# Shared Information-Based Late Fusion for Four Mammogram Views Retrieval using Data-driven Distance Selection

Amira Jouirou[1] [a], Abir Baâzaoui[1] [b] and Walid Barhoumi[1,2] [c]

[1] *Université de Tunis El Manar, Institut Supérieur d'Informatique, Research Team on Intelligent Systems in Imaging and Artificial Vision (SIIVA), LR16ES06 Laboratoire de Recherche en Informatique, Modélisation et Traitement de l'Information et de la Connaissance (LIMTIC), 2 Rue Abou Raihane Bayrouni, 2080 Ariana, Tunisia*

[2] *Université de Carthage, Ecole Nationale d'Ingénieurs de Carthage, 45 Rue des Entrepreneurs, 2035 Tunis-Carthage, Tunisia*

Keywords: Content-based Mammogram Retrieval, Data-driven Distance Selection, Four Mammogram Views, Random Forest, Shared Information, Late Fusion.

Abstract: Content-Based Mammogram Retrieval (CBMR) represents the most effective method for the breast cancer diagnosis, especially CBMR based on the fusion of different mammogram views. In this work, an efficient four-view CBMR method is proposed in order to further improve the mammogram retrieval performance. The proposed method consists in combining the retrieval results of the provided four views from the screening mammography, which are the Medio-Lateral Oblique (MLO) and the Cranio-Caudal (CC) views of the Left (LMLO and LCC) and the Right (RMLO and RCC) breasts. In order to personalize each query view in the final result, a classified mammogram dataset has been used to retrieve the relevant mammograms to the query. Indeed, the proposed method takes as input four query views corresponding to the four different views (LMLO, LCC, RMLO and RCC) and displays the most similar mammogram cases to each breast view using a dynamic data-driven distance selection and the shared information. In particular, we explore the use of random forest machine learning in order to predict the most appropriate similarity measure to each query view and the late fusion from the four view result-level, through the shared information concept, for the final retrieval. According to their clinical cases, the retrieved mammograms can be analyzed in order to help radiologists to make the right decision relatively to the four-view mammogram query. The reported experimental results from the challenging Digital Database for Screening Mammography (DDSM) dataset proved the effectiveness of the proposed four-view CBMR method.

## 1 INTRODUCTION

Breast cancer is the most common form of cancer worldwide among women, with a high mortality rate. In fact, in most cases, breast cancer leads to death. Nevertheless, thanks to the early detection, the number of breast cancer related deaths was been reduced in the last decade (Boudraa et al., 2020). The best tool to carry out the early breast cancer detection is mammography, where through certain typical signatures like masses and microcalcifications can help in the early diagnosis of this dangerous cancer (Sapate et al., 2020). However, manual diagnosis of mammographic images is a very difficult task that radiologists frequently perform subjectively. Consequently, the Computer-Aided Diagnosis (CADx) concept was introduced in order to aid radiologists in mammogram interpretation (Arora et al., 2020). Because of the high misclassifications and the mistrust from experts, the most effective alternative is the Content-Based Mammogram Retrieval (CBMR), which proves its efficiency in the mammogram clinical case identification (Singh et al., 2018). Indeed, depending on the visual content, the CBMR approach consists of recovering, from a given dataset of past cases, the most similar mammograms to a query mammogram (Kiruthika et al., 2019). Since the retrieved images are provided with proven diagnostics, CBMR systems allow to effectively assist clinicians to make an accurate decision regarding the query image. Moreover, in order to improve the retrieval performance, modern CBMR systems have been evolved from Single View (SV)-CBMR, which uses only one view of mammogram query (Rayen and Subhashini, 2020), to Multi View (MV)-CBMR, which allows to use sev-

[a] https://orcid.org/0000-0001-7931-2389
[b] https://orcid.org/0000-0001-7206-3842
[c] https://orcid.org/0000-0003-2123-4992



