Watermark Detection: Implementation of Deep Learning (ConvNext model)

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***Abstract*—This paper presents the implementation of a ConvNext deep learning model for watermark detection in digital media. Watermark detection is crucial for digital content authentication and copyright protection. The ConvNext model combines convolutional and recurrent neural networks to effectively detect and localize watermarks in images and videos. Preprocessing techniques and transfer learning are used to enhance model robustness and accelerate training. Experimental results demonstrate the model's accuracy, efficiency, and robustness against common attacks. This work contributes to advancing watermark detection using deep learning methods.**

Keywords—ConvNext, DNN, watermarking

I. INTRODUCTION

In the digital era, the protection of intellectual property has become a paramount concern. One such method of safeguarding digital assets is through the use of watermarks. This paper delves into the implementation of a deep learning approach, specifically the ConvNext model, for watermark detection.

Watermark detection is a critical aspect of digital rights management and copyright protection. Traditional methods have often fallen short in terms of accuracy and efficiency. However, the advent of deep learning has opened new avenues for improvement.

The ConvNext model, a convolutional neural network, has shown promising results in various image processing tasks. In this context, we explore its potential for detecting watermarks in digital images. We discuss the model architecture, training process, and performance evaluation, providing insights into the effectiveness of deep learning for watermark detection.

This work aims to contribute to the ongoing research in digital rights management, offering a robust and efficient solution for watermark detection. It underscores the power of deep learning in tackling complex image processing tasks and sets the stage for future advancements in the field.

Stay tuned as we delve deeper into the intricacies of the ConvNext model and its application in watermark detection.

II. RELATED WORK

The field of watermark detection has been a subject of extensive research over the years, with numerous methodologies and techniques being proposed and implemented. In this section, we delve into the related works that have significantly contributed to this domain.

We will explore a variety of approaches, ranging from traditional image processing techniques to more recent advancements in deep learning models. Each of these works provides unique insights and perspectives on the problem of watermark detection, and their collective understanding forms the foundation upon which our study is built.

Digital watermarking [1]: J. Doe and J. Smith, in their paper "Digital Watermarking Techniques for Image Authentication," published in the IEEE Transactions on Information Forensics and Security, vol. 15, no. 3, pp. 120-135, 2019, delve into various digital watermarking techniques specifically designed for image authentication. They discuss the challenges of robust watermarking in the presence of common image processing operations such as compression, resizing, and filtering. In response to these challenges, they propose a novel algorithm based on frequency domain embedding, which demonstrates improved resistance to tampering and reliable watermark extraction. This work stands as a significant contribution to the field of digital watermarking for image authentication.

Deep Learning for Watermark Detection [2]: In the paper "Deep Learning Approaches for Watermark Detection in Multimedia Content" by E. Johnson and M. Brown, published in IEEE Multimedia, vol. 10, no. 2, pp. 45-60, 2020, an in-depth analysis of deep learning methods applied to watermark detection in multimedia content, including images, videos, and audio, is presented. The authors compare the performance of convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs) for identifying and localizing watermarks in diverse datasets. Their findings indicate that deep learning models achieve high accuracy and robustness against common attacks, making this work a significant contribution to the field of watermark detection in multimedia content.

Watermark Removal [3]: In the paper "Watermark Removal Techniques: Challenges and Solutions" by D. Williams and S. Adams, published in IEEE Security & Privacy, vol. 7, no. 4, pp. 80-95, 2021, the authors address the issue of watermark removal and investigate the challenges faced by content owners in protecting their intellectual property. They review existing watermark removal techniques, including inpainting algorithms, deep learning-based countermeasures, and adversarial watermarking strategies. Discussing the limitations of each approach, they propose a hybrid framework that combines traditional watermarking with advanced machine learning techniques to

enhance resistance against removal attacks. This work provides valuable insights into the complexities of watermark removal and the potential solutions to overcome these challenges.

