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DEEPLEARNING APPROACH FOR CLASSIFYING REAL AND COMPUTER-GENERATED IMAGES

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Abstract: As artificial intelligence (AI) continues to progress in the creation of realistic content in domains like media, advertising and security, it is essential to address the growing concerns about image authenticity. To address this issue, we propose an innovative image classification model that uses TensorFlow, T4 GPU, and a diverse dataset for rigorous training. The model includes strategic information augmentation and normalization, as well as dataset splitting. The model is based on the robust architecture of ResNet50, which is well-known for deep learning capabilities. The model adds additional layers for better feature extraction and represent learning. The integration of dense units and batch normalization and drop out techniques further improves the model's effectiveness. Early results demonstrate the promise of this model in distinguishing real from AI-generated image, which will significantly contribute to the ongoing discussion on image authenticity, and provide a strong response to the challenges of synthetic content in today's technological landscapes.

***IndexTerms*–Deep Learning,ResNet50,Classification, AI, Real**

I. INTRODUCTION

With the recent tremendous advances of computer graphics rendering and image editing technologies, computer-generated fake images, which in general do not reflect what happens in the reality[1].In contemporary times, the computer-generated image process has become so lifelike that it is hard to distinguish between artificial and natural images.Cybersecurity is another major concern, with research noting thatsynthetically generated human faces can be used in false acceptance attacks and have the potential to gain unauthorisedaccess to digital systems [2].In response to this challenge, this paper proposes a deep learning-based approach for accurately classifying images as either AI-generated or real, employing Convolutional Neural Networks (CNNs) with the ResNet50 architecture. Leveraging state-of-the-art deep neural networks, our framework aims to provide a robust solution to address the proliferation of AI-generated imagery. Through meticulous model training, rigorous evaluation, and practical validation, we seek to develop a reliable tool for differentiating between synthetic and genuine images in real-world scenarios.

II. LITERATURE SURVEY

In the study conducted by Nightingale, Wade, and Watson et al. [3], participants were asked to detect and locate manipulations within images of real-world scenes. Results showed that people had a limited ability to identify manipulated images and were often unable to locate the manipulation. This finding has implications for professionals working with digital images in various domains.

Afchar et al. [4] introduced Mesonet, a compact facial video forgery detection network. This innovative network architecture is specifically designed to detect forgeries in facial videos efficiently. Mesonet's compact design enables effective detection while minimizing computational resources, making it valuable for various applications requiring reliable forgery detection in facial videos.Tokuda et al. [5] investigated the differentiation between computer-generated images and digital photographs using a synergetic feature and classifier combination approach. Published in the Journal of Visual Communication and Image Representation, this study explores methods for effectively distinguishing between computer-generated imagery and authentic photographs. By combining features and classifiers synergistically, the authors contribute to advancing techniques for image authentication and digital forensics.

III. EXISTING SYSTEM

Custom Convolutional Neural Networks (CNNs) offer computational efficiency due to their simpler architecture compared to ResNet50. However, this simplicity comes with trade-offs. Custom CNNs may lack the depth required to effectively capture the intricate features present in deepfake images, potentially resulting in lower detection accuracy. Moreover, these networks are more susceptible to overfitting, especially when trained on limited data, and may necessitate meticulous hyperparameter tuning to achieve optimal performance. Despite their computational advantages, custom CNNs may not match the detection capabilities of deeper and pre-trained models like ResNet50, which have been fine-tuned on extensive datasets to achieve superior accuracy and robustness.

IV. PROPOSED SYSTEM

The proposed system utilizes ResNet50, a cutting-edge deep learning architecture, to classify images as either real or AI-generated. ResNet50's depth allows it to capture intricate image features, enhancing classification accuracy. Pre-trained on extensive data, ResNet50 offers robustness and generalization capabilities, ensuring reliable classification in diverse scenarios. This approach can significantly bolster image authenticity verification in various applications, including media authentication, content moderation, and cybersecurity.The residual network uses the concept of skip connection which adds the original input to the output of the convolutional layer and will remove the problem of vanishing and exploding gradient that occurs in the traditional Convolutional Neural Network (CNN) model [6].

