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**Araştırma Makalesi / Research Article**

**Unsupervised Image Hashing Using a Deep Convolutional Encoder-Decoder Model for Fast Image Retrieval**

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| ***Keywords***  Unsupervised learning; Deep learning; Encoder-decoder;  Hash codes | **Abstract** |
| Image hashing methods transform high-dimensional image features into low-dimensional binary codes while preserving semantic similarity. Among image hashing techniques, supervised image hashing approaches outperform unsupervised and semisupervised methods. However, labeling image data requires extra time and expert effort. In this study, we proposed a deep learning-based and unsupervised image hashing method for unlabeled image data. The proposed hashing method is built in an end-to-end fashion. It consists of an encoder-decoder model. We used a part of a pretarined network as an encoder model, which provides fast convergence in the training phase, and efficient image features. Hash codes are extracted by optimizing those intermediate features. Experiments performed on two benchmark image datasets demonstrate the competitive results compared to supervised image hashing methods. |

**Derin Konvolüsyonel Kodlayıcı-Kod Çözücü ile Görüntü Hash Kodlarının Çıkartılarak Hızlı Görüntü Erişiminin Gerçekleştirilmesi**

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| **Anahtar Kelimeler**  Denetimsiz öğrenme; Derin öğrenme; Kodlayıcı ve kod çözücü  Hash kodları | **Abstract** |
| Görüntü hash kodlarını elde eden metodlar, yüksek boyutlu ve sayısal olan görüntü özniteliklerini görüntüler arasındaki anlamsal ilişkileri koruyacak şekilde daha düşük boyutlu ikili kodlara dönüştürürler. Hash teknikleri arasında denetimli öğrenmeye dayalı yöntemler, denetimsiz ve yarı denetimli metodlara göre daha verimlidirler. Ancak denetimli öğrenmeye dayalı yöntemler görüntülerin anlamsal etiketlerini kullanırlar ve bu da extra bir çalışma ve uzman emeği gerektirir. Bu çalışmada etiketsiz görüntüler için denetimsiz ve derin öğrenmeye dayalı bir yöntem sunulmuştur. Bu yöntem uçtan uca kesintisiz entegre bir yöntemdir. Yöntem kodlayıcı-kod çözücü tabanlıdır. Kodlayıcı kısmında önceden denetimli olarak eğitilmiş bir derin ağın bloklarını kullanmamız, eğitim aşamasında hızlı yakınsama ve görüntü özniteliklerinin verimli olmasını sağlamıştır. Hash kodları ise bu özniteliklerin optimize edilmesi ile çıkarılmıştır. İki bilinen görüntü dataseti ile gerçekleştirilen deney sonuçları önerilen yöntemin denetimli yöntemlere göre rekabetçi sonuçlar verdiğini göstermiştir. |

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# 1. Introduction

Artificial intelligence has become an increasingly demanded tool in various domains [Mchergui et al. 2022, Baduge et al. 2022, Minh et al. 2022, Nahavandi et al. 2022, Aslan and Subaşı 2022, Akalın and Veranyurt 2022, Mutlu et al. 2021, Şendir et al. 2019 ]. Among them, the need for efficient and fast image retrieval is indispensable. Hashing methods allow quick retrieval as the Hamming distance can be calculated faster with a simple XOR operation. On the other hand, deep learning-based image features are more efficient. That is why deep learning-based image hashing methods have recently been prevalent [Wang et al. 2022, Singh and Gufta 2022, Patel and Kasat 2017].

Hashing methods are divided into three main groups based on image label information. Supervised image hashing methods require labeled images in the training phase [Qin et al. 2022, Passalis and Tefas 2021, Mojoo and Kurita 2021]. However, image labeling is an extra process that requires additional time and expert effort. Especially for large-scale datasets, it is cumbersome. It is critical for sensitive areas such as healthcare [Hastaneler]. Those methods are generally more efficient than those unsupervised and semisupervised methods. Unsupervised methods do not need labeled image data [Wang et al. 2021, Yu et al. 2021, Zhang et al. 2021]. The ground truth of the data is the image data itself. This is a significant advantage for learning-based and unsupervised hashing methods. However, their efficiency is generally lower than the supervised methods [Patel and Kasat 2017]. On the other hand, semisupervised methods require label information partially [Tang et al. 2019, Shi et al. 2020, Tian et al. 2020].

