final

April 21, 2025

[1]:
```
import os
import pandas as pd
import numpy as np
import tensorflow as tf
import seaborn as sns
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten,␣
↪Dense, Dropout, GlobalAveragePooling2D
from tensorflow.keras.applications import ResNet50, EfficientNetB0, Xception
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score, confusion_matrix
import matplotlib.pyplot as plt
from PIL import Image
```

[2]:
```
# Dataset base directory
dataset_root = r"C:\Users\SujithVarmaMudunuruI\OneDrive - Manipal University␣
↪Jaipur\Desktop\Big_Dataset\real_vs_fake\real-vs-fake"
```

[3]:
```
# Load CSVs
train_df = pd.read_csv("train.csv")
val_df = pd.read_csv("valid.csv")
test_df = pd.read_csv("test.csv")
```

[37]:
```
train_df.head()
```

[37]:

	Unnamed: 0	original_path	id	label	label_str	path
0	0	/kaggle/input/flickrfaceshq-dataset-nvidia-par…	31355	1	real	C:\Users\SujithVarmaMudunuruI\OneDrive - Manip…
1	1	/kaggle/input/flickrfaceshq-dataset-nvidia-par…	02884	1	real	C:\Users\SujithVarmaMudunuruI\OneDrive - Manip…
2	2	/kaggle/input/flickrfaceshq-dataset-nvidia-par…	33988			
3	3	/kaggle/input/flickrfaceshq-dataset-nvidia-par…	53875			
4	4	/kaggle/input/flickrfaceshq-dataset-nvidia-par…	24149			

```
2      1      real  C:\Users\SujithVarmaMudunuruI\OneDrive - Manip…
3      1      real  C:\Users\SujithVarmaMudunuruI\OneDrive - Manip…
4      1      real  C:\Users\SujithVarmaMudunuruI\OneDrive - Manip…
```

[38]:
```
train_df["label"].unique()
```

[38]:
```
array([1, 0], dtype=int64)
```

[39]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 6 columns):
 #   Column         Non-Null Count   Dtype 
---  ------         --------------   ----- 
 0   Unnamed: 0     100000 non-null  int64 
 1   original_path  100000 non-null  object
 2   id             100000 non-null  object
 3   label          100000 non-null  int64 
 4   label_str      100000 non-null  object
 5   path           100000 non-null  object
dtypes: int64(2), object(4)
memory usage: 4.6+ MB
```

[40]:
```
val_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Unnamed: 0     20000 non-null  int64 
 1   original_path  20000 non-null  object
 2   id             20000 non-null  object
 3   label          20000 non-null  int64 
 4   label_str      20000 non-null  object
 5   path           20000 non-null  object
dtypes: int64(2), object(4)
memory usage: 937.6+ KB
```

[41]:
```
test_df.info()
```

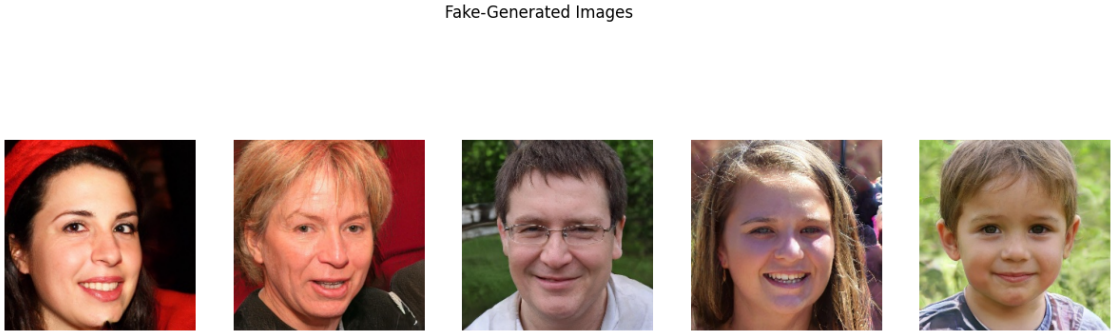
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Unnamed: 0     20000 non-null  int64 
```

```
 1   original_path  20000 non-null  object
 2   id             20000 non-null  object
 3   label          20000 non-null  int64
 4   label_str      20000 non-null  object
 5   path           20000 non-null  object
dtypes: int64(2), object(4)
memory usage: 937.6+ KB
```

