

Configuration Manual

MSc Research Project
Data Analytics

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MSc Project Submission Sheet
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Programme:Data Analytics..... **Year:**2024.....

Module: MSc Research Project
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Lecturer: Teerath Kumar Menghwar

Submission Due Date:29/01/2025.....

Project Title: Enhancing Deepfake Detection with Multi-Modal Transformers

Word Count: **Page Count:**

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Configuration Manual

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1 Introduction

Deepfakes, created using **Generative Adversarial Networks (GANs)**, have become a significant challenge in ensuring media authenticity. These manipulated images, videos, and audio are increasingly realistic, posing risks to **cybersecurity**, **misinformation campaigns**, and **digital fraud**. Detecting such falsified media is crucial to maintaining trust and integrity in information systems.

While advancements in machine learning have improved deepfake detection, existing methods often fail when tested against **high-quality manipulations** or real-world distortions. The primary challenge lies in the adaptability and robustness of these detection systems in varying conditions. This research focuses on enhancing detection accuracy by leveraging **state-of-the-art machine learning models** tailored for both image- and audio-based detection tasks.

2 Hardware and Software Requirements

2.1 Hardware Requirements

The hardware configuration of the system for this research project and executed are as follow:

- Processor: Intel Core i5 or higher.
- RAM: 16 GB or more.
- GPU: NVIDIA Tesla or similar (for model training).
- Storage: At least 100 GB of free space.

2.2 Software Requirements

- Operating System: Windows 10 / Linux / macOS.
- Programming Language: Python 3.7 or above.
- IDE: Google Colab or Jupyter Notebook.
- Libraries:
TensorFlow, Keras, OpenCV, Librosa, NumPy, Matplotlib, and Seaborn.

3 Environment Setup

3.1 Google Colab Setup

- Open [Google Colab](#).
- Enable GPU: **Runtime** > **Change runtime type** > **Hardware Accelerator** > **GPU**.

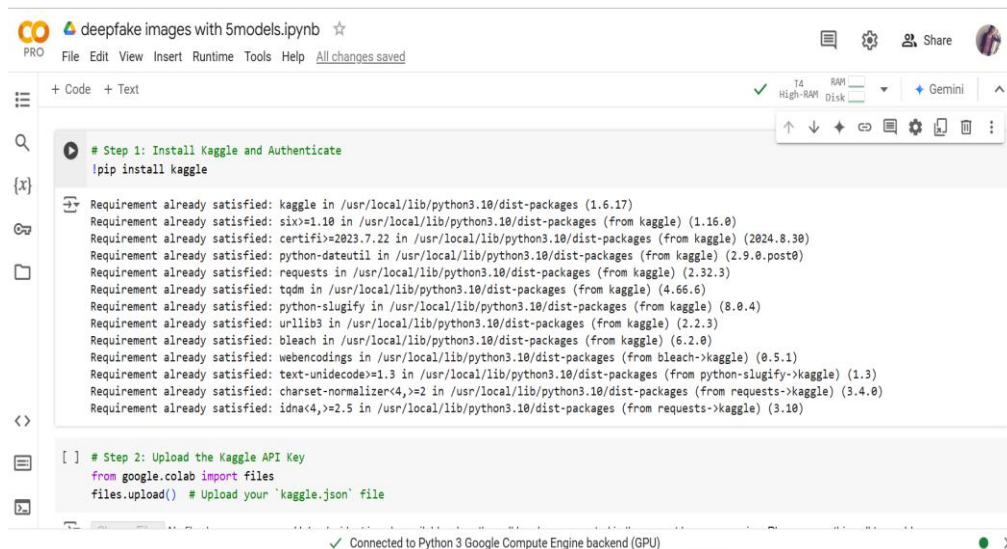


Figure 1: Screenshot of Google Colab with GPU enabled

3.2 Installing Libraries

Run the following command to install required libraries:

```
[ ] import tensorflow as tf
    from tensorflow.keras.applications import ResNet50
    from tensorflow.keras.models import Model
    from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
    from tensorflow.keras.preprocessing.image import ImageDataGenerator
    from tensorflow.keras.optimizers import Adam
    from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
    from sklearn.metrics import classification_report, confusion_matrix
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
```