We have proposed an unsupervised method in this study. It consists of an encode-decoder model. Hash codes are generated by transforming image features extracted from an intermediate layer between the encoder and the decoder blocks. Encode-decoder models are also called autoencoders. An encoder block encodes high-dimensional image features into low-dimensional features, also called intermediate features. The decoder block reconstructs images by using those features. At the decoder's end, there should be a loss function that computes the error between original and rebuilt image features. The output of that loss is used for the back-propagation during the training phase. The typical loss functions used at the end of the decoder models are mean square error (MSE), also called L2 loss, or binary cross entropy loss [Int. S. 1].

The most common usage area of autoencoders is image denoising [Keerthi et al. 2021, Qiu et al. 2020] and image segmentation [Myronenko A. 2019, Baur et al. 2021]. In the proposed method, we used a part of the Resnet50 pretrained network [Int. S. 2]. Since it is trained on the ImageNet dataset [Int. S. 3] in a supervised way, it generates efficient features for the decoder side. That is, convergency becomes fast during training. This is a good idea for implementing transfer learning from a supervised domain to an unsupervised one. The highlights of this study can be summarized in the following.

• The proposed method is unsupervised, independent of the training phase's image label. However, efficient supervised features are transferred and then trained unsupervised. This is a significant domain adaptation idea.

• A loss function in an intermediate layer between encode and decoder block optimizes hash codes and balances the distribution of ‘one’ and ‘zeros’ in the hash codes.

• Experiments performed on MS Coco [Int. S. 4] multilabel benchmark and Retinamnist datasets [Int. S. 5] demonstrate the competitive results in the unsupervised image hashing category.

The rest of the study consist of the following chapters. The detail of the proposed method, hash code extraction, and retrieval are presented in section II. Performance metrics used for the experiments are given in section III. Section IV provides experiments performed on two image datasets. Finally, section V is the conclusion section.

**2. Material and Method**

The proposed method mainly consists of training and retrieval phases. In the training phase, whole layers are trained, including ResNet50. In the

retrieval phase, a prediction is performed and taken from the hash layer. Those predictions are image features that consist of the real number. Features



**Figure 1.** An overview of the proposed method. Full architecture is trained in the training phase.

are then converted into hash codes by a quantization process.

**2.1 Training phase**

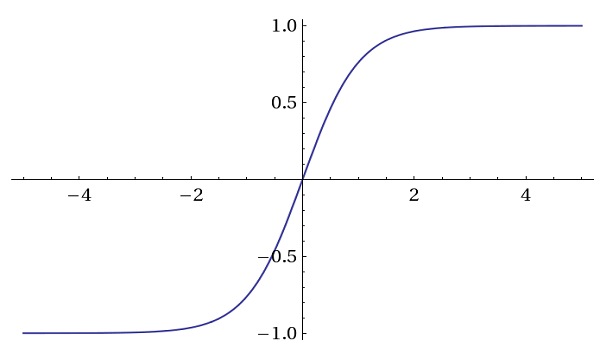
The training phase consists of encoder-decoder blocks and custom layers placed between those blocks for the hash code extraction. An overview of the training phase is illustrated in Figure 1.

The encoder block is constructed by ResNet50. It is trained for the ImagetNet dataset having 1000 categories. Resnet has residual connections that reduce the vanishing gradient descent effect and increase classification accuracy. We only removed the last fully connected (FC) layers and the classification layer from ResNet50. In that way, ResNet50 functions like an encoder. Using ResNet50 as an encoder is o wise idea that provides domain adaptation between supervised and unsupervised domains.

The standard output shape of the ResNet50 is (8,8,2048). A flatten layer is added next to it to convert that shape into a one-dimensional tensor. An encoder should encode high-dimensional inputs into low-dimensional data for compression. So we used two low-dimensional FC layers next to the flatten layer. Their sizes are 2048 and 256, respectively. Those sizes provide a soft transition for dimension reduction.

We prepared a custom layer called the hash layer placed next to those FC layers. Hash layer has a tangent hyperbolic (*tanh*) activation. Given an input *x, tanh* is defined as follows,

(1)

Tanh is a scaled version of the sigmoid function. Its depiction is given in Figure 2. Its mean is zero. That provides fast convergence. As seen in Figure 2, whatever its input, outputs will be constrained in the [-,1, 1] interval. This property is necessary for converting image features into hash (binary) codes in the quantization process in the retrieval phase.