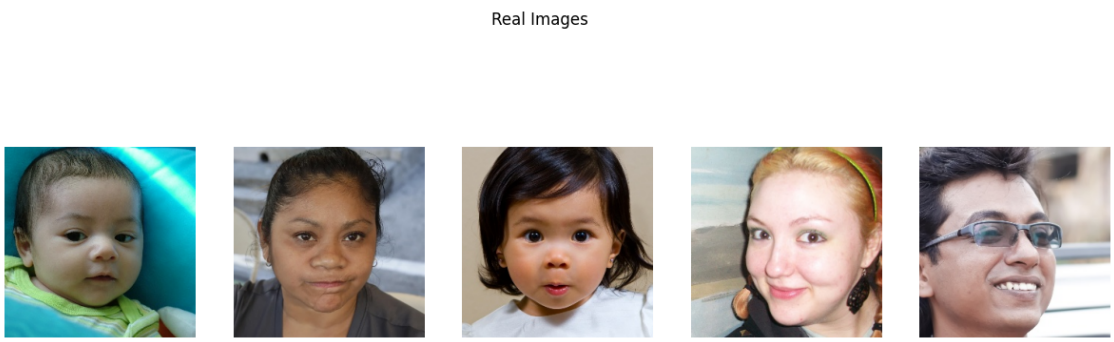
[4]:
```
# Data Path
fake_image_dir = r"C:\Users\SujithVarmaMudunuruI\OneDrive - Manipal University␣
 ↪Jaipur\Desktop\Big_Dataset\real_vs_fake\real-vs-fake\train\fake"
real_image_dir = r"C:\Users\SujithVarmaMudunuruI\OneDrive - Manipal University␣
 ↪Jaipur\Desktop\Big_Dataset\real_vs_fake\real-vs-fake\train\real"

# Function to Show Images
def display_images_from_dir(directory, title, max_images=5):
    images = []
    aspect_ratios = []
    garbage_count = 0
    fig, axes = plt.subplots(1, max_images, figsize=(15, 5))

    for idx, filename in enumerate(os.listdir(directory)):
        if idx >= max_images:
            break
        filepath = os.path.join(directory, filename)
        try:
            with Image.open(filepath) as img:
                images.append(img)
                width, height = img.size
                aspect_ratios.append(width / height)
                axes[idx].imshow(img)
                axes[idx].axis("off")

        except Exception as e:
            print(f"Error with file {filename}: {e}")
            garbage_count += 1

    plt.suptitle(title)
    plt.show()

    print(f"Total images processed: {min(len(os.listdir(directory)),␣
 ↪max_images)}")


# Display fake images
print("Fake-Generated Images:")
display_images_from_dir(fake_image_dir, "Fake-Generated Images")
```

```
# Display real images
print("\nReal Images:")
display_images_from_dir(real_image_dir,"Real Images")
```

```
Fake-Generated Images:
```




```
Total images processed: 5

Real Images:
```




```
Total images processed: 5
```

[5]:
```
# Build full image paths from 'path' column
train_df["path"] = train_df["path"].apply(lambda x: os.path.join(dataset_root,␣
↪x))
val_df["path"] = val_df["path"].apply(lambda x: os.path.join(dataset_root, x))
test_df["path"] = test_df["path"].apply(lambda x: os.path.join(dataset_root, x))
```

[6]:
```
# Image parameters
batch_size = 32
img_height, img_width = 128, 128
```

[7]:
```
# Data generators
datagen = ImageDataGenerator(rescale=1./255)
```

[8]:
```
train_generator = datagen.flow_from_dataframe(
    train_df,
    x_col="path",
    y_col="label_str",
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode="binary"
)
```

```
Found 100000 validated image filenames belonging to 2 classes.
```

[9]:
```
validation_generator = datagen.flow_from_dataframe(
    val_df,
    x_col="path",
    y_col="label_str",
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode="binary"
)
```

```
Found 20000 validated image filenames belonging to 2 classes.
```

[10]:
```
test_generator = datagen.flow_from_dataframe(
    test_df,
    x_col="path",
    y_col="label_str",
    target_size=(img_height, img_width),
    batch_size=batch_size,
    class_mode="binary",
    shuffle=False
)
```

```
Found 20000 validated image filenames belonging to 2 classes.
```

[11]:
```
def build_simple_cnn():
    return Sequential([
        Input(shape=(img_height, img_width, 3)),
        Conv2D(32, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Conv2D(64, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Conv2D(128, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Flatten(),
```

```
        Dense(128, activation="relu"),
        Dropout(0.5),
        Dense(1, activation="sigmoid")
    ])
```

[12]:
```
def build_resnet():
    base = ResNet50(weights="imagenet", include_top=False,␣
 ↪input_shape=(img_height, img_width, 3))
    return Sequential([
        base,
        GlobalAveragePooling2D(),
        Dense(128, activation="relu"),
        Dropout(0.5),
        Dense(1, activation="sigmoid")
    ])
```

[13]:
```
def build_efficientnet():
    base = EfficientNetB0(weights="imagenet", include_top=False,␣
 ↪input_shape=(img_height, img_width, 3))
    return Sequential([
        base,
        GlobalAveragePooling2D(),
        Dense(128, activation="relu"),
        Dropout(0.5),
        Dense(1, activation="sigmoid")
    ])
```

[14]:
```
def build_xception():
    base = Xception(weights="imagenet", include_top=False,␣
 ↪input_shape=(img_height, img_width, 3))
    return Sequential([
        base,
        GlobalAveragePooling2D(),
        Dense(128, activation="relu"),
        Dropout(0.5),
        Dense(1, activation="sigmoid")
    ])
```

[15]:
```
def build_mesonet():
    return Sequential([
        Input(shape=(img_height, img_width, 3)),
        Conv2D(8, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Conv2D(8, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Conv2D(16, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
```

```
        Conv2D(16, (3,3), activation="relu"),
        MaxPooling2D((2,2)),
        Flatten(),
        Dense(16, activation="relu"),
        Dropout(0.5),
        Dense(1, activation="sigmoid")
    ])
```