Figure 2: Importing libraries and packages

4. Data Preparation

4.1 Accessing Datasets

- Download datasets from Kaggle and upload them to Google Drive.
- Path setup in Colab:
This section provides instructions on accessing Kaggle datasets using the Kaggle API in Google Colab.

```

# Step 2: Upload the Kaggle API Key
from google.colab import files
files.upload() # Upload your "kaggle.json" file

# Step 3: Set up Kaggle API for Dataset Download
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json

# Step 4: Download the Dataset
!kaggle datasets download -d manjilkarki/deepfake-and-real-images

Dataset URL: https://www.kaggle.com/datasets/manjilkarki/deepfake-and-real-images
License(s): unknown
Downloading deepfake-and-real-images.zip to /content
99% 1.66G/1.68G [00:07<00:00, 282MB/s]
100% 1.68G/1.68G [00:07<00:00, 246MB/s]

```

https://www.kaggle.com/datasets/manjilkarki/deepfake-and-real-images

Figure 3: the dataset being downloaded using the API

4.2 Preprocessing

```

# Paths to dataset directories
train_dir = '/content/dataset/Dataset/Train'
val_dir = '/content/dataset/Dataset/Validation'
test_dir = '/content/dataset/Dataset/Test'

# Image dimensions and batch size
IMG_SIZE = (224, 224)
BATCH_SIZE = 32

# Create ImageDataGenerator for augmentation and normalization
train_datagen = ImageDataGenerator(
    rescale=1.0/255.0, # Normalize to [0, 1]
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest'
)

val_test_datagen = ImageDataGenerator(rescale=1.0/255.0)

```

Figure 4: The preprocessing pipeline

5. Model Implementation

- Import the ResNet50 model from tensorflow.keras.applications with the pre-trained weights from ImageNet.
- Set the input shape to (224, 224, 3) to match image dimensions and exclude the top layers for fine-tuning.

- Freeze the first layers of the ResNet50 model (except the last 10 layers) to retain pre-trained weights and speed up training.



```

from tensorflow.keras.layers import GlobalAveragePooling2D, Dense, Dropout
from tensorflow.keras.optimizers import Adam

# Load ResNet50 base model
base_model = ResNet50(input_shape=(224, 224, 3), include_top=False, weights='imagenet')

# Add classification layers
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.5)(x) # Regularization
output = Dense(1, activation='sigmoid')(x)

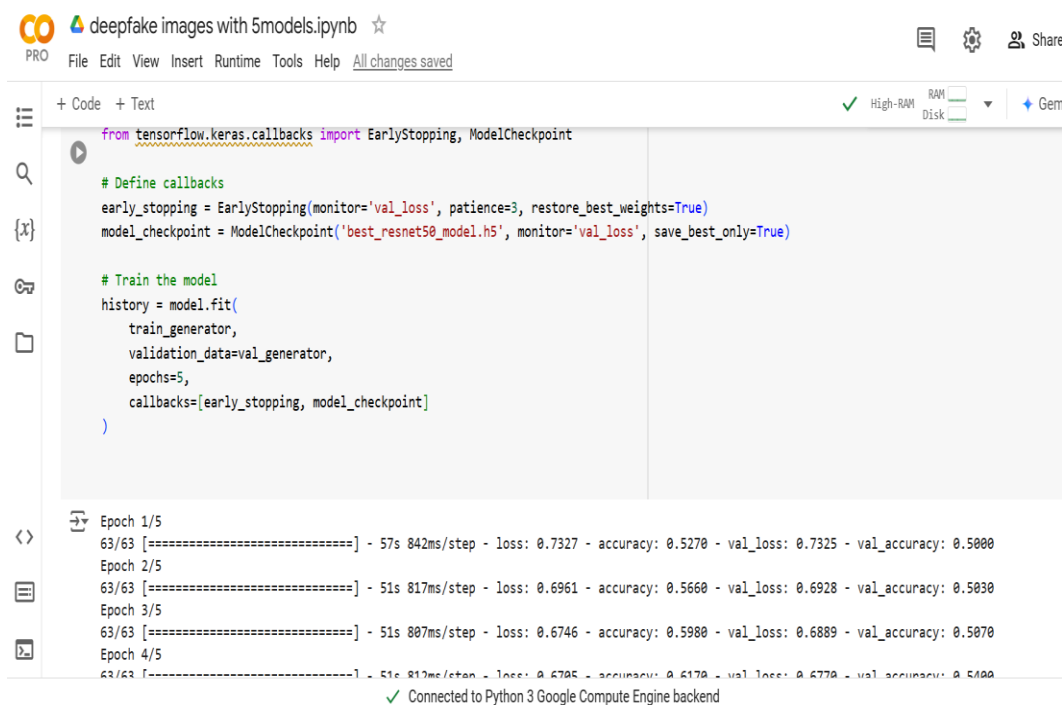
model = Model(inputs=base_model.input, outputs=output)

# Freeze initial layers for transfer learning
for layer in base_model.layers[:-10]:
    layer.trainable = False

# Compile the model
model.compile(optimizer=Adam(learning_rate=1e-5),
              loss='binary_crossentropy',
              metrics=['accuracy'])

