]			
conv_pw_6_bn	(None, 14, 14, 512)	2,048	
conv_pw_6[0][0] (BatchNormalization)			
conv_pw_6_relu (ReLU)	(None, 14, 14, 512)	0	
conv_pw_6_bn[0][0]			
conv_dw_7	(None, 14, 14, 512)	4,608	
conv_pw_6_relu[0][0] (DepthwiseConv2D)			
conv_dw_7_bn	(None, 14, 14, 512)	2,048	
conv_dw_7[0][0] (BatchNormalization)			

conv_dw_7_relu (ReLU) conv_dw_7_bn[0][0]	(None, 14, 14, 512)	0	
conv_pw_7 (Conv2D) conv_dw_7_relu[0][0]	(None, 14, 14, 512)	262,144	
conv_pw_7_bn conv_pw_7[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_pw_7_relu (ReLU) conv_pw_7_bn[0][0]	(None, 14, 14, 512)	0	
conv_dw_8 conv_pw_7_relu[0][0] (DepthwiseConv2D)	(None, 14, 14, 512)	4,608	
conv_dw_8_bn conv_dw_8[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_dw_8_relu (ReLU) conv_dw_8_bn[0][0]	(None, 14, 14, 512)	0	
conv_pw_8 (Conv2D) conv_dw_8_relu[0][0]	(None, 14, 14, 512)	262,144	
conv_pw_8_bn conv_pw_8[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_pw_8_relu (ReLU) conv_pw_8_bn[0][0]	(None, 14, 14, 512)	0	
conv_dw_9	(None, 14, 14, 512)	4,608	

conv_pw_8_relu[0][0] (DepthwiseConv2D)			
conv_dw_9_bn conv_dw_9[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_dw_9_relu (ReLU) conv_dw_9_bn[0][0]	(None, 14, 14, 512)	0	
conv_pw_9 (Conv2D) conv_dw_9_relu[0][0]	(None, 14, 14, 512)	262,144	
conv_pw_9_bn conv_pw_9[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_pw_9_relu (ReLU) conv_pw_9_bn[0][0]	(None, 14, 14, 512)	0	
conv_dw_10 conv_pw_9_relu[0][0] (DepthwiseConv2D)	(None, 14, 14, 512)	4,608	
conv_dw_10_bn conv_dw_10[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_dw_10_relu (ReLU) conv_dw_10_bn[0][0]	(None, 14, 14, 512)	0	
conv_pw_10 (Conv2D) conv_dw_10_relu[0][0]	(None, 14, 14, 512)	262,144	
conv_pw_10_bn	(None, 14, 14, 512)	2,048	

conv_pw_10[0][0] (BatchNormalization)			
conv_pw_10_relu (ReLU) conv_pw_10_bn[0][0]	(None, 14, 14, 512)	0	
conv_dw_11 conv_pw_10_relu[0][0] (DepthwiseConv2D)	(None, 14, 14, 512)	4,608	
conv_dw_11_bn conv_dw_11[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_dw_11_relu (ReLU) conv_dw_11_bn[0][0]	(None, 14, 14, 512)	0	
conv_pw_11 (Conv2D) conv_dw_11_relu[0][0]	(None, 14, 14, 512)	262,144	
conv_pw_11_bn conv_pw_11[0][0] (BatchNormalization)	(None, 14, 14, 512)	2,048	
conv_pw_11_relu (ReLU) conv_pw_11_bn[0][0]	(None, 14, 14, 512)	0	
conv_pad_12 conv_pw_11_relu[0][0] (ZeroPadding2D)	(None, 15, 15, 512)	0	
conv_dw_12 conv_pad_12[0][0] (DepthwiseConv2D)	(None, 7, 7, 512)	4,608	



conv_dw_12_bn conv_dw_12[0][0] (BatchNormalization)	(None, 7, 7, 512)	2,048
conv_dw_12_relu (ReLU) conv_dw_12_bn[0][0]	(None, 7, 7, 512)	0
conv_pw_12 (Conv2D) conv_dw_12_relu[0][0]	(None, 7, 7, 1024)	524,288
conv_pw_12_bn conv_pw_12[0][0] (BatchNormalization)	(None, 7, 7, 1024)	4,096
conv_pw_12_relu (ReLU) conv_pw_12_bn[0][0]	(None, 7, 7, 1024)	0
conv_dw_13 conv_pw_12_relu[0][0] (DepthwiseConv2D)	(None, 7, 7, 1024)	9,216
conv_dw_13_bn conv_dw_13[0][0] (BatchNormalization)	(None, 7, 7, 1024)	4,096
conv_dw_13_relu (ReLU) conv_dw_13_bn[0][0]	(None, 7, 7, 1024)	0
conv_pw_13 (Conv2D) conv_dw_13_relu[0][0]	(None, 7, 7, 1024)	1,048,576
conv_pw_13_bn conv_pw_13[0][0] (BatchNormalization)	(None, 7, 7, 1024)	4,096