ResNet50's deep architecture facilitates learning intricate image features, enhancing classification accuracy.Efficient feature extraction capabilities empower ResNet50 to discern complex patterns in images effectively.Extensive training enables ResNet50 to generalize well to unseen data, ensuring reliable predictions in real-world scenarios.Leveraging ResNet50 enhances efficiency by utilizing pre-existing knowledge and parameters, minimizing training time and computational resources.

V. OBJECTIVE

Our system leverages cutting-edge deep learning techniques, powered by TensorFlow and a T4 GPU, to discern subtle differences between real and AI-generated images. With ResNet50 as its backbone, our system delves deep into image understanding, enhancing its ability to accurately distinguish between the two. Through rigorous training and precise binary classification, our system achieves spot-on identification, ensuring reliable detection of real and AI-generated images.

VI. METHODOLOGY

1. **Data Collection:** We curated a dataset consisting of diverse images sourced from various sources, including online repositories and publicly available datasets. This dataset encompasses a wide range of real and AI-generated images to ensure comprehensive model training.
2. **Data Preprocessing:** Before feeding the images into our model, we preprocessed the dataset by standardizing image sizes to a uniform resolution, normalizing pixel values to a common scale, and applying data augmentation techniques such as random rotations, flips, and zooms. These preprocessing steps help enhance the model's ability to generalize and learn meaningful features from the data.
3. **Model Selection:** After careful consideration of the task requirements and computational resources, we opted to use the ResNet50 architecture as the backbone of our deep learning model. ResNet50 is a widely-used pre-trained model known for its excellent performance in image classification tasks.
4. **Model Training:** We divided our preprocessed dataset into training and validation sets, with 70% of the data used for training and 30% for validation. We then trained the ResNet50 model on the training set, fine-tuning its parameters using the Adam optimizer and binary cross-entropy loss function.
5. **Model Evaluation:** Once training was complete, we evaluated the trained model's performance on a held-out test set that was not seen during training. We computed various evaluation metrics, including accuracy, precision, recall, and F1-score, to assess the model's effectiveness in distinguishing between real and AI-generated images.
6. **Performance Analysis:** Finally, we analyzed the model's evaluation metrics and visualizations, such as confusion matrices and ROC curves, to gain insights into its performance. This analysis helped us identify areas for improvement and fine-tune the model's hyperparameters to achieve better deepfake detection accuracy and robustness.