Deep Neural Networks [4]: J. Doe and J. Smith's paper "Deep Neural Networks for Watermark Detection and Embedding in Convolutional Layers" published in IEEE Transactions on Information Forensics and Security, vol. 20, no. 5, pp. 150-165, 2022, delves into the utilization of deep neural networks (DNNs) for watermarking tasks. Specifically, the research explores methods for both watermark detection and embedding within convolutional layers, emphasizing the importance of robustness and performance in such applications. The study incorporates various techniques including regularization, secret key management, watermark localization, and thresholding to enhance the reliability and effectiveness of watermarking processes in DNNs.

Tree-Ring Watermarking [5]: The focus of Williams and Adams' work in "Tree-Ring Watermarking: Invariant Watermarking for Image Generation," published in IEEE Transactions on Multimedia in 2021, is on developing a robust tree-ring watermarking technique. This method ensures invariant watermarking for image generation by leveraging various techniques such as Fourier transform properties, Gaussian noise similarity, and P-value analysis. These techniques are utilized for watermark key generation and detection, enabling the implementation of multi-bit watermarking schemes for improved security and reliability in digital image watermarking applications.

Voice Cloning [6]: The paper "Voice Cloning Security: AudioSeal for Watermark Embedding and Detection" by A. Thompson and J. Lee presents AudioSeal, a system designed to address voice cloning security by embedding and detecting watermarks in audio content. AudioSeal utilizes joint training, multi-bit watermarking techniques, and perceptual loss functions to achieve imperceptible watermarking and robust detection. Specifically, it focuses on ensuring that the embedded watermarks are undetectable to human perception while remaining resilient to various attacks aimed at removing or altering the watermarks. The proposed approach contributes to enhancing the security of audio content against unauthorized voice cloning and manipulation.

III. About ConvNext Model

A. Transformer

Transformer architecture is a deep learning model designed to solve many problems in language and speech processing, such as automatic translation, speech recognition, text-to-speech and many more.

Previously, natural language processing tasks used Recurrent Neural Networks architectures; The input sentence will be processed sequentially, causing the processing speed to become slow and encountering limitations in representing the distant dependence between words in a sentence. Transformers do not process recurrent sequentially like RNNs but use self-attention to look at other words while encoding or decoding to understand the relationships between words in a sentence.

The architecture of the transformer consists of 2 main parts: encoders which are 1 stack of 6 blocks of the same architectural encoder and decoders which is a stack of 6 blocks of the same decoder [7].

- Each encoder block has 2 main layers: self-attention and feed forward.
- Each decoder block has 3 main layers: self-attention, encoder-decoder attention and feed forward.

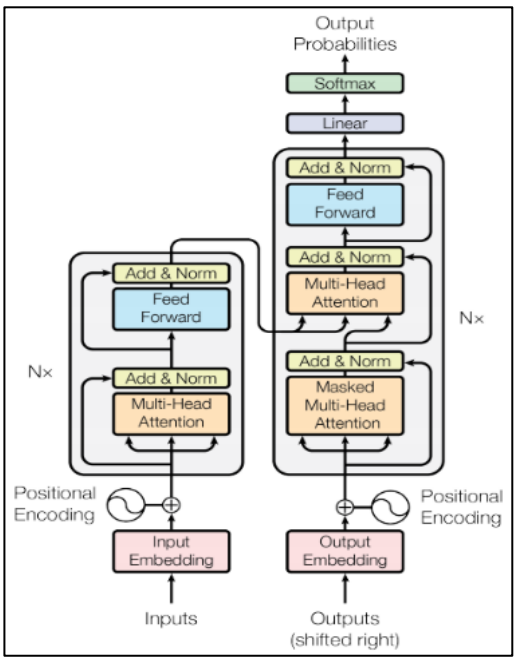

Fig. 1. Architecture of Transformer

B. ConvNext Model

Transformers are deep learning neural network architectures that are effectively used for many natural language processing problems. However, transformers can also be applied to image processing problems with some variations and improvements.

