Proposal of a New Approach Using Deep Learning for QR Code Embedding

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Abstract: The purpose of this research is to enhance the technique of embedding QR codes into arbitrary images using deep learning. Previous approaches faced the issue of compromising the quality when embedding QR codes into arbitrary images. We address this problem by proposing a deep learning model and learning method that can improve the quality of embedded images and accurately recover QR codes. Specifically, we design a new model using deep learning that embeds QR codes into images while minimizing the degradation of image quality. The effectiveness of the proposed model and learning method is validated through experiments, demonstrating the enhancement of image quality in the embedded images and accurate QR code recovery.

1 INTRODUCTION

In recent years, with the widespread use of the internet, exchanging information and communication has become convenient. However, on the other hand, the leakage of personal information and organizational assets has become a significant problem. As a countermeasure, there is a technique called steganography. Steganography is the art of concealing one piece of digital data (audio, images) within another piece of digital data.

In a previous research(Kumabuchi and Kobayashi, 2022), two models were created using deep learning: one to embed QR codes into images and the other to restore QR codes from images with embedded QR codes. However, there was a significant issue with embedding QR codes into images, as it substantially compromised the quality of the original images. In this research, similar to the previous study, we aim to create new Encoder and Decoder models to embed QR codes into images and restore them without compromising the quality of the original images. We propose and evaluate a model capable of achieving this goal

In a previous research, we referred to the model proposed by Simon Jégou(Jégou et al., 2017). for semantic segmentation, which improved upon the Unet(Ronneberger et al., 2015) model, and used it as a basis for our work. In this study, we further refined that model to devise a method for embedding QR codes while preserving their distinctive features.

2 PRINCIPLE

In this PRINCIPLE, the embedding and restoration procedures of the QR code are explained with the aid of Figure1, along with the learning steps.

1. Input a three-channel image and a one-channel QR code into two separate models.
2. Concatenate the two output feature maps at an intermediate layer and input them into the ConcatImageModel.
3. In the QR code embedding model, train with the three-channel image as the ground truth.
4. Pseudo-image and normalize it before inputting it into the Restoration Model.
5. Train the Restoration Model using the output image as input and the one-channel QR code image as the ground truth.
6. Next, compute the loss for both models using the Mean Squared Error (MSE) from the following equation (1), and then calculate the weighted loss using the following equation (2).
7. Use the computed loss values to update the weights of both models.

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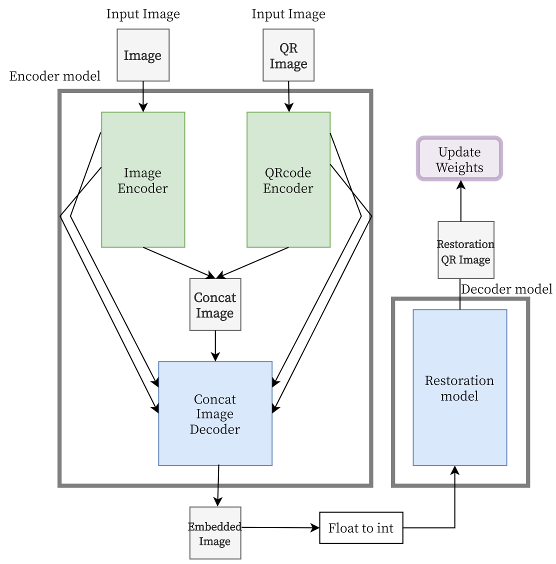


Figure 1: Overall Structure.

$$Loss = mse = \frac{1}{M_1 \cdot M_2} \sum_{n=1}^{M_1} \sum_{n=1}^{M_2} \{y(i,j) - x(i,j)\}^2 \quad (1)$$

$$loss = \alpha \cdot \mathrm{Loss}_{Encoder} + \beta \cdot \mathrm{Loss}_{Decoder} \quad (2)$$

3 MODEL CREATION

3.1 Datasets

The dataset used in this research consists of indoor images shown in Figure 2 and images generated using Python's QR code library as depicted in Figure 3. For the training process, 8000 images and QR codes were utilized for each category, and an additional set of 1000 images was reserved for testing purposes.

Figure 2: Indoor image.

3.2 Conventional Model

In this research, we aimed to enhance the performance by utilizing an improved model compared to the conventional approach. Before explaining the model used in this study, let's first describe the conventional model. The conventional model combines

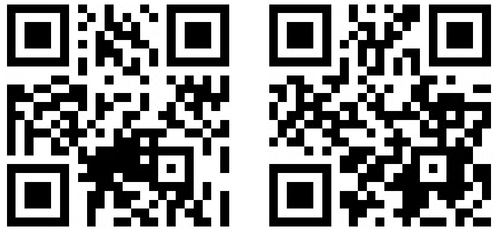


Figure 3: QR Image.

a 3-channel image with a QR code and inputs them together into a single Encoder-Decoder model. However, in our model, we take a different approach by performing dimensionality reduction separately for the QR code and the 3-channel image using distinct models. This enables us to embed the QR code into the 3-channel image while preserving its distinctive features. +