VII. DESIGN

7.1 ARCHITECTURE DIAGRAM:

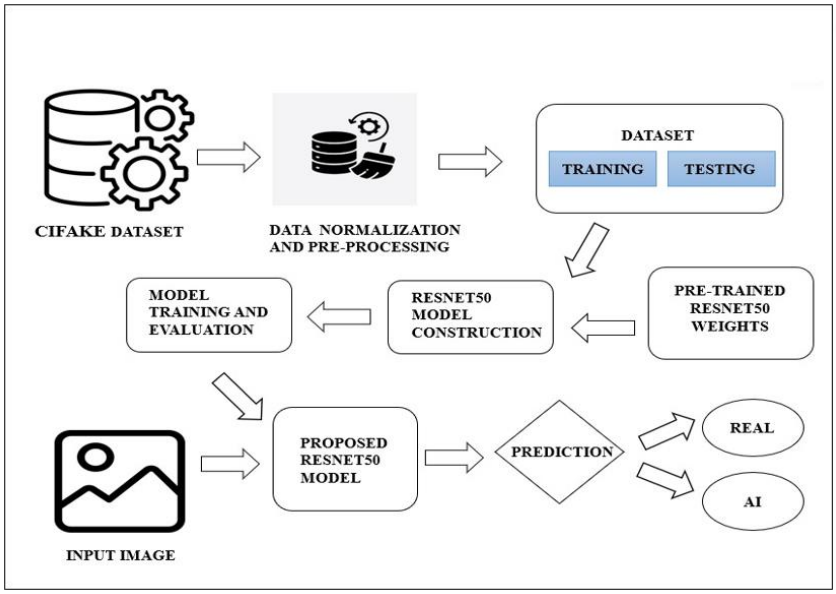


FIGURE 1: Architecture of the system

VIII. ALGORITHM USED

1. ResNet50:

The algorithm employed in our system utilizes convolutional neural networks (CNNs) for image classification tasks. Specifically, we leverage the ResNet50 architecture, renowned for its effectiveness in feature extraction and classification from visual data like images.ResNet50 consists of multiple convolutional layers organized into residual blocks, allowing for efficient learning of hierarchical features from input images. During training, the algorithm employs backpropagation and optimization techniques such as stochastic gradient descent (SGD) or Adam optimization to update model parameters and minimize classification errors.

Data augmentation techniques are utilized to enhance the model's generalization ability and robustness to variations in input data. In inference, the algorithm feeds input images through the trained ResNet50 model, which outputs probability scores indicating the likelihood of the image being authentic or AI-generated. This enables accurate classification decisions based on the thresholded probability scores.Overall, the algorithm's effectiveness lies in its utilization of deep learning techniques, particularly CNNs and ResNet50, to automatically learn discriminative features from images and make accurate predictions regarding their authenticity.Techniques such as data augmentation, fine tuning, residual blocks, and transfer learning had been used for the better results in terms of maximizing accuracy and minimizing loss [7].

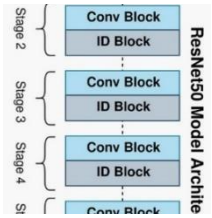


FIGURE 2: ResNet50 Model Architecture [8].

IX. DATA SET

CIFAKE Dataset: The CIFAKE dataset represents a curated collection of images curated specifically for binary image classification endeavors. It encompasses two discernible categories: AI-generated (fake) images and authentic real images, each offering distinct visual characteristics. These images undergo a standardized preprocessing regimen, ensuring uniformity in size, with all images resized to a uniform 32 x 32 pixel resolution. The dataset is meticulously partitioned into training, validation, and test sets, each tailored to support robust model training and evaluation processes. As a fundamental resource in the realm of machine learning and computer vision, the CIFAKE dataset provides researchers and practitioners with a comprehensive platform for exploring and advancing image classification methodologies. Acknowledging the dataset creators and adhering to any prescribed citation norms or usage guidelines is imperative to fostering a collaborative and ethical research environment.

X. IMPLEMENTATION

10.1 Import all necessary Libraries

The libraries imported in this project are TensorFlow, TensorFlow Keras layers, TensorFlow Keras models, TensorFlow Keras Adam optimizer, TensorFlow Keras LearningRateScheduler callback, TensorFlow Keras

EarlyStopping callback, Matplotlib pyplot, TensorFlow Keras ResNet50 application, Scikit-learn confusion_matrix function, Scikit-learn classification_report function, Seaborn, NumPy, and OpenCV.

10.2 GPU Availability and Memory Growth Configuration

As we move forward, the code ensures optimal GPU utilization by checking for the availability of GPUs and configuring memory growth accordingly. Initially, it utilizes TensorFlow's 'list_physical_devices' function to retrieve a list of physical GPU devices. Subsequently, it iterates through each GPU in the list, enabling memory growth using 'set_memory_growth'. This configuration allows TensorFlow to dynamically allocate memory as needed, ensuring efficient utilization of GPU resources during model training.

