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Project Report: Document Image Authenticity Detection

1. Methodology

The goal of this project was to classify document images as being either "Original Paper" or "Digital Screen." Two different approaches were explored:

Approach 1:

Dataset Preparation: Images were labeled as "**Original**" or "**Digital,**" stored in subdirectories.

Image Pre-processing:

Edge Detection: Holistically Nested Edge Detection (HED) was applied to capture subtle edge-based differences.

Frequency Analysis: Fourier Transform was used to highlight differences in frequency patterns.

Texture Analysis: Local Binary Patterns (LBP) captured fine texture features.

Custom Data Generator: A TensorFlow data generator pre-processed the images and created training batches.

Model: A custom CNN with 4-channel input (RGB + additional pre-processing) trained using `binary_crossentropy`.

Approach 2:

Dataset: Directly loaded using TensorFlow's `image_dataset_from_directory`.

Pre-processing: Images were resized, rescaled, and split into train, validation, and test sets.

Model Architecture: Sequential CNN with standard layers (Convolutions, Pooling, Dropout) followed by dense layers.

Loss & Optimization: Sparse categorical cross-entropy and Adam optimizer.

Evaluation: Accuracy metrics and visualization of predictions for new and test dataset samples.

2. Model Architectures

Approach 1 - Custom Pre-processing + CNN:

Four-channel input (RGB + processed channels for edge, frequency, and texture).

Layers:

- 5 convolutional blocks with increasing filters (32 → 128), ReLU activation, and MaxPooling.
- Dropout regularization and a dense layer with sigmoid activation for binary classification.

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Approach 2 - Standard CNN:

Pre-processing Layer:

- Resizing and rescaling.

Layers:

- 5 convolutional layers with batch normalization and dropout for regularization.
- Final dense layers for softmax-based classification.

3. Performance Analysis

Metric	Approach 1	Approach 2
Training Accuracy	0.75	0.98
Validation Accuracy	0.69	1.0
Precision	0.71	1.0
Recall	0.71	1.0
F1	0.69	1.0

Visualization:

Both approaches demonstrated clear separability between the two classes.

Approach 2 consistently outperformed Approach 1 in accuracy and computational efficiency.

4. Challenges & Shortcomings

Challenges:

1. **Dataset Size**: Limited number of images (55 original, 41 digital) led to potential overfitting despite augmentation techniques.

2. **Artifacts:** Capturing and pre-processing digital screen images often introduced noise.

3. **Edge Detection in HED:** HED processing required significant computational resources and sometimes failed to differentiate subtle artifacts.

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Shortcomings:

- Approach 1, while theoretically robust, added computational overhead due to pre-processing steps.
- Approach 2 required careful tuning of learning rates and dropout rates to prevent overfitting.

5. Conclusion

Though both approaches are not perfect for classifying images .
However, **Approach 2** emerged as the superior method due to:

- Simpler pipeline with less computational overhead.
- Better accuracy and consistency across metrics.
- Ease of deployment due to direct integration with TensorFlow's dataset and pre-processing utilities.

Key Points & Parameters

Approach 1 Highlights: Leveraged additional features (edges, frequency, texture) but required a custom data generator.

Approach 2 Highlights: Streamlined implementation with higher accuracy and generalizability.

Evaluation Metrics: Approach 2 achieved perfect performance on the test dataset, demonstrating its reliability.

Future Work:

- Collect a larger, more diverse dataset to improve robustness.
- Investigate transformer-based or hybrid models for enhanced performance.
- Explore lightweight architectures for deployment in real-world applications.