Jouirou, A., Baâzaoui, A. and Barhoumi, W.
Shared Information-Based Late Fusion for Four Mammogram Views Retrieval using Data-driven Distance Selection.
DOI: 10.5220/0010261701440155
In *Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2021) - Volume 4: VISAPP*, pages 144-155
ISBN: 978-989-758-488-6

eral views of mammogram query (Liu et al., 2020b). In the related literature, as best as we know, all proposed MV-CBMR systems have been based on the use of two views, which are the Medio-Lateral Oblique (MLO) and Cranio-Caudal (CC) views of only one breast. However, the screening mammography provides two different views for each breast: LMLO and LCC views that correspond to the left breast, and RMLO and RCC views that are taken from the right breast (Khan et al., 2019). Thus, the fusion of the different views of mammograms can significantly improve the performances of CBMR systems. Indeed, two types of fusion can be applied within the framework of MV-CBMR systems: early fusion and late fusion. The main difference between these two classes of fusion methods resides in the emplacement of the fusion procedure within the global retrieval process. In fact, for the multi-view early fusion methods (Narvaez et al., 2011), the fusion procedure represents the first step in the online phase of the retrieval. It consists on merging the features of the different views into one vector in order to retrieve the relevant mammograms. For the multi-view late fusion methods (Dhahbi et al., 2015b; Liu et al., 2011), the fusion procedure represents the last step in the online phase of the retrieval. It consists on merging the results of each view of the breast for the final retrieval. According to the experimental results, the multi-view late fusion methods have shown their superiority over the multi-view early fusion ones. In fact, the produced results in many studies confirm that the fusion of perspective high-level decisions or results is consistently better than the fusion of low-level features (Jouirou et al., 2019).

Furthermore, with the intention of improving the final results of the retrieval, we have demonstrated, in a previous work (Baâzaoui et al., 2020), the effectiveness of using a meta-learner that dynamically defines the most suitable query-dependent similarity measure for each treated mammogram. This returns to adopt a machine learning model in order to predict the most adequate distance metric for each query image. Compared with the traditional medical image retrieval based on static distances (Gao et al., 2020; Rasheed et al., 2020; Wu et al., 2020), this dynamic distance ensures the top precision in addition to the preservation of both the semantic and the visual similarities (Soudani and Barhoumi, 2019). As mentioned in (Baâzaoui et al., 2020), there are two types of Distance Metric Learning (DML) within the framework of CBMR, including unsupervised DML-CBMR methods (Gu et al., 2017) and supervised DML-CBMR ones (Yang et al., 2010; Wei et al., 2017). The unsupervised DML-CBMR methods are based on constructing a low-dimensional manifold while preserving the geometric relationships between data points. The supervised DML-CBMR methods consist on exploiting the class label information in order to identify the most informative dimensions to the classes of examples.

In this paper, we propose a new MV-CBMR method based on the late fusion. The main contribution of the proposed method resides in the use of the four views of the mammograms for an effective retrieval. In fact, the proposed four-view CBMR method takes as input the four views of a mammogram query and displays the relevant mammograms to each view with their clinical cases in order to assist radiologists while taking the right decision. The relevant mammograms are extracted from a classified mammogram dataset. Indeed, the used dataset is portioned according to their views (LMLO, LCC, RMLO, RCC) and global clinical case (normal, abnormal) in order to determine after that the class of severity (benign *vs*. malignant) of each abnormal query mammogram. Therefore, each view of the mammogram query is compared to the sub-dataset that contains mammograms with the same view and general clinical case as the query view. Similarly to (Baâzaoui et al., 2020), a dynamic similarity assessment has been adopted in order to retrieve the most similar mammograms for each query mammogram. This dynamic selection of the most appropriate distance, according to the input query view, aims to ensure the effectiveness of the proposed method for retrieving the most similar images, clinically speaking, for each view. Indeed, we explore the use of the distance learning via the random forest machine learning in order to learn how to predict the adequate distance for each input query according to its visual content. As well, in order to improve the accuracy rate, an effective late fusion module is introduced. This module is mainly based on the shared information concept, which allows to guide effectively the process of selecting the relevant mammograms to both views of the same breast, while adopting the same process for the dynamic query-dependent assessment of similarity between two mammograms. Then, according to the retrieved mammograms and their clinical cases, the final decision can be effectively performed. Realized experiments on the challenging DDSM (Digital Database for Screening Mammography) dataset show that the implemented four-view CBMR method can be a valuable assistance in the diagnosis of the breast cancer.

The remaining part of this paper is organized as follows. Section 2 describes the proposed method. Experimental results are presented in Section 3 and a summary discussion is provided in Section 4. Finally, a conclusion and some ideas for future works are detailed in Section 5.