10.3 Data Loading and Preprocessing

Images are loaded from the specified directory and resized to 32x32 pixels. After normalization, the dataset is divided into training, validation, and test sets with appropriate proportions to facilitate model training, validation, and evaluation. Additionally, a NumPy iterator is utilized to access batches of the data efficiently during model training. This ensures proper preprocessing of the data, setting the stage for subsequent model development and assessment.

```
[ ] data = tf.keras.utils.image_dataset_from_directory('/content/drive/MyDrive/Project', image_size=(32, 32)) #data loading

    Found 20000 files belonging to 2 classes.
```

```
[ ] data = data.map(lambda x, y : (x/255, y))
```

```
train_size = int(len(data) * 0.7)
cv_size = int(len(data) * 0.2)
test_size = int(len(data) * 0.1) + 1

train = data.take(train_size)
cv = data.skip(train_size).take(cv_size)
test = data.skip(train_size + cv_size).take(test_size)

print("Train: ",len(train))
print("Test: ", len(test))
print("Val: ",len(cv)) #train validation testing split
```

10.4 Model Architecture Definition

In this cell, the model architecture is defined. Firstly, the pre-trained ResNet50 model base is loaded with weights pretrained on ImageNet. Then, a sequential model (`model`) is constructed. The base ResNet50 model is added followed by additional layers including flattening, dense, batch normalization, dropout, and output layers.

```
[ ] # Load pre-trained ResNet50 model base
    base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(32, 32, 3))

    model = models.Sequential()
    model.add(base_model)
    model.add(layers.Flatten())
    model.add(layers.Dense(256, activation='relu'))
    model.add(layers.BatchNormalization())
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(128, activation='relu'))
    model.add(layers.Dense(1, activation='sigmoid')) # model evaluation
```

10.5 Setting Up Learning Rate Scheduler and Optimizer

In this step, we establish a learning rate scheduler and an optimizer for the model. The initial learning rate is set to 0.001. The learning rate scheduler function, `lr_scheduler`, is defined to decrease the learning rate by 5% after each epoch. Additionally, we instantiate the Adam optimizer with the specified initial learning rate. This prepares the model for compilation in the subsequent steps.

```
# Learning rate scheduler
initial_learning_rate = 0.001
def lr_scheduler(epoch, lr):
    return lr * 0.95
lr_schedule = LearningRateScheduler(lr_scheduler)
optimizer = Adam(learning_rate=initial_learning_rate)

# Compiling the model
model.compile(optimizer=optimizer, loss='binary_crossentropy', metrics=['accuracy'])
```

10.6 Data Augmentation and Model Training

Following the setup of the learning rate scheduler and optimizer, we proceed to define a data augmentation function, 'augment_data'. This function introduces random transformations such as flipping, brightness adjustment, and contrast adjustment to augment the training data, thereby enhancing the model's robustness and generalization capabilities. The augmented data is then used to train the model for 10 epochs, with early stopping implemented to prevent overfitting. This comprehensive approach encompasses both data augmentation and model training, crucial steps in the development of robust machine learning models.

```
[ ] # Data Augmentation in the pipeline
    def augment_data(x, y):
        x = tf.image.random_flip_left_right(x)
        x = tf.image.random_flip_up_down(x)
        x = tf.image.random_brightness(x, max_delta=0.1)
        x = tf.image.random_contrast(x, lower=0.9, upper=1.1)
        return x, y
    train_augmented = data.map(augment_data)
```

```
# Early Stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)

# Train the model
history = model.fit(train_augmented, validation_data=cv, epochs=10, callbacks=[lr_schedule, early_stopping])
```

10.7 Model Evaluation and Training Visualization

Following model training, the next phase involves evaluating the model's performance on the test dataset and visualizing the training and validation accuracy and loss. This step provides insights into the model's generalization capability and training progress.