[16]:
```
models = {
    "CNN": build_simple_cnn(),
    "ResNet50": build_resnet(),
    "EfficientNetB0": build_efficientnet(),
    "Xception": build_xception(),
    "MesoNet": build_mesonet()
}
```

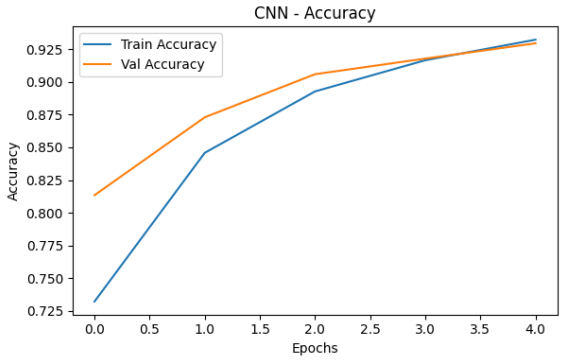
[17]:
```
histories = {}
accuracies = {}

for name, model in models.items():
    model.compile(optimizer="adam", loss="binary_crossentropy",␣
 ↪metrics=["accuracy"])
    histories[name] = model.fit(
        train_generator,
        validation_data=validation_generator,
        epochs=5
    )
    loss, acc = model.evaluate(test_generator)
    accuracies[name] = acc
```

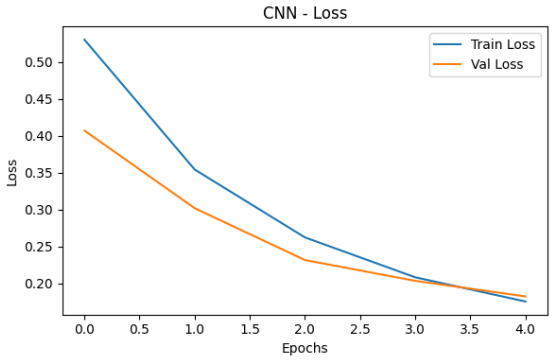
```
Epoch 1/5
3125/3125 [==============================] - 99s 31ms/step - loss: 0.5300 -
accuracy: 0.7322 - val_loss: 0.4070 - val_accuracy: 0.8134
Epoch 2/5
3125/3125 [==============================] - 97s 31ms/step - loss: 0.3543 -
accuracy: 0.8458 - val_loss: 0.3020 - val_accuracy: 0.8730
Epoch 3/5
3125/3125 [==============================] - 95s 30ms/step - loss: 0.2624 -
accuracy: 0.8927 - val_loss: 0.2318 - val_accuracy: 0.9058
Epoch 4/5
3125/3125 [==============================] - 92s 30ms/step - loss: 0.2084 -
accuracy: 0.9165 - val_loss: 0.2036 - val_accuracy: 0.9178
Epoch 5/5
3125/3125 [==============================] - 100s 32ms/step - loss: 0.1757 -
accuracy: 0.9322 - val_loss: 0.1826 - val_accuracy: 0.9294
625/625 [==============================] - 21s 33ms/step - loss: 0.1841 -
accuracy: 0.9291
```

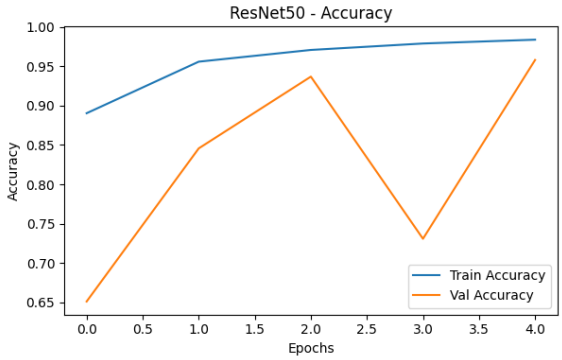
```
Epoch 1/5
3125/3125 [==============================] - 291s 92ms/step - loss: 0.2670 -
accuracy: 0.8902 - val_loss: 1.1287 - val_accuracy: 0.6512
Epoch 2/5
3125/3125 [==============================] - 282s 90ms/step - loss: 0.1235 -
accuracy: 0.9557 - val_loss: 0.3365 - val_accuracy: 0.8456
Epoch 3/5
3125/3125 [==============================] - 275s 88ms/step - loss: 0.0816 -
accuracy: 0.9706 - val_loss: 0.1622 - val_accuracy: 0.9367
Epoch 4/5
3125/3125 [==============================] - 275s 88ms/step - loss: 0.0597 -
accuracy: 0.9787 - val_loss: 1.1175 - val_accuracy: 0.7308
Epoch 5/5
3125/3125 [==============================] - 275s 88ms/step - loss: 0.0471 -
accuracy: 0.9836 - val_loss: 0.1170 - val_accuracy: 0.9578
625/625 [==============================] - 18s 29ms/step - loss: 0.1177 -
accuracy: 0.9577
Epoch 1/5
3125/3125 [==============================] - 212s 66ms/step - loss: 0.2049 -
accuracy: 0.9156 - val_loss: 1.8025 - val_accuracy: 0.5000
Epoch 2/5
3125/3125 [==============================] - 212s 68ms/step - loss: 0.0715 -
accuracy: 0.9736 - val_loss: 6.1937 - val_accuracy: 0.5000
Epoch 3/5
3125/3125 [==============================] - 208s 67ms/step - loss: 0.0489 -
accuracy: 0.9825 - val_loss: 0.9177 - val_accuracy: 0.5000
Epoch 4/5
3125/3125 [==============================] - 209s 67ms/step - loss: 0.0361 -
accuracy: 0.9874 - val_loss: 1.5030 - val_accuracy: 0.5000
Epoch 5/5
3125/3125 [==============================] - 213s 68ms/step - loss: 0.0298 -
accuracy: 0.9896 - val_loss: 2.2031 - val_accuracy: 0.5013
625/625 [==============================] - 18s 29ms/step - loss: 2.2080 -
accuracy: 0.5014
Epoch 1/5
3125/3125 [==============================] - 285s 90ms/step - loss: 0.1601 -
accuracy: 0.9330 - val_loss: 0.2320 - val_accuracy: 0.9234
Epoch 2/5
3125/3125 [==============================] - 279s 89ms/step - loss: 0.0455 -
accuracy: 0.9840 - val_loss: 0.0558 - val_accuracy: 0.9804
Epoch 3/5
3125/3125 [==============================] - 280s 89ms/step - loss: 0.0305 -
accuracy: 0.9894 - val_loss: 0.1373 - val_accuracy: 0.9511
Epoch 4/5
3125/3125 [==============================] - 281s 90ms/step - loss: 0.0230 -
accuracy: 0.9923 - val_loss: 0.0343 - val_accuracy: 0.9883
Epoch 5/5
3125/3125 [==============================] - 279s 89ms/step - loss: 0.0182 -
```

