

II. METHODS

Fig. 1. shows our proposed CBMIR scheme that consists of two main modules: feature extraction and feature matching. The overall procedure is explained below:

Step 1). First, generate an edge map of the input medical image by applying an edge detection algorithm (e.g., Canny edge detector). Then, combine them together to produce an edge overlaid image that highlights its structural features.

Step 2). Calculate a histogram from the edge overlaid image as initial feature vector (ϕ) of size $M = 256$.

Step 3). Apply DWT decomposition to feature vector ϕ at various levels $l = \{1, 2, 3, 4\}$ to reduce its size as $\alpha = M/2^l$. At each decomposition level l , only the approximate DWT coefficients are retained to form the final feature vector φ .

Step 4). The final step is to compare the query image features φ_q with that of the stored images φ_s in the feature matching module using cosine distance metric.

III. RESULTS AND DISCUSSIONS

In this section, we evaluate the efficiency of proposed medical image retrieval scheme on brain tumor dataset [3] that consists of 2,124 images in total. These images are of varying sizes and are uniformly distributed among three tumor types. All these images were stored in the database, and for query they were rotated 90 degrees counterclockwise.

The efficacy of proposed CBMIR scheme was assess using precision, recall and mean average precision (mAP). In general, precision determines the proportion of relevant retrieved images, while recall measures the system's ability to correctly identify all relevant images. Additionally, the mAP score defined in (1) considers average precision (AP) across the ranked list positions where relevant images appeared.

$$mAP = \frac{1}{Q} \left(\sum_{q=1}^Q AP_q \right), \quad (1)$$

where, $AP_q = \frac{1}{G} \sum_{n=1}^N \frac{TP@n}{n} \times f(n)$ is the AP score for each query image. Also, N is the total number of images stored in the database, G is the number of ground-truth images for a query image, and $TP@n$ is the number of true positive matches at rank n . Also, if the n^{th} image is a ground truth, then $f(n) = 1$ otherwise, $f(n) = 0$. Higher values of these metrics indicate superior performance of an image retrieval.

The performance of proposed scheme was compared with Bag of Words (BoW) method implemented in [3] by varying the number of features (α) as shown in Fig. 2. (a). Here, the number of retrieved images was set to be 10. In terms of the mAP score, proposed scheme outperformed BoW method by

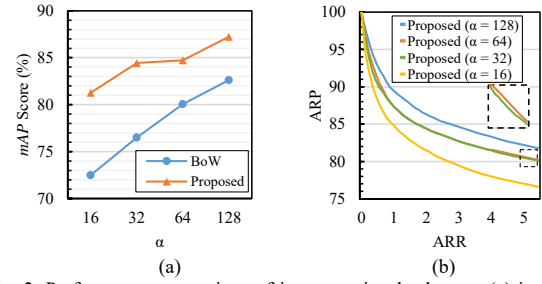


Fig. 2. Performance comparison of image retrieval schemes. (a) is mAP score by varying feature vector size (retrieved images number is 10). (b) Precision-Recall curve (retrieved images number varied between 1 to 50).

5% to 9% across different values of α . It is noteworthy that our approach is closely related to BoW technique, but when comparing with an advanced method proposed in [3], our scheme achieved 7% lower mAP score. However, this performance gain can be attributed to the learned distance metric, which is computationally expensive. For a fair comparison, when considering this technique with the Euclidean distance, its mAP score is degraded by 27% compared to ours. In addition, Fig. 2. (b) plots the Precision-Recall curve to analyze the impact of DWT decomposition on retrieval performance of proposed scheme. The curves are plotted by varying the number of retrieved images (i.e., 1 to 50). It can be seen that higher number of features is beneficial in retrieving larger number of images.

IV. CONCLUSION

This study developed a histogram-based feature extraction strategy tailored to meet the requirements of grayscale medical image retrieval applications. Simulation results showed that proposed method outperformed conventional approaches on the same dataset, indicating its potential for improved retrieval performance in medical imaging. Histogram-based feature descriptors are invariant to perceptual encryption transformation functions. Therefore, in the future we are interested in implementing our scheme considering privacy preservation.

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References

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