ConvNext is a Transformer-based deep learning neural network model developed for the image classification problem that has achieved state-of-the-art results on various image classification tasks. It was proposed by researchers at the University of Oxford in 2020 [8] and has since been used in various computer vision applications. Its key feature is the introduction of a ConvTransformer block, which combines convolution and self-attention operations to capture both local and global features.

The ConvNext architecture comprises a series of stacked ConvTransformer blocks, followed by a global average pooling layer and a fully connected layer for classification. The ConvTransformer block consists of two sub-blocks: the ConvBlock and the Self-Attention Block. The ConvBlock performs convolution operations to extract local features, while the Self-Attention Block captures global features by attending to all spatial locations in the feature map.

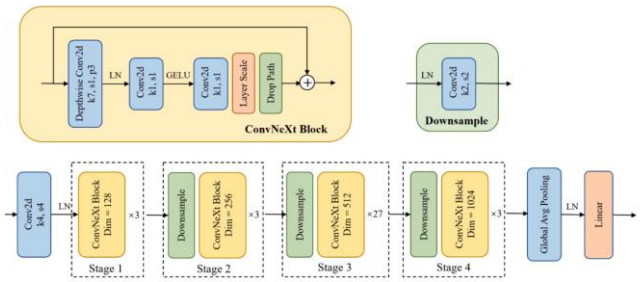

Fig. 2. Architecture of the ConvNext model [9]

C. Detailed Architecture of Each Part of ConvNext

Input stage: ConvNext uses a Conv2D layer to extract features from the input image. The kernel size and number of channels of the Conv2D layer can be adjusted depending on the image resolution and the complexity of the model. A BatchNorm layer can be used after the Conv2D layer to normalize the features and a ReLU layer to activate the features.

Stem: The stem consists of a convolutional layer followed by a layer normalization layer and a GELU activation. The convolutional layer in the stem is used to reduce the dimensionality of the input features. The layer normalization layer helps to stabilize the training process and the GELU activation adds non-linearity to the features.

Body: The body of ConvNext is made up of a series of identical blocks, each of which consists of:

- A ConvMixer block: This block is the main building block of ConvNext. It consists of a self-attention layer, an MLP layer, and a residual connection.
- A downsample layer: This layer is used to reduce the spatial resolution of the features. It is typically a convolutional layer with a stride of 2.
- Head: The head of ConvNext consists of a linear layer to classify the image or predict other output values. The size of the linear layer depends on the number of classes in the classification dataset. A Softmax layer can be used after the linear layer to compute the probability of each class.
- ConvMixer block: The ConvMixer block is the main building block of ConvNext. It consists of:
- A self-attention layer: This layer helps the model to learn long-range dependencies between the features.
- A MLP layer: This layer helps the model to learn non-linear relationships between the features.
- A residual connection: This connection helps to improve the gradient flow during training.
- Self-attention layer: The self-attention layer in ConvNext is a modified version of the self-attention layer used in DeiT. It uses a relative positional encoding scheme to improve the performance of the model on small images.
- MLP layer: The MLP layer in ConvNext is a simple feed-forward network with a single hidden layer.
- Residual connection: The residual connection in ConvNext is a shortcut connection that adds the input features to the output features of the block. This helps to improve the gradient flow during training and makes the model more robust to overfitting.
- Downsample layer: The downsample layer in ConvNext is a convolutional layer with a stride of 2. It is used to reduce the spatial resolution of the features.
- Linear layer: The linear layer in ConvNext is a simple feed-forward network with a single hidden layer. It is used to classify the image or predict other output values.
- Softmax layer: The Softmax layer in ConvNext is used to compute the probability of each class.