**Figure 2**. An illustration of the *tanh* function.

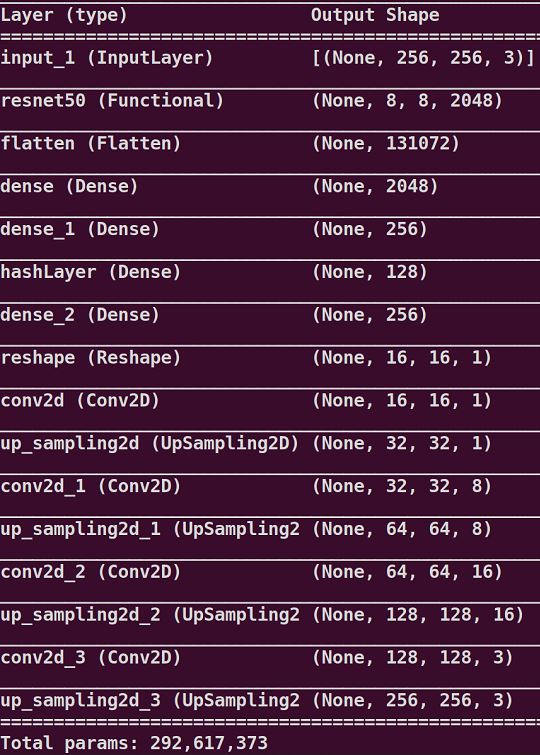
Hamming distance in image hashing methods is indispensable since XOR operation is high-speed, which offers fast retrieval. Hamming distance between two binary codes is the number of different reciprocal bits. An ideal image hashing algorithm should be unbiased for the number of zeros and ones. In other words, the number of zeros and ones should be near. This property is called the bit-balance property. Bit-balance has a pleasant characteristic for providing unbiased Hamming distances. We have defined a loss function over the hash layer that provides bit-balance property.

Let K *R* represent the hash layer's input data, where *K* is the number of outputs of the FC layer before hash layer, and *L* represents the number of inputs of the hash layer. Since the activation function of the hash layer is *tanh,* its output data will be . Based on this information, a bit-balance loss is defined as follows,

(2)

In equation 2, *Y* varies in the [-1,1] interval. Minimizing the loss function during training will force the mean value of the outputs (*Y*) to be zero. The loss given in equation 2 will be minimized together with the regression loss, defined at the end of the decoder during the training phase. That provides bit-balance property. The Dense layer next to the hash layer is placed to give the decoder’s output identical to the original image sizes.

The decoder model starts with a reshape layer. This layer converts one-dimensional image features into two-dimensional image-like tensors. The rest of the layers consist of convolution and upsampling layers. Upsampling layers gradually increase the size of tensors. Finally, the last upsampling layer reconstructs images as identical size to the original images. For the Coco dataset, the hierarchical structure and the output shape of the layers are given in Figure 3.