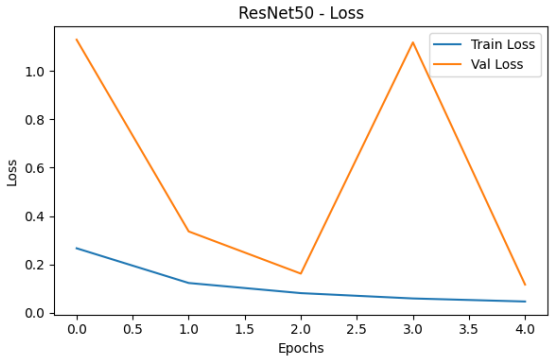
```
accuracy: 0.9936 - val_loss: 0.0403 - val_accuracy: 0.9856
625/625 [==============================] - 17s 27ms/step - loss: 0.0404 -
accuracy: 0.9857
Epoch 1/5
3125/3125 [==============================] - 95s 30ms/step - loss: 0.6129 -
accuracy: 0.6581 - val_loss: 0.5066 - val_accuracy: 0.7530
Epoch 2/5
3125/3125 [==============================] - 92s 30ms/step - loss: 0.5218 -
accuracy: 0.7490 - val_loss: 0.4653 - val_accuracy: 0.7782
Epoch 3/5
3125/3125 [==============================] - 93s 30ms/step - loss: 0.4773 -
accuracy: 0.7805 - val_loss: 0.4255 - val_accuracy: 0.7986
Epoch 4/5
3125/3125 [==============================] - 94s 30ms/step - loss: 0.4429 -
accuracy: 0.7999 - val_loss: 0.3776 - val_accuracy: 0.8328
Epoch 5/5
3125/3125 [==============================] - 93s 30ms/step - loss: 0.4230 -
accuracy: 0.8136 - val_loss: 0.4111 - val_accuracy: 0.7896
625/625 [==============================] - 15s 25ms/step - loss: 0.4089 -
accuracy: 0.7898
```

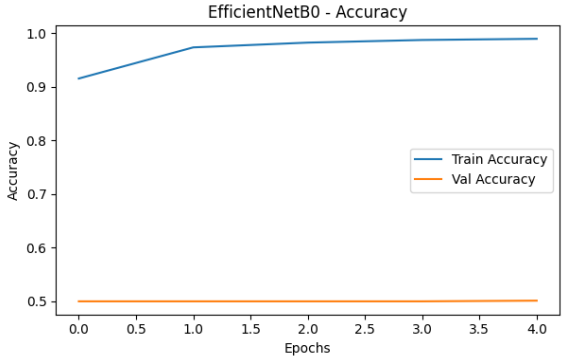
[18]:
```python
def plot_history(histories):
    for name, history in histories.items():
        plt.figure(figsize=(12, 4))

        # Accuracy
        plt.subplot(1, 2, 1)
        plt.plot(history.history['accuracy'], label='Train Accuracy')
        plt.plot(history.history['val_accuracy'], label='Val Accuracy')
        plt.title(f"{name} - Accuracy")
        plt.xlabel('Epochs')
        plt.ylabel('Accuracy')
        plt.legend()

        # Loss
        plt.subplot(1, 2, 2)
        plt.plot(history.history['loss'], label='Train Loss')
        plt.plot(history.history['val_loss'], label='Val Loss')
        plt.title(f"{name} - Loss")
        plt.xlabel('Epochs')
        plt.ylabel('Loss')
        plt.legend()

        plt.tight_layout()
        plt.show()

plot_history(histories)
```