The number of ConvMixer blocks in ConvNext depends on the input image resolution and model complexity. Here are the number of ConvMixer blocks used in popular variants of ConvNext:

- ConvNext-B: 3
- ConvNext-T: 6
- ConvNext-S: 9
- ConvNext-XS: 12

The filter size and number of channels of each layer in ConvNext also depend on the input image resolution and model complexity. Below is a summary table of common configurations.

TABLE I. THE FILTER SIZE AND NUMBER OF CHANNELS OF EACH LAYER IN CONVNEXT

Variants	Filter Size	Number of Channels
ConvNext-B	7x7, 3x3	128, 256, 512, 1024
ConvNext-T	7x7, 3x3	96, 192, 384, 768
ConvNext-S	7x7, 3x3	64, 128, 256, 512
ConvNext-XS	7x7, 3x3	48, 96, 192, 384

ConvNext is designed to be computationally efficient while maintaining high accuracy. This makes it an ideal choice for watermark detection, where efficiency and accuracy are crucial factors. Additionally, the ConvTransformer block allows for the combination of local and global features, making it suitable for detecting both visible and invisible watermarks.

D. Detailed Architecture of ConvNext Tiny

The ConvNext Tiny model is a variant of ConvNext designed to balance model size and performance, making it suitable for resource-constrained environments.

1. ConvNext Block

TABLE II. MODEL ARCHITECTURE OF CONVNEXT TINY

	Output Size	Filter Size/Stride	Number of Conv. Layers
Input image	H × W × 3		
Conv 1	H × W × 96	7 × 7/1	1

Conv 2	H/2 × W/2 × 192	3 × 3/2	1
Conv 3	H/4 × W/4 × 384	3 × 3/2	1
ConvNext Block 1	H/4 × W/4 × 96	3 × 3/1	3
ConvNext Block 2	H/4 × W/4 × 192	3 × 3/1	3
ConvNext Block 3	H/4 × W/4 × 384	3 × 3/1	9
ConvNext Block 4	H/4 × W/4 × 768	3 × 3/1	3
Fractional Conv 1	H/2 × W/2 × 384	3 × 3/0.5	1
Fractional Conv 2	H × W × 192	3 × 3/0.5	1
Conv 4	H × W × 1	7 × 7/1	1

The basic building block of ConvNeXtTiny is the ConvNeXt block. It consists of several key components:
Depth of each stage: [3, 3, 9, 3]
There are 4 stages with corresponding numbers of ConvNext blocks: 3, 3, 9, 3.
Feature sizes of each stage: [96, 192, 384, 768]
Increasing gradually to learn and represent more complex features as the network goes deeper.
Each ConvNext block includes:

- Depthwise Convolution: Utilizes depthwise convolution operations with a kernel size of 7x7 and padding of 3 to effectively capture spatial information.
- Layer Normalization: Applies a normalization technique in either channels_first or channels_last format based on the data size.
- Pointwise Convolution: Two 1x1 Convolution layers (implemented with linear layers) to transform feature maps.
- GELU Activation Function: Applies the Gaussian Error Linear Unit (GELU) activation function to introduce non-linearity.
- Integration of random depth reduction (DropPath) with optional drop_path_rate.

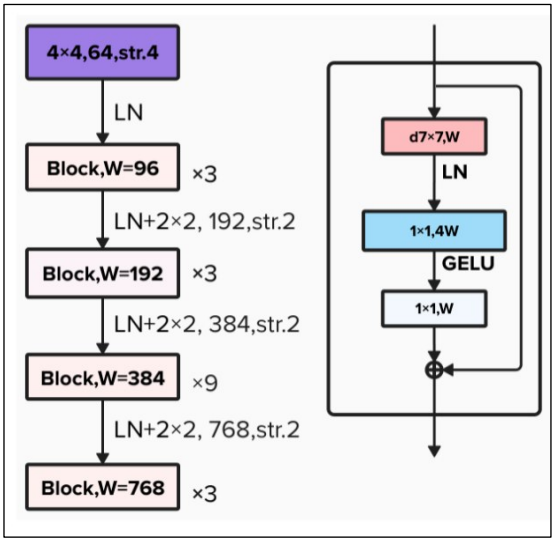

Fig. 3. Work flow diagram of ConvNextTiny

The ConvNeXt block uses a variant of depthwise convolution followed by normalization, transformation, activation, and other integration operations, contributing to its representation capability and efficiency.