# 2 PROPOSED METHOD

The proposed four-view CBMR method is composed of an offline stage and four online stages, including curvelet-based signature extraction, similarity measure, data-driven distance selection and shared information-based late fusion (Figure 1). The offline stage consists mainly on extracting the signatures of mammograms from normal and abnormal LCC, LMLO, RCC and RMLO mammograms within the investigated sub-datasets using curvelet transform and moment theory. This choice is mainly due to the fact that curvelet transform is one of the most suitable descriptors that allow to extract the discriminative mammogram features. It provides an efficient representation of smooth objects with discontinuities along curves, without the need of a segmentation step (Jouirou et al., 2015). Moreover, the use of curvelet moments is performed in order to reduce the size of the signatures without losing information of the original space (Dhahbi et al., 2015a). Similarly to the offline stage, the online signature extraction of the submitted four-view query is performed using the curvelet moments. In fact, the online retrieval process is triggered by the user who submits four mammograms as a query element rather than a single query mammogram. These four mammograms represent the provided four views from screening mammography for the same patient. In fact, they annotated each query view to select the general clinical case of each view: normal (mammogram without lesion) or abnormal (mammogram with lesion). For the normal case, the Chi-squared distance has been applied in order to retrieve the relevant mammograms; whereas for the abnormal case, a dynamic distance has been adopted in order to resend the relevant mammograms. The prediction of the most appropriate distance, according to the studied query mammogram, is performed through the random forest machine learning. After retrieving the most similar mammograms to each view of the query, a late fusion process must be performed for making the final decision. This latter is based on the shared information between the outputs (retrieved mammograms of the CC and MLO views) and the query views of each breast. The main objective of this step is to provide, for each breast, the relevant mammograms and the final decision of its clinical case. It is worth mentioning that the proposed method suggests the final decision of each breast by providing the percentage of malignancy and benignity for the abnormal cases.

## 2.1 Data-driven Distance Selection

Since there is no standalone similarity measure that provides the best results for all queries, the use of the appropriate similarity measure for each query is very promising (Baâzaoui et al., 2020; Soudani and Barhoumi, 2019). As well, for the same query, the appropriate measure is not the same for its different views. Thereby, applying the most adequate similarity measure to each query view allows improving the retrieval performance. The first step toward determining the query-dependent distance metric is to use various similarity measures. In fact, the used measures can be regrouped into standard similarity measures and statistic similarity measures. More precisely, the investigated standard similarity measures are: the Euclidean distance (1), the Manhattan distance (2) and the Canberra distance (3), whereas the studied statistic similarity measures are the Chi-squared distance (4) and the Pearson Correlation Coefficient distance (5).

$$Euc(q,r) = \sqrt{\sum_{i=1}^{16} (S_i(q) - S_i(r))^2}, \quad (1)$$

$$Man(q,r) = \sum_{i=1}^{16} |(S_i(q) - S_i(r))|, \quad (2)$$

$$Canb(q,r) = \sum_{i=1}^{16} \frac{|(S_i(q) - S_i(r))|}{|S_i(q)| + |S_i(r)|}, \quad (3)$$

$$\chi^2(q,r) = \sqrt{\sum_{i=1}^{16} \frac{(S_i(q) - S_i(r))^2}{S_i(q) + S_i(r)}}, \quad (4)$$

$$PCC(q,r) = \frac{COV(S(q), S(r))}{\sigma(S(q)) * \sigma(S(r))}, \quad (5)$$

where, $COV$ is the covariance of the two signatures, which are composed of 16 attributes, of the two compared images $q$ and $r$ ($S(q)$ for the query mammogram signature and $S(r)$ for the signature of the mammogram belonging to the corresponding sub-dataset), and $\sigma$ is the standard deviation.

The prediction of each query-based distance is performed through the random forest machine learning. Thus, for each view of the query, a prediction of the most appropriate similarity measure is carried out in order to retrieve the relevant mammograms.