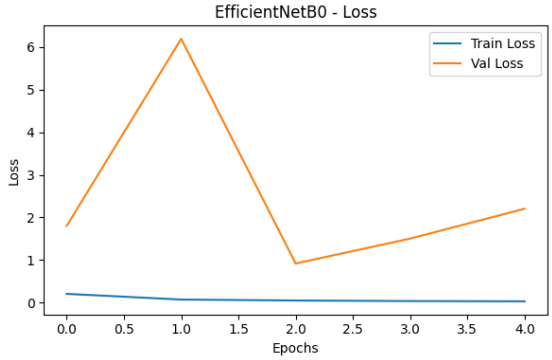

CNN - Accuracy
Train Accuracy
Val Accuracy
Accuracy
Epochs

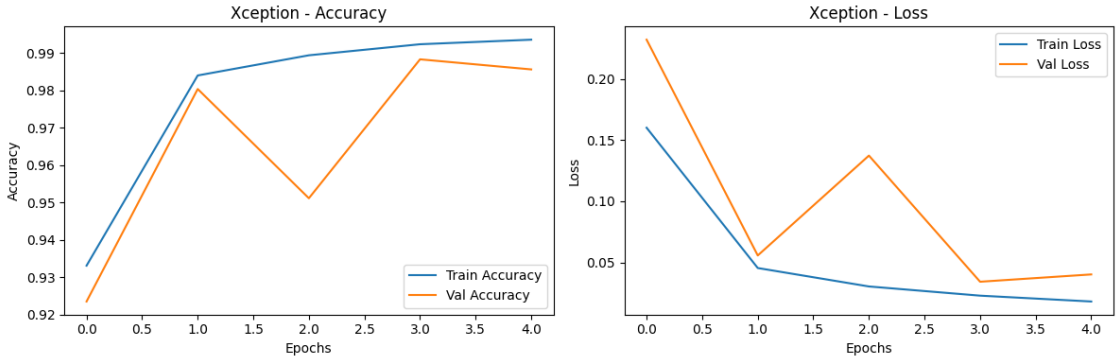

CNN - Loss
Train Loss
Val Loss
Loss
Epochs

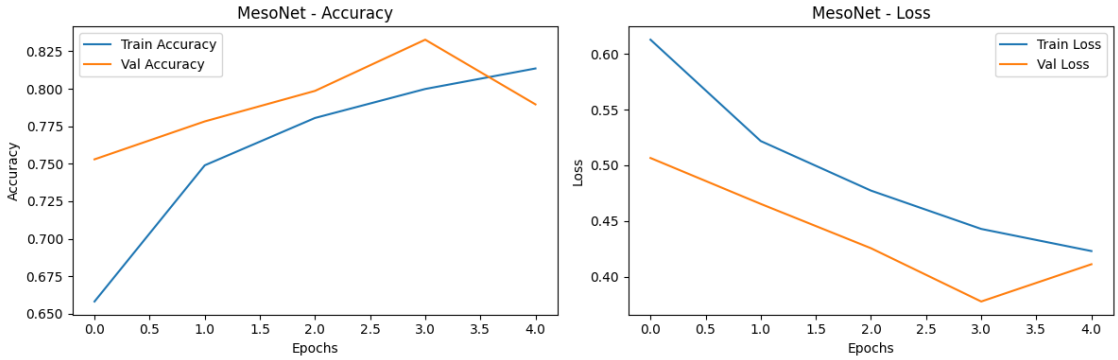

ResNet50 - Accuracy
Train Accuracy
Val Accuracy
Accuracy
Epochs


ResNet50 - Loss
Train Loss
Val Loss
Loss
Epochs

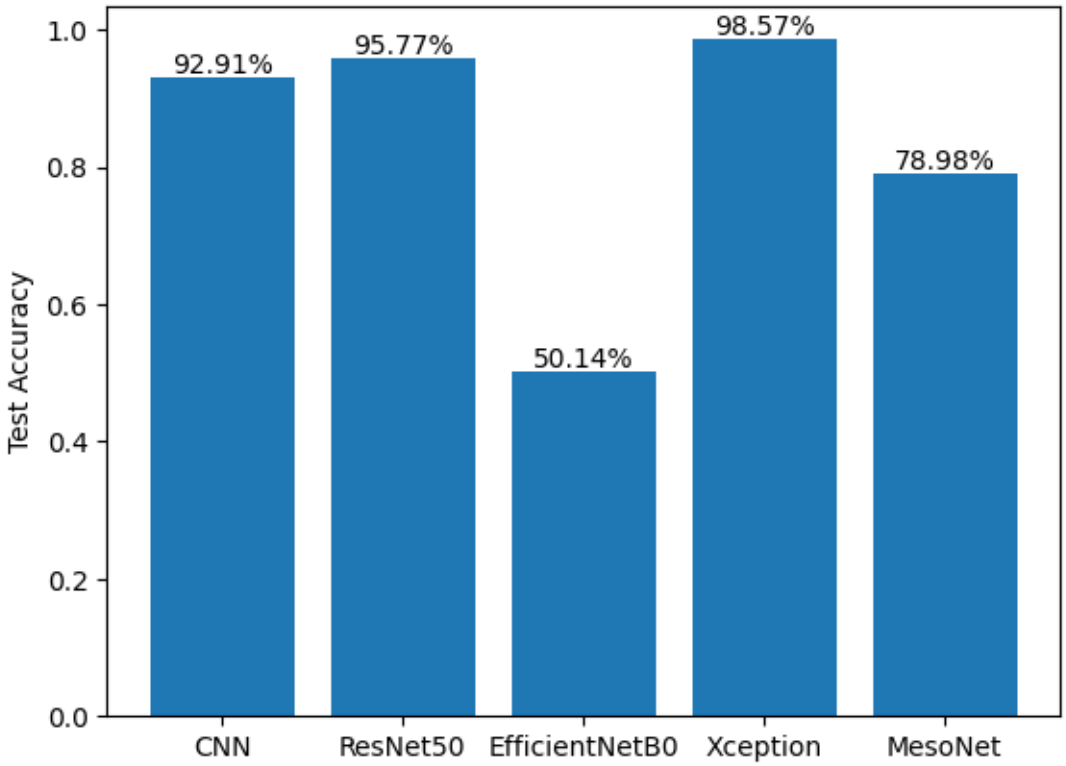

EfficientNetB0 - Accuracy
Train Accuracy