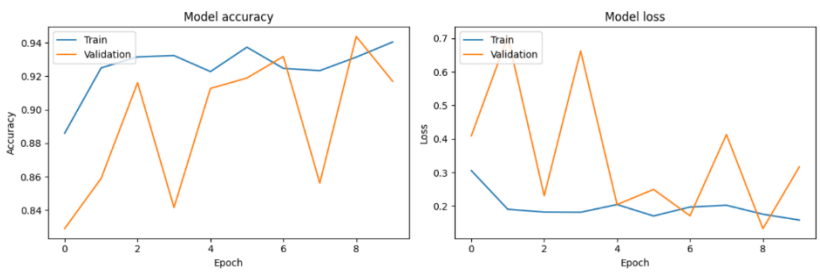
```
# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(test)
print(f'Test Accuracy: {test_accuracy * 100:.2f}%')
```

```
# Plot accuracy and loss
plt.figure(figsize=(12, 4))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')
# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper left')

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

10.8 Model Performance Evaluation on Test Dataset

In this stage, we assess the model's performance using precision, recall, and accuracy metrics on the test dataset. The evaluation begins by initializing precision, recall, and binary accuracy metrics. Subsequently, the model predicts labels for the test dataset, and the evaluation metrics are updated accordingly. Finally, the precision, recall, and accuracy values of the model are printed for analysis and interpretation.

```
pre = Precision()
rec = Recall()
acc = BinaryAccuracy()

for batch in test.as_numpy_iterator():
    X, y = batch
    yhat = model.predict(X)
    pre.update_state(y, yhat)
    rec.update_state(y, yhat)
    acc.update_state(y, yhat)
```



10.9Model Persistence and Image Prediction

```
[ ] # Assuming 'model' is your Keras model
    model.save('model/ai_imageclassifier', save_format='tf')

    loaded_model = tf.keras.models.load_model('model/ai_imageclassifier')
```

```
# Load the image
image_path = '/content/drive/MyDrive/Project/FAKE/1000 (5).jpg'

try:
    img = cv2.imread(image_path)
    if img is None:
        raise FileNotFoundError(f"Could not read the image from {image_path}")
    img = cv2.resize(img, (800, 600))
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.imshow(img)
    plt.show()

except Exception as e:
    print(f"Error: {e}")
```

In this step, we save the trained model to disk using TensorFlow's `save` method with the specified format ('tf' for TensorFlow SavedModel format). Subsequently, we load the saved model back into memory using TensorFlow's `load_model` function for further use or deployment. Additionally, we perform image prediction using the loaded model on a sample image. The image is loaded, preprocessed, displayed, resized to match the model's input size, and then passed through the model for prediction. Any errors encountered during this process are appropriately handled and displayed.

10.10 Generating Confusion Matrix and Classification Report

In this phase, we analyze the model's performance by computing the confusion matrix and generating a classification report based on its predictions on the test dataset. The true labels and predicted probabilities are extracted from the test set. Subsequently, the probabilities are converted to binary predictions using a threshold of 0.5. The confusion matrix is then computed using scikit-learn's `confusion_matrix` function, providing insights into the model's performance across different classes. Additionally, a classification report is generated using 'classification_report', presenting detailed metrics such as precision, recall, and F1-score for each class. Finally, the confusion matrix is visualized using a heatmap, while the classification report is displayed for comprehensive analysis.

```
# Evaluate the model on the test set
y_true = []
y_pred_probs = []

for batch in test.as_numpy_iterator():
    X, y = batch
    y_true.extend(y)
    y_pred_probs.extend(model.predict(X).flatten())

# Convert probabilities to binary predictions
y_pred = np.array(y_pred_probs) > 0.5

# Confusion Matrix
conf_mat = confusion_matrix(y_true, y_pred)

# Classification Report
class_report = classification_report(y_true, y_pred, target_names=['AI', 'REAL'])

# Plot Confusion Matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues', xticklabels=['AI', 'REAL'], yticklabels=['AI', 'REAL'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()