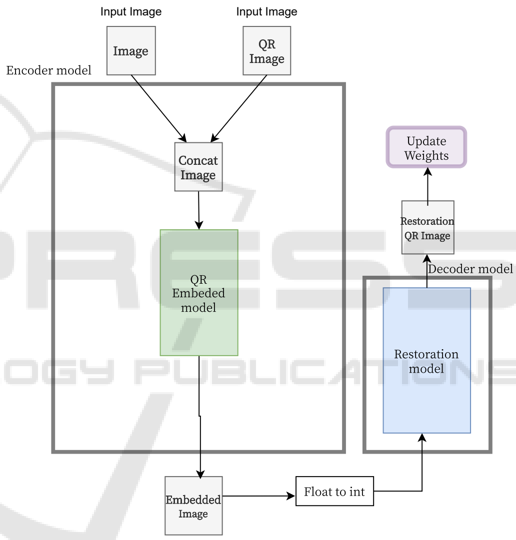


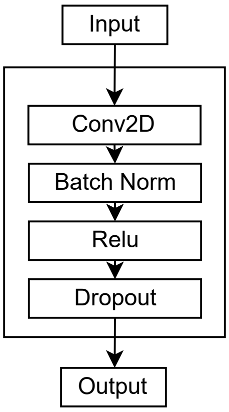
Figure 4: Conventional Model.

3.3 Model Structure

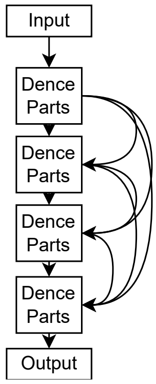
The overall structure of this research is as shown in Figure 1, comprising two models. The Encoder Model in the figure serves as a model for embedding QR codes. On the other hand, the Decoder Model is used for recovering QR codes embedded in images. In the following subsections, I will provide a detailed explanation of the structure of each model.

3.3.1 Encoder Model

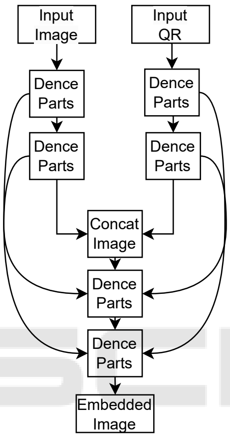
The structure of the Encoder model is an Encoder-Decoder architecture. In this architecture, both three-channel images and QR codes are input into the same Encoder shown in Figure 5c. Dimensional compres-



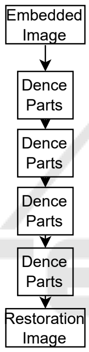
(a) Dence parts.



(b) Dence block.



(c) Encoder Model.



(d) Decoder model.

Figure 5: Detail Structure.

sion is performed, and the intermediate layers are concatenated before decoding is done. The model structure consists of Dense Blocks, as depicted in Figure 5b. Inside the Dense Block, there are convolutional layers, batch normalization layers, ReLU layers, and Dropout layers as shown in Figure 5a. The use of skip connections for all layers prevents the vanishing gradient problem

3.3.2 Decoder Model

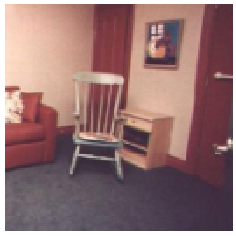
The Decoder model aims to restore a QR code from an image containing an embedded QR code. The Decoder model has a simple structure, consisting of four connected Dense blocks as shown in the Figure 5d.

4 EXPERIMENTAL

In this EXPERIMENTAL, we conducted a 200-epoch training using the learning procedure described in the principles and the model illustrated in Figure1. Subsequently, we utilized the trained model to compare the output results with those obtained from the conventional model, thus examining the differences between them

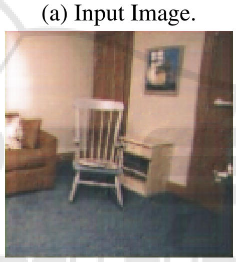
4.1 Results of Conventional Models

After training the model using the architecture shown in Figure 5, we obtained the results for the test images, as shown in Figure 7. However, it is evident that while the conventional model can restore the QR code, the images with embedded QR codes result in a loss of image quality in the input images



(a) Input Image.

(b) Input QRcode.



(c) Embedded Image.

(d) Restoration QRcode.

Figure 6: Conventional model result.

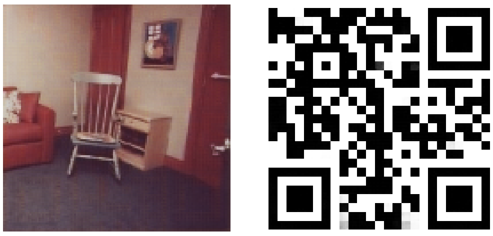
4.2 Results of this Research Model

After training the model using the procedure shown in Figure 1, we obtained results for test images as shown in Figures 8 and 9. In comparison to the results of the conventional model depicted in Figure 6, it was confirmed that not only can QR codes be restored, but they can also be embedded more clearly into the images. Furthermore, the presence of areas in Figure 8 where embedding is not complete is believed to be due to high brightness values.

5 CONCLUSION

In this research, we developed new Encoder and Decoder models to improve the performance of both image embedding and QR code restoration. As a result, we were able to obtain output images with embedded QR codes that closely resembled the input im-

(a) Input Image. (b) Input QRcode.



(c) Embedded Image. (d) Restoration QRcode.

Figure 7: This research model result.

(a) Input Image. (b) Input QRcode.

(c) Embedded Image. (d) Restoration QRcode.

Figure 8: This research model result.

ages, and the restored QR codes were in a readable state.

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