conv_pw_13_relu (ReLU) conv_pw_13_bn[0][0]	(None, 7, 7, 1024)	0
Reshape_to_Sequence conv_pw_13_relu[0][0] (Reshape)	(None, 49, 1024)	0
Multi_Head_Attention Reshape_to_Sequence[0... (MultiHeadAttention) Reshape_to_Sequence[0...	(None, 49, 1024)	33,580,032
Reshape_to_Spatial Multi_Head_Attention[... (Reshape)	(None, 7, 7, 1024)	0
Gaussian_Noise_1 Reshape_to_Spatial[0]... (GaussianNoise)	(None, 7, 7, 1024)	0
Global_Avg_Pooling Gaussian_Noise_1[0][0] (GlobalAveragePooling2D)	(None, 1024)	0
Reshape_for_LSTM Global_Avg_Pooling[0]... (Reshape)	(None, 1, 1024)	0
LSTM_Layer (LSTM) Reshape_for_LSTM[0][0]	(None, 128)	590,336
Output_Layer (Dense) LSTM_Layer[0][0]	(None, 4)	516

Total params: 37,399,748 (142.67 MB)

Trainable params: 34,170,884 (130.35 MB)

Non-trainable params: 3,228,864 (12.32 MB)

```
history = cnn_model.fit(  
    train_gen_new,  
    validation_data=valid_gen_new,  
    epochs=5,  
    batch_size=16,  
    verbose=1  
)
```

Epoch 1/5

937/937 ————— 101s 100ms/step - accuracy: 0.8971 - loss: 0.2696 - val\_accuracy: 0.9717 - val\_loss: 0.0825

Epoch 2/5

937/937 ————— 99s 105ms/step - accuracy: 0.9670 - loss: 0.0909 - val\_accuracy: 0.9664 - val\_loss: 0.1052

Epoch 3/5

937/937 ————— 99s 105ms/step - accuracy: 0.9795 - loss: 0.0607 - val\_accuracy: 0.9691 - val\_loss: 0.0950

Epoch 4/5

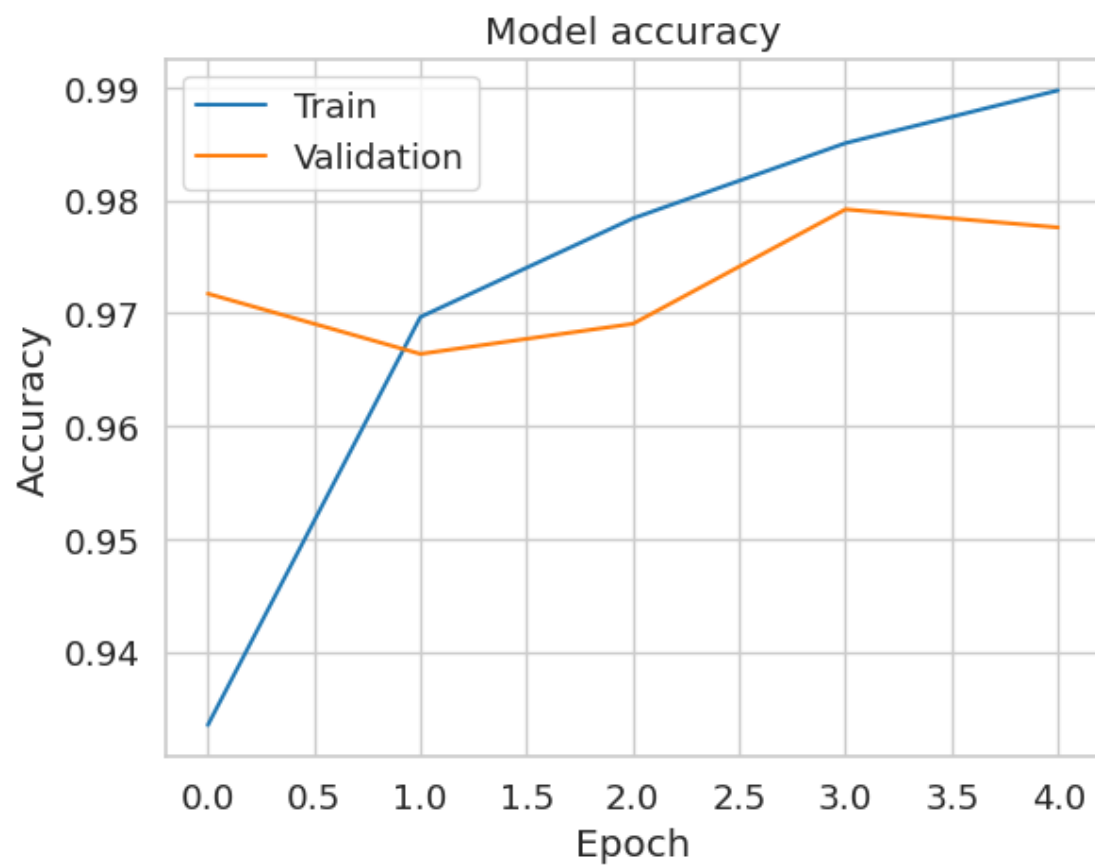
937/937 ————— 98s 104ms/step - accuracy: 0.9863 - loss: 0.0431 - val\_accuracy: 0.9792 - val\_loss: 0.0601