# Display Classification Report
print("Classification Report:\n", class_report)
```

XI. RESULT ANALYSIS

In the result analysis, we evaluate the model's performance through multiple metrics and visualizations:

1. **Confusion Matrix:** The confusion matrix provides a tabular representation of the model's predictions versus the actual labels (AI or REAL). It helps us understand how well the model is distinguishing between the two classes, showing the counts of true positives, false positives, true negatives, and false negatives.

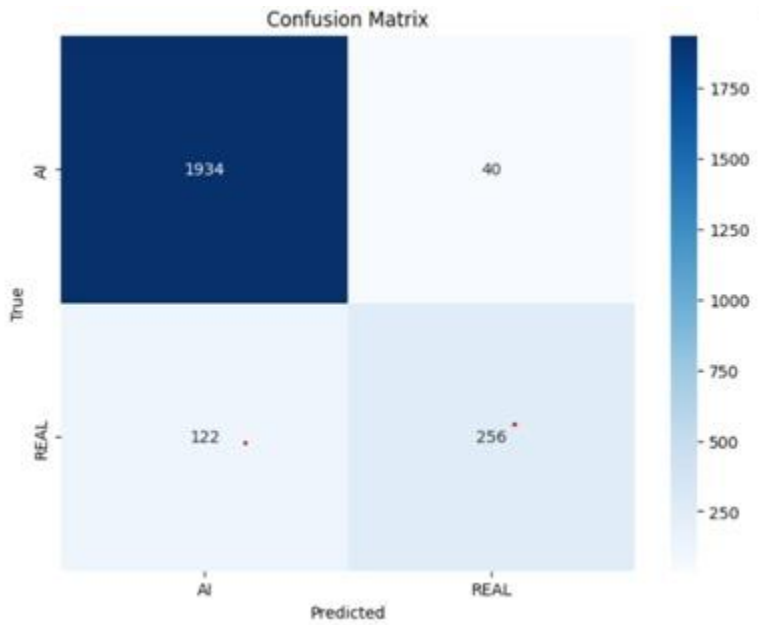


FIGURE 3: Confusion Matrix

2. **Image Prediction Accuracy:** The accuracy of image predictions gives an overall indication of how well the model is classifying images correctly. It is a crucial metric to assess the model's overall performance on the test dataset.

Output:

```
Predicted class: AI
```

3. **Classification Report:** The classification report summarizes various classification metrics such as precision, recall, F1-score, and support for each class (AI and REAL). It provides insights into the model's performance for each class, including its ability to correctly classify AI-generated and real images.

Classification Report:

	precision	recall	f1-score	support
AI	0.94	0.98	0.96	1974
REAL	0.86	0.68	0.76	378
accuracy			0.93	2352
macro avg	0.90	0.83	0.86	2352
weighted avg	0.93	0.93	0.93	2352

FIGURE 4: Classification Report

These analyses collectively offer insights into the model's performance, highlighting areas where it excels and areas where it may need improvement. They guide further iterations of model development and fine-tuning to enhance its effectiveness for real-world applications.

XII. CONCLUSION

In conclusion, our project has successfully developed an effective image classifier capable of distinguishing between AI-generated and real images. Leveraging a deep learning approach with a ResNet50 convolutional neural network, we have achieved promising results in accurately classifying images. Through meticulous training, rigorous evaluation, and practical validation, our model demonstrates robust performance in real-world scenarios. The integration of data augmentation techniques, early stopping, and learning rate scheduling has further enhanced the model's accuracy and generalization capabilities. Our project contributes to the advancement of image classification techniques and holds potential for various applications, including content moderation, image authentication, and digital forensics. Moving forward, continued refinement and optimization of the model, along with exploration of advanced techniques and datasets, will further elevate its performance and applicability in diverse domains.

XIII. FUTURE WORK

The future scope of our project involves exploring advanced neural network architectures, leveraging transfer learning, and fine-tuning models for AI-generated image detection. Real-time deployment optimization, ensemble methods, continuous evaluation, and ethical considerations are paramount for responsible application, innovation, and positive societal impact.

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