Val Accuracy
Accuracy
Epochs


EfficientNetB0 - Loss
Train Loss
Val Loss
Loss
Epochs





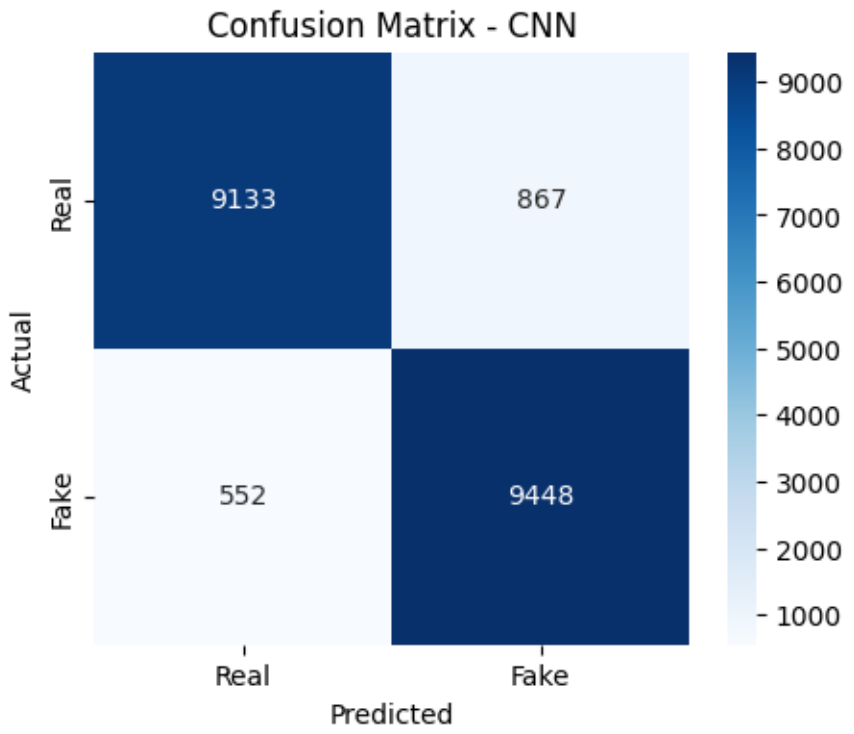
[19]:
```
fig, ax = plt.subplots()
bars = ax.bar(accuracies.keys(), accuracies.values())
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,
        height,
        f"{height * 100:.2f}%",
        ha="center",
        va="bottom"
    )
ax.set_ylabel("Test Accuracy")
plt.show()
```