**Figure 3**. The layer output shapes of theproposed method for the Coco dataset.

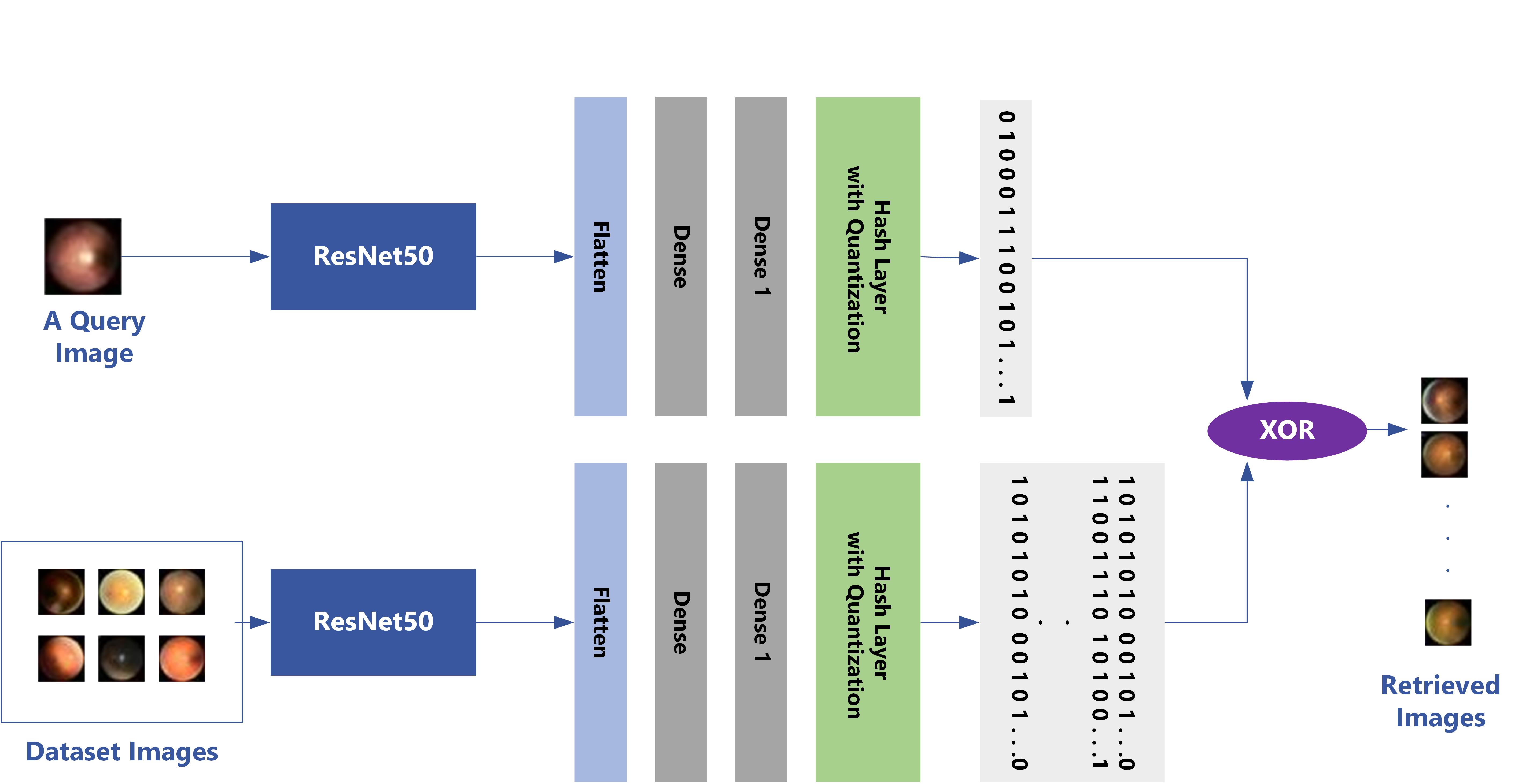
A regression loss is placed at the decoder's end to reduce the error between original and reconstructed images. The mean square error (MSE) is the mean error of the L2 loss in literature. Let  represent the authentic images, and be the output of the decoder. MSE error between them is given by,

(3)

Overall loss function to be minimized during the training phase will be as the following,

(4)

We investigate the optimum α and β weights by assigning values between zero and one. However, we did not observe any impact of those weights on the loss value and retrieval result. For this reason, we assign identical values to each loss.



**Figure 4**. The retrieval phase of the proposed method.

**2.2 Retrieval phase**

Hash codes are generated after the network is fully trained. Then a snapshot of the weights and the model are taken. As seen in Figure 4, We do not use the loss functions and decoder module. They are only used in the training phase to optimize the network parameters. Extraction is issued by predictions from the hash layer and quantizing them Since the activation function of the hash layer is a tanh, predictions will be between [-1, 1] intervals.

Suppose that the prediction taken from the hash layer is represented by , hen the following quantization process obtains hash codes,

***H =*** *.*  (5)

As seen in Figure 4, retrieval can now be performed by finding Hamming distance between a query and the whole dataset items. We chose the number of outputs of the hash layer as 32,48, 64 for the Retina dataset and 64,128,256 for the Coco dataset. That is, corresponding hash codes are generated.

**3. Performance Metrics**

Precision (*P*), average precision (*AP*), and Mean Average Precision (*MAP*) scores are used for the evaluations. They are obtained as follows. A

retrieved image is evaluated as true-positive (*tp*), relevant if it holds all the labels of the queries;

Otherwise, false negative (*fn*), irrelevant. The precision scores for k retrieved images are obtained as follows.

(6)

where *tp@k* denotes the number of relevant items among k retrieved items, and *fp@k* denotes irrelevant items. Then, an AP score for each query set is obtained as follows.

(7)

where is the number of relevant items among *k* retrieved items, is a precision score for each item retrieved, and is an indicator factor. It equals 1 if the *r-th* retrieved sample is *tp*. Otherwise, it is set to zero.