```

Figure 5: ResNet50 Model Building



```

from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
model_checkpoint = ModelCheckpoint('best_resnet50_model.h5', monitor='val_loss', save_best_only=True)

# Train the model
history = model.fit(
    train_generator,
    validation_data=val_generator,
    epochs=5,
    callbacks=[early_stopping, model_checkpoint]
)

```

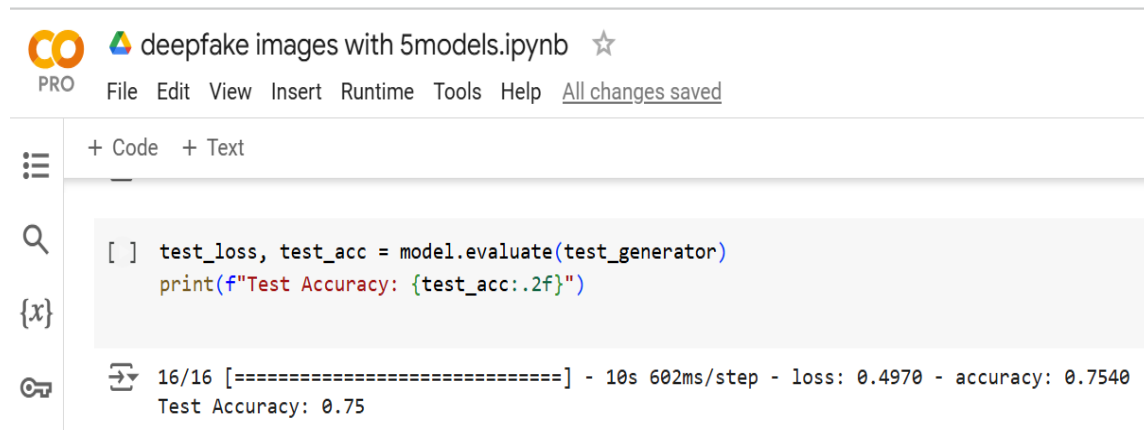
Epoch 1/5
 63/63 [=====] - 57s 842ms/step - loss: 0.7327 - accuracy: 0.5270 - val_loss: 0.7325 - val_accuracy: 0.5000
 Epoch 2/5
 63/63 [=====] - 51s 817ms/step - loss: 0.6961 - accuracy: 0.5660 - val_loss: 0.6928 - val_accuracy: 0.5030
 Epoch 3/5
 63/63 [=====] - 51s 807ms/step - loss: 0.6746 - accuracy: 0.5980 - val_loss: 0.6889 - val_accuracy: 0.5070
 Epoch 4/5
 63/63 [=====] - 51s 817ms/step - loss: 0.6705 - accuracy: 0.6170 - val_loss: 0.6770 - val_accuracy: 0.5100

Fig 6: Training model ResNet50

6. Model Evaluation

6.1 Evaluate on Test Data:

- Use the evaluate() function to assess the model's performance on the test dataset. The function computes the loss and accuracy metrics for the model based on the data from the test generator.
- After evaluation, print the test accuracy to see how well the model is performing on unseen data



The screenshot shows a Jupyter Notebook titled "deepfake images with 5models.ipynb". The code cell contains the following Python code:

```
[ ] test_loss, test_acc = model.evaluate(test_generator)
    print(f"Test Accuracy: {test_acc:.2f}")
```

The output of the code cell is:

```
16/16 [=====] - 10s 602ms/step - loss: 0.4970 - accuracy: 0.7540
Test Accuracy: 0.75
```

Figure 7: Evaluating model

7. References

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