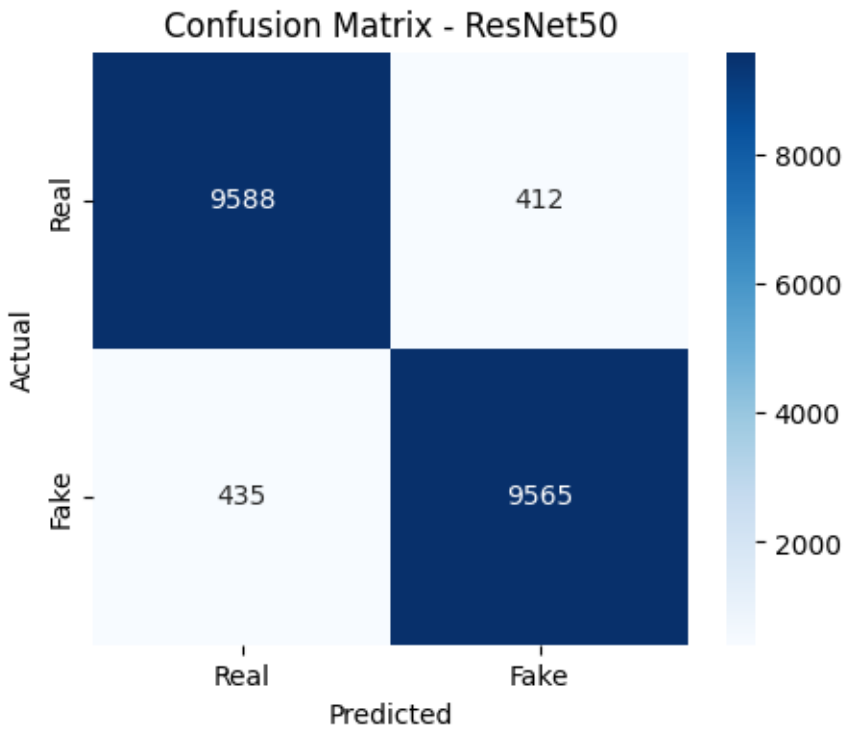
[20]:
```python
def evaluate_model(model, test_generator, model_name="Model"):
    # Predict probabilities
    y_probs = model.predict(test_generator)

    # Convert probabilities to class predictions
    y_pred = (y_probs > 0.5).astype(int).flatten()

    # True labels
    y_true = test_generator.classes

    # Compute Metrics
    acc = accuracy_score(y_true, y_pred)
    prec = precision_score(y_true, y_pred)
    rec = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)
    auc = roc_auc_score(y_true, y_probs)

    # Print metrics
    print(f"Evaluation Metrics for {model_name}:")
    print(f"Accuracy:  {acc:.4f}")
    print(f"Precision: {prec:.4f}")
    print(f"Recall:    {rec:.4f}")
```

```
    print(f"F1 Score:  {f1:.4f}")
    print(f"AUC-ROC:   {auc:.4f}")

    # Confusion Matrix
    cm = confusion_matrix(y_true, y_pred)

    plt.figure(figsize=(5, 4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Real",␣
 ↪"Fake"], yticklabels=["Real", "Fake"])
    plt.title(f"Confusion Matrix - {model_name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return{
        "Accuracy": acc,
        "Precision": prec,
        "Recall": rec,
        "F1-Score": f1,
        "AUC-ROC":auc
        }
results = {}

for name, model in models.items():
    print(f"\nEvaluating {name}...")
    results[name] = evaluate_model(model, test_generator, model_name=name)
```

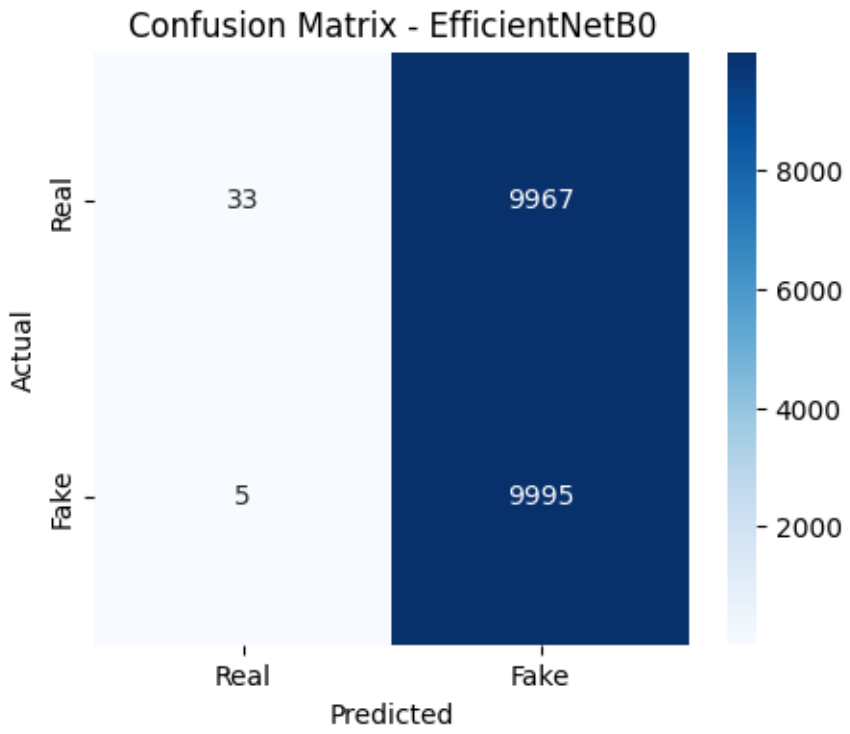
```
Evaluating CNN…
625/625 [==============================] - 15s 24ms/step
Evaluation Metrics for CNN:
Accuracy:  0.9291
Precision: 0.9159
Recall:    0.9448
F1 Score:  0.9302
AUC-ROC:   0.9791
```