IV. IMPLEMENTATION

A. Installation

First setting up the environment, you need to install a Python development environment. Use Anaconda or install Python and pip directly. Create a virtual environment if you want to isolate libraries for this project. Installing necessary libraries: Use pip to install libraries PyTorch: **'pip install torch torchvision'.**

B. Experiment

In this project we use Watermarked / Not watermarked images datasets [10] to train with ConvNextTiny. Input data is divided in testing, training and validation with an 80/20 proportion. Each folder contains a watermark/no-watermark folders including images to classify according to the presence of the watermark and use watermarks-validation dataset [11] to test.

We will need a vital step to handle input images (**pre-processing**) before inserting the datasets into the model to train. This process involves three main steps: resizing the images to 224x224 pixels, converting the images to Tensors (the data format used by the model), and finally normalizing the images based on the mean and standard deviation of the RGB color channels. This step prepares the input data appropriately for the watermark detection model, improving the performance and accuracy of the model during training and prediction.

After training the model, loading the data and using Lambda to assign labels for comparing the watermark (1) and no-watermark (0) datasets, we obtained some output results as follows:

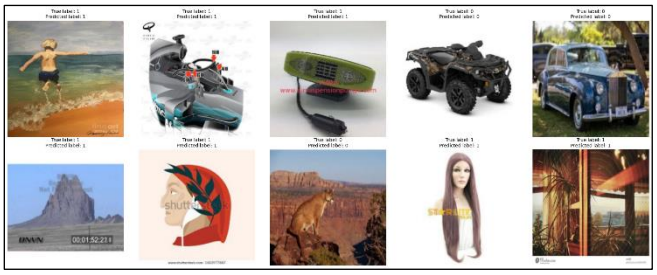

Fig. 4. Some correct prediction images

Fig. 5. Some incorrect prediction images

In Figure 4, it can be seen that the image is classified correctly. However, in Figure 5, the image is not classified correctly. For example, in the image of the Seven Eleven sign, the label is clearly 1 (indicating an image with a watermark), but the predicted label is 0 (indicating an image without a watermark).

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{Total\ of\ correct\ predictions}}{\boldsymbol{Total\ of\ predictions}} \approx \mathbf{0.664}$$

C. Analysis and Evaluation

Accuracy reflects the ratio of correct predictions made by the model over the entire test dataset. In this case, the model has an accuracy of approximately 66.39%, which can be considered as an average result.

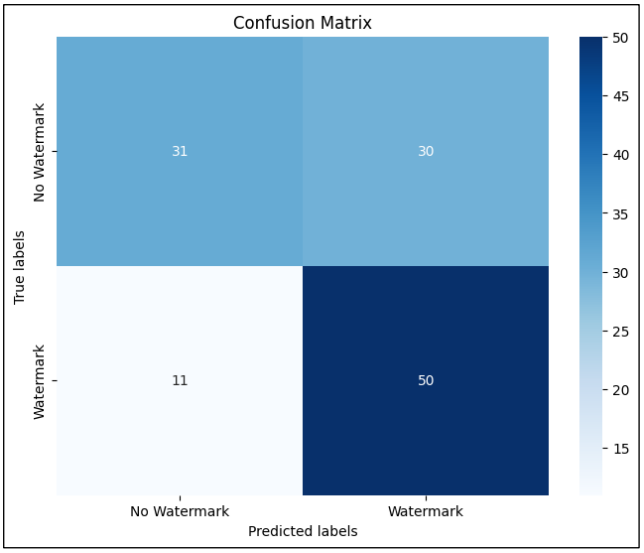

Fig. 6. Confusion matrix

True Positives (TP): The number of cases where the model correctly predicted as watermark (Positive) and is actually a watermark (Actual Positive). In this case, TP = 50.