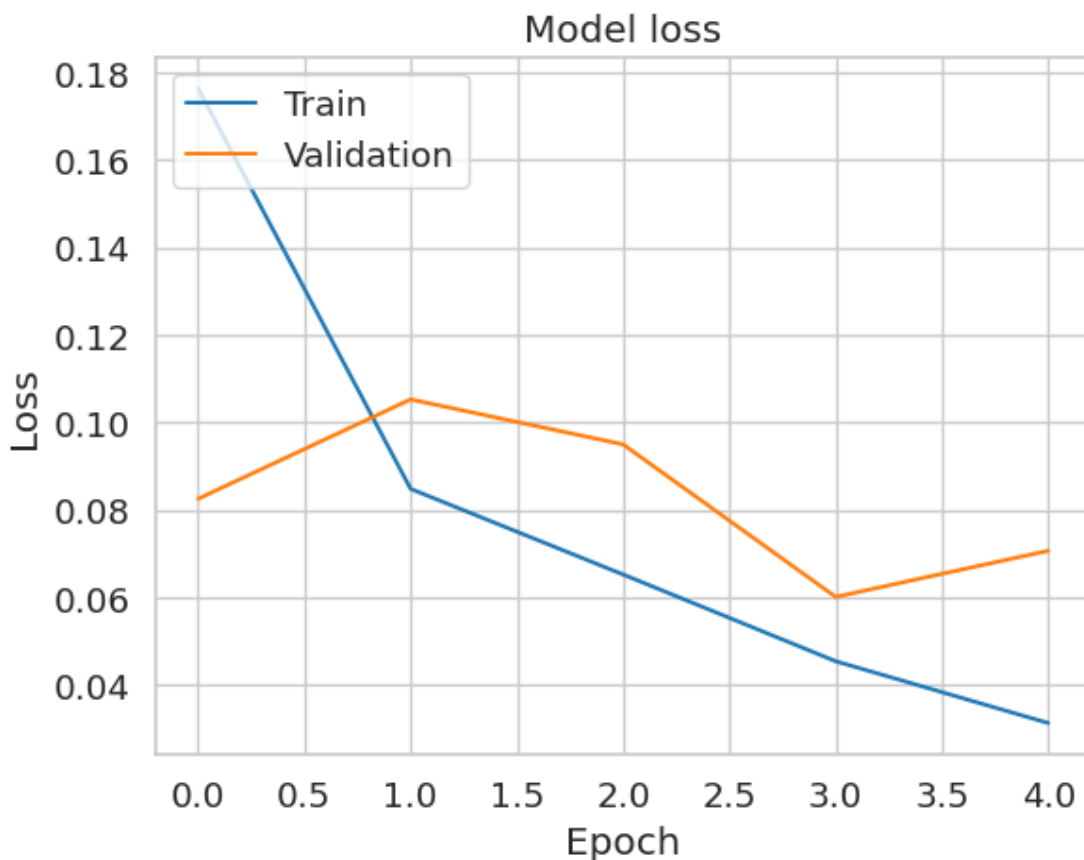
Epoch 5/5

937/937 ————— 98s 104ms/step - accuracy: 0.9897 - loss: 0.0322 - val\_accuracy: 0.9776 - val\_loss: 0.0707

```
plt.plot(history.history['accuracy'])  
plt.plot(history.history['val_accuracy'])  
plt.title('Model accuracy')  
plt.ylabel('Accuracy')  
plt.xlabel('Epoch')  
plt.legend(['Train', 'Validation'], loc='upper left')  
plt.show()
```

```
plt.plot(history.history['loss'])  
plt.plot(history.history['val_loss'])  
plt.title('Model loss')  
plt.ylabel('Loss')  
plt.xlabel('Epoch')  
plt.legend(['Train', 'Validation'], loc='upper left')  
plt.show()
```





```
test_labels = test_gen_new.classes
predictions = cnn_model.predict(test_gen_new)
predicted_classes = np.argmax(predictions, axis=1)
```

118/118 ————— 9s 74ms/step

```
report = classification_report(test_labels, predicted_classes,
target_names=list(test_gen_new.class_indices.keys()))
print(report)
```

	precision	recall	f1-score	support
0	0.96	0.99	0.98	469
1	0.97	0.99	0.98	468
2	1.00	1.00	1.00	469
3	0.99	0.94	0.97	468
accuracy			0.98	1874
macro avg	0.98	0.98	0.98	1874
weighted avg	0.98	0.98	0.98	1874

```
conf_matrix = confusion_matrix(test_labels, predicted_classes)
```

```
conf_matrix
```

```
array([[465,  2,  0,  2],
       [ 5, 462,  0,  1],
       [ 0,  0, 469,  0],
       [14, 14,  0, 440]])
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=list(test_gen_new.class_indices.keys()),
            yticklabels=list(test_gen_new.class_indices.keys()))
plt.title('Confusion Matrix')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