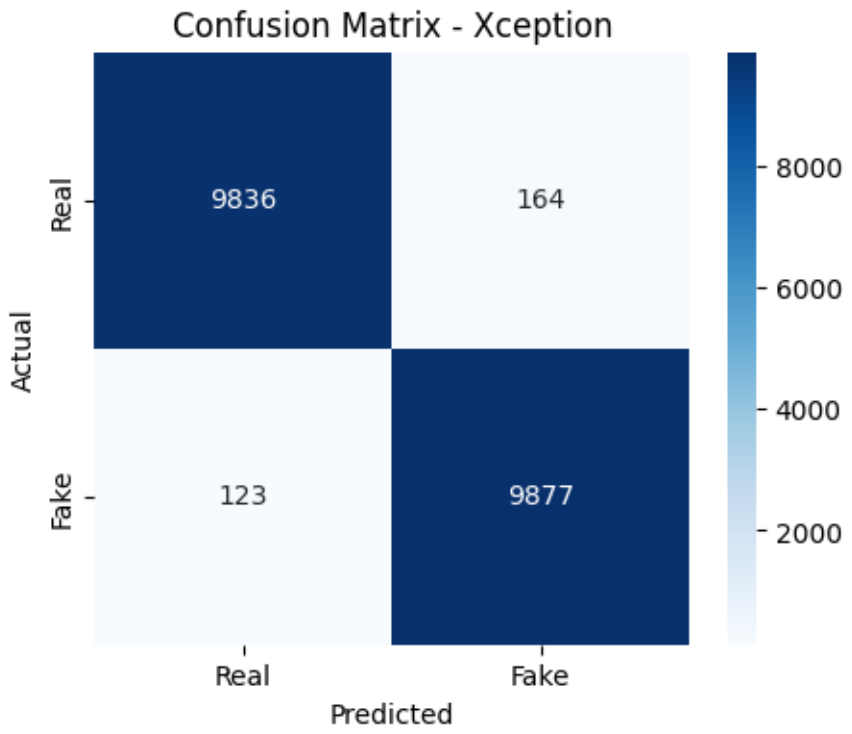

```
Evaluating ResNet50…
625/625 [==============================] - 17s 26ms/step
Evaluation Metrics for ResNet50:
Accuracy:  0.9577
Precision: 0.9587
Recall:    0.9565
F1 Score:  0.9576
AUC-ROC:   0.9926
```



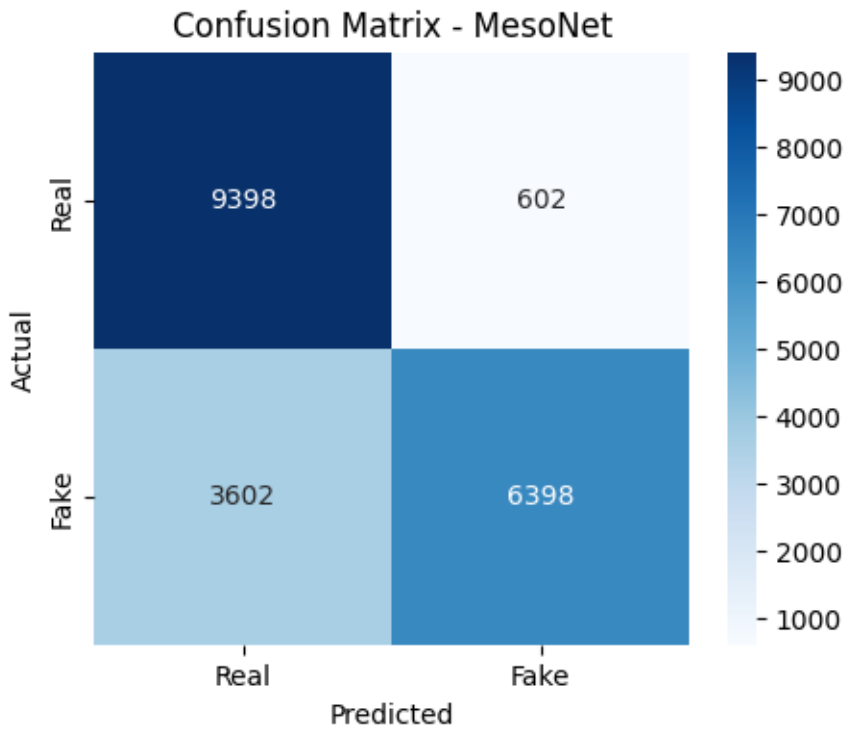

```
Evaluating EfficientNetB0…
625/625 [==============================] - 17s 26ms/step
Evaluation Metrics for EfficientNetB0:
Accuracy:  0.5014
Precision: 0.5007
Recall:    0.9995
F1 Score:  0.6672
AUC-ROC:   0.5640
```




```
Evaluating Xception…
625/625 [==============================] - 16s 25ms/step
Evaluation Metrics for Xception:
Accuracy:  0.9857
Precision: 0.9837
Recall:    0.9877
F1 Score:  0.9857
AUC-ROC:   0.9990
```




```
Evaluating MesoNet…
625/625 [==============================] - 15s 25ms/step
Evaluation Metrics for MesoNet:
Accuracy:  0.7898
Precision: 0.9140
Recall:    0.6398
F1 Score:  0.7527
AUC-ROC:   0.9214
```



[23]:
```
#Saving model
xception_model = models["Xception"]
xception_model.save('xception_model.h5')

from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image

model = load_model('xception_model.h5')
```

[36]:
```
sample_path = r"C:\Users\SujithVarmaMudunuruI\OneDrive - Manipal University␣
 ↪Jaipur\Desktop\Big_Dataset\real_vs_fake\real-vs-fake\train\fake\0C5A51CXL0.
 ↪jpg"
img = image.load_img(sample_path, target_size=(img_height, img_width))
x = image.img_to_array(img) / 255.0
x = np.expand_dims(x, axis=0)

pred = model.predict(x)[0][0]
label = "Real" if pred > 0.5 else "Fake"

plt.imshow(img)
plt.title(f"Prediction: {label} ({pred:.4f})")
plt.axis("off")
plt.show()
```

```
1/1 [==============================] - 0s 11ms/step
```