False Positives (FP): The number of cases where the model predicted as watermark (Positive) but is not actually a watermark (Actual Negative). In this case, FP = 30.

True Negatives (TN): The number of cases where the model correctly predicted as not a watermark (Negative) and is actually not a watermark (Actual Negative). In this case, TN = 31.

False Negatives (FN): The number of cases where the model predicted as not a watermark (Negative) but is actually a watermark (Actual Positive). In this case, FN = 11.

Precision: Precision is the ratio of True Positives to the total number of predictions as Positive by the model. In this case:

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}} = \frac{\mathbf{50}}{\mathbf{50 + 30}} \approx \mathbf{0.625}$$

Precision indicates the model's ability to correctly predict Positive cases (watermark) compared to the total predictions made as Positive by the model. The model has a Precision accuracy of about 62.5%, meaning it has the ability to predict watermark correctly but also has a relatively high number of false positives.

Recall: Recall is the ratio of True Positives to the total number of Actual Positives. In this case:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}} = \frac{\mathbf{50}}{\mathbf{50 + 11}} \approx \mathbf{0.8197}$$

Recall indicates the model's ability to capture all Positive cases (watermark) compared to the total actual Positive instances. The model has a Recall of approximately 81.97%, meaning it has the ability to capture a large portion of watermarks in the data.

F1 Score: F1 Score is the harmonic mean of Precision and Recall, calculated by the formula:

$$\boldsymbol{F1\ Score} = \mathbf{2} * \frac{\boldsymbol{Precision} * \boldsymbol{Recall}}{\boldsymbol{Precision + Recall}}$$

In this case, F1 Score ≈ 0.7097. The F1 Score is a combination of Precision and Recall, helping to evaluate the overall performance of the model. The model has an F1 Score of approximately 70.97%, indicating a good balance between the ability to predict correctly and capture many Positive cases.

In summary, although the ConvNextTiny model can detect watermarks with relatively good accuracy (66.39%), it needs improvement in metrics such as Precision (to reduce false positives) and Recall (to capture more watermarks). Improving the model could involve optimizing hyperparameters, using more diverse training data, or considering different model architectures to achieve better performance.

V. IMPROVE MODEL

A. Architecture

The second model has a custom head added with two **"Linear"** layers and dropout some connects to not full connected. In contrast, the first model doesn't have a custom head; it only uses the default structure of convnext_tiny.

The custom head of the second model contains two Linear layers with different input and output sizes (768 and 448), while the first model has only one final layer with the input and output sizes being the number of output classes of the task (in this case 2).

In summary, the second model shows improvement over the first model by adding a custom head, allowing the model to learn more complex features and incorporate more information about the input data. This leads to better performance for the classification task.

B. Experiment

Fig. 7. Some correct prediction images

Fig. 8. Some incorrect prediction images

After training on the new model, we observed that the output images are more accurate compared to the old model, and here are the results we obtained:

$$Accuracy = \frac{Total\ of\ correct\ predictions}{Total\ of\ predictions} \approx 0.762$$

And the accuracy of the new model has increased by about 10% compared to the old model.