MAP scores are obtained by calculating the mean values of the average precision scores obtained for top k returned images for a single query.MAP scores are obtained as follows,

(8)

**4.Experiments**

The proposed encoder-decoder model has been implemented in Tensorflow's Keras library [Int. S. 6]. The training part of the datasets is used during training. Since this is an unsupervised method, the ground truths are also the training images. The network is trained by Adam optimizer [ ] with 100 epochs. The learning rate was set to 0.01, and the batch size to 32. Training is repeated for the various size of the hash layer as 16, 32, 64, 128, and 256. During training, MSE loss reduced the error between the ground truths and predicted images, and another loss defined over the hash layer provides bit-balance property.

Loading the whole dataset into the memory consumes the computer's resources. If you use a large-scale dataset, this is essential. To overcome that issue, we prepared custom python generators. Although there are ready tı use Keras generators, we designed our own. This provides us with more control, customizations, and easy error detection. Thanks to the python generators, only the current batches of images are loaded into the memory during training.

Hash codes should be extracted via the best-trained sample of the network. So after training, the snapshot of the network model and network parameters were saved. Each time snapshots were taken for the various sizes of the hash layer. Hash codes are extracted by performing predictions using test images. The location of the prediction is the hash layer.

Retrieval metrics used for the top returned images in hamming radius r. A hamming distance vector is created between a query and the whole items in the dataset. What we mean by r is that only those returned images retrieved whose hamming distance to the query is less or equal to the hamming radius. For evaluations, we randomly chose 5000 queries from the test split of the Coco and 150 queries from retinamnist datasets.

Suppose that r is set to 20 and 20 images are retrieved whose hamming distances to the query are less or equal to 20. For each retrieved image, a precision score is, and for 20 images, an average precision score is created. For the whole query images, we mean a map score is obtained by the mean value of the average precision scores for test sets. Evaluations are repeated for 16, 32, and 64-bit hash codes for retinamnis; for Coco, it is 64,128 and 256-bit. We use different hash code sizes for datasets because of varying dataset sizes. High-dimensional hash codes should always be used in large-scale datasets. The map scores for those hash codes and various hamming radius is presented in Tables 1-2.

**Table 1.** MAP scores of top retrieved images in specific hamming radius. Results were obtained by using MS Coco dataset.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Size (Bits)** | **map@5** | **map@10** | **map@15** | **map@20** |
| 64 | 0.7454 | 0.7444 | 0.7406 | 0.7364 |
| 128 | 0.8351 | 0.8306 | 0.8254 | 0.8103 |
| 256 | 0.8417 | 0.8402 | 0.8369 | 0.8323 |

**Table 2.** MAP scores of top retrieved images in specific hamming radius. Results were obtained by using the Retinemnist dataset.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Size (Bits)** | **map@5** | **map@10** | **map@15** | **map@20** |
| 16 | 0.4250 | 0.4071 | 0.3802 | 0.3671 |
| 32 | 0.7415 | 0.6443 | 0.5422 | 0.4602 |
| 64 | 0.8360 | 0.7576 | 0.6982 | 0.6354 |

**Table 3.** Comparison of the proposed method with the most recent studies using the Coco dataset (the mAP for the first 5000 results for different hash code lengths are reported).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Size (Bits)** | Qin, Qibing, et al. 2022 | Passalis et al. 2021 | Mojoo et al. 2021 | **Ours** |
| 16 | 0.772 | - | 0.806 | - |
| 32 | 0.802 | 0.854 | 0.807 | **0.6851** |
| 64 | - | 0.883 | - | **0.7340** |

There is no recent hashing study on the retinamnist dataset. However, the most recent supervised studies using MS Coco dataset compared with the proposed method and presented in Table 3. As seen in Table 3, the results are competitive. Note that we compare our unsupervised method with supervised methods. Despite this, our approach yielded competitive results. The related codes of this study, such as training, hash code extractions, hash codes, and evaluations, are publicly available.

**5 Conclusion**

Supervised image hashing methods generally outperform unsupervised and semisupervised methods in terms of retrieval efficiency. However, supervised learning use label information which is not an easy job. In this study, we propose a solution for improving the retrieval efficiency of the unsupervised image hashing method we proposed. The idea is to implement a domain adaptation between the supervised and unsupervised domains. ResNet50, a known supervised pretrained network, is used as an encoder model of the method. However, thanks to the decoder model, images are trained without label information. This adaption provides fast convergence during training and efficient hash codes after training while extracting hash codes. Experiment results confirm that idea. This idea can apply to video hashing. We plan to prepare the same or similar domain adaptation approaches for video hashing.

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