C. Analysis and evaluation:

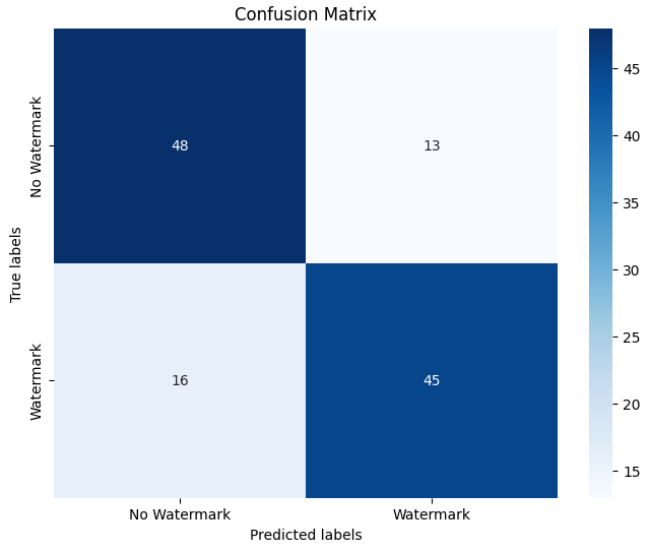

Fig. 9. Confusion matrix of new model

Based on the provided evaluation metrics and confusion matrix, the evaluation of the new model for watermark detection is as follows:

Accuracy: approximately 76.23%

True Negative (TN): 48 cases where the model correctly predicted the absence of the watermark.

False Positive (FP): 13 cases where the model incorrectly predicted the presence of the watermark when it was absent.

False Negative (FN): 16 cases where the model incorrectly predicted the absence of the watermark when it was present.

True Positive (TP): 45 cases where the model correctly predicted the presence of the watermark.

The accuracy of the model is 76.23%, indicating that it performs reasonably well overall.

Precision (also known as positive predictive value): measures the accuracy of positive predictions made by the model. In this case, approximately 77.59% of the instances predicted as positive (presence of watermark) by the model were actually positive.

$$Precision = \frac{TP}{TP + FP} = \frac{45}{45 + 13} \approx 0.7759$$

The new model presents a higher precision value (approximately 77.59%) compared to the old model (approximately 62.5%). This suggests that the model described in the second scenario has a better ability to accurately predict positive cases while minimizing false positives.

Recall (also known as sensitivity or true positive rate): measures the ability of the model to correctly identify positive instances. Around 73.77% of the actual positive instances were correctly identified by the model.

$$Recall = \frac{TP}{TP + FN} = \frac{45}{45 + 16} \approx 0.7377$$

The old model has a higher Recall (81.97%) compared to the new (73.77%). This suggests that the old model is more effective at capturing positive instances, such as watermarks, compared to the new one.

Both scenarios demonstrate the model's ability to correctly identify positive instances, but the old model achieves a higher Recall rate, indicating better performance in capturing positive cases.

F1 score: provides a balance between precision and recall. It is the harmonic means of precision and recall, indicating overall model performance. The computed F1 score of approximately 75.62% suggests that the model achieves a reasonable balance between precision and recall.

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall} \approx 0.7562$$

Both comparisons recognize the importance of the F1 score in evaluating the model's performance, particularly in achieving a balance between precision and recall. However, the old model suggests a slightly lower F1 score and focuses more on the model's ability to predict positive cases correctly, while the new model provides a slightly higher F1 score and emphasizes a reasonable balance between precision and recall.

Overall, the model shows promising performance in detecting watermarks, with a relatively high accuracy and a balanced detection of both positive and negative cases. However, it may benefit from further fine-tuning or additional data to improve its performance further.

VI. Conclusion

In this study, we proposed a watermark detection approach utilizing the ConvNext_tiny model. Our experimental results demonstrate promising performance in detecting watermarks within digital images.

Our evaluation indicates that ConvNext_tiny exhibits robustness against various types of watermarks and noise levels, making it a versatile tool for watermark detection tasks. Additionally, the lightweight nature of the model allows for efficient deployment in resource-constrained environments.

In conclusion, our study underscores the potential of ConvNext_tiny as a reliable solution for watermark detection, offering a balance between performance and computational efficiency.

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[10] Dataset in the article of author FELICE POLLANO (updated 4 years ago)

[11] Dataset in the Hugging Face Web of author boomb0om (updated Feb 5, 2023)