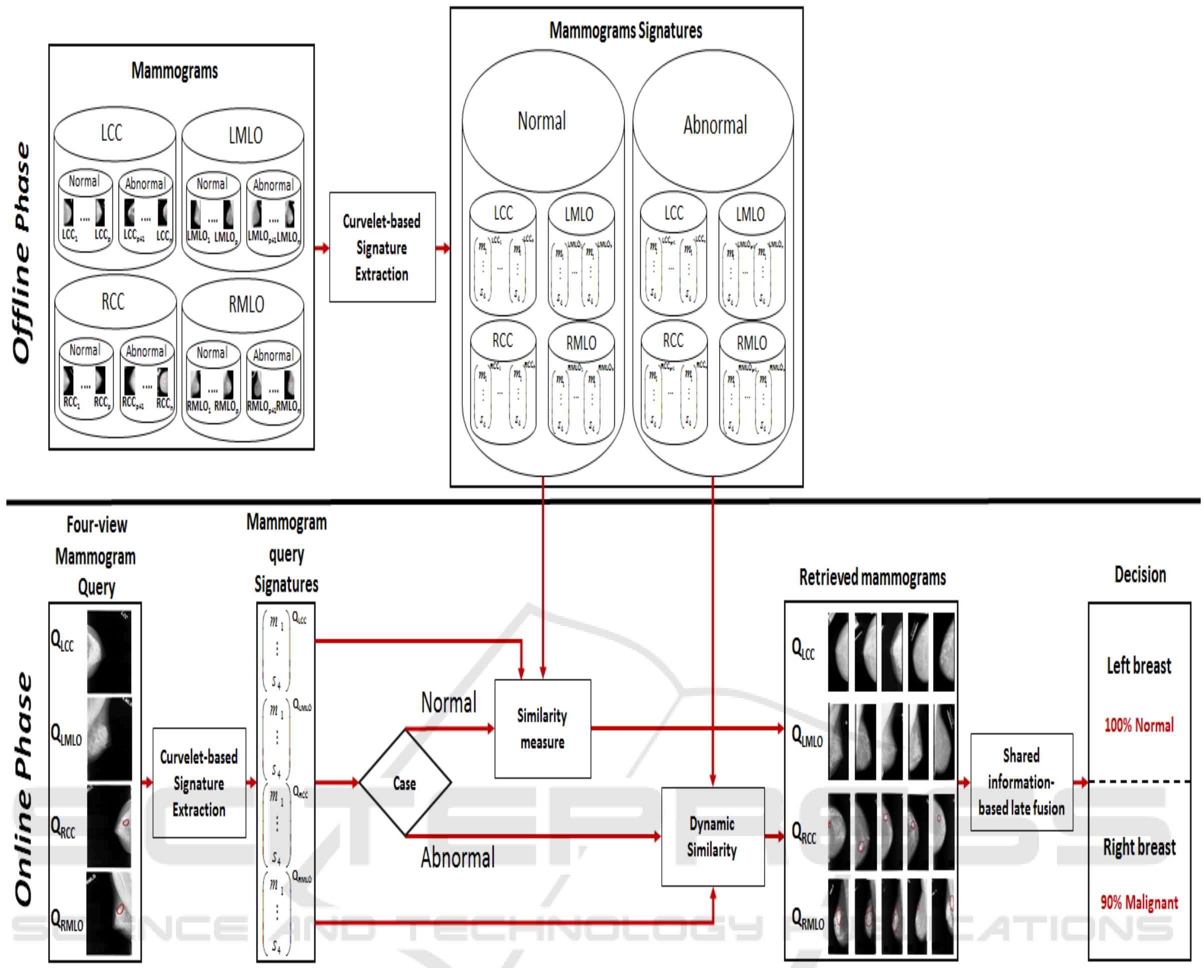


Figure 1: Flowchart of the proposed four-view CBMR method.

The choice of the random forest, as a machine learning tool, is mainly due to the fact that it has been successfully used for the dynamic distance selection within the mammogram case (Baâzaoui et al., 2020). Moreover, it is characterised by its simplicity and its multi-class nature. As well, it has proven its superiority over other supervised classifiers, especially within the framework of multiple classification problems. Thus, the used random forest machine learning algorithm contains two main phases, namely the learning phase and the predicting phase. In the learning phase, a set of features $F = S(1) \ \dots \ S(m)$ corresponding to the signatures of the training mammograms $m$ is processed as input along with their classifications $C = c(1) \ \dots \ c(m)$ that correspond to the adequate distance for each signature, while selecting the number $N$ of the used trees, to train a classification or regression tree $T_n$ on $F_n, C_n$ $(n \in \{1, N\})$. The prediction of the appropriate class (*i.e.* the best performing distance) for the query signature $S(q)$ is thereafter made by averaging the predictions from all the individual regression trees on $S(q)$ (6) or by taking the majority vote in the case of classification trees.

$$T' = \frac{1}{N} \sum_{n=1}^{N} T_n(S(q)). \tag{6}$$

In addition, for the estimate of the uncertainty of the prediction, the standard deviation of the predictions of all individual regression trees on $S(q)$ is performed (7).

$$\sigma = \sqrt{\frac{\sum_{n-1}^{N} (T_n(S(q)) - T')^2}{N-1}}. \tag{7}$$

The overview of the proposed dynamic similarity model for each input mammogram query view is summarized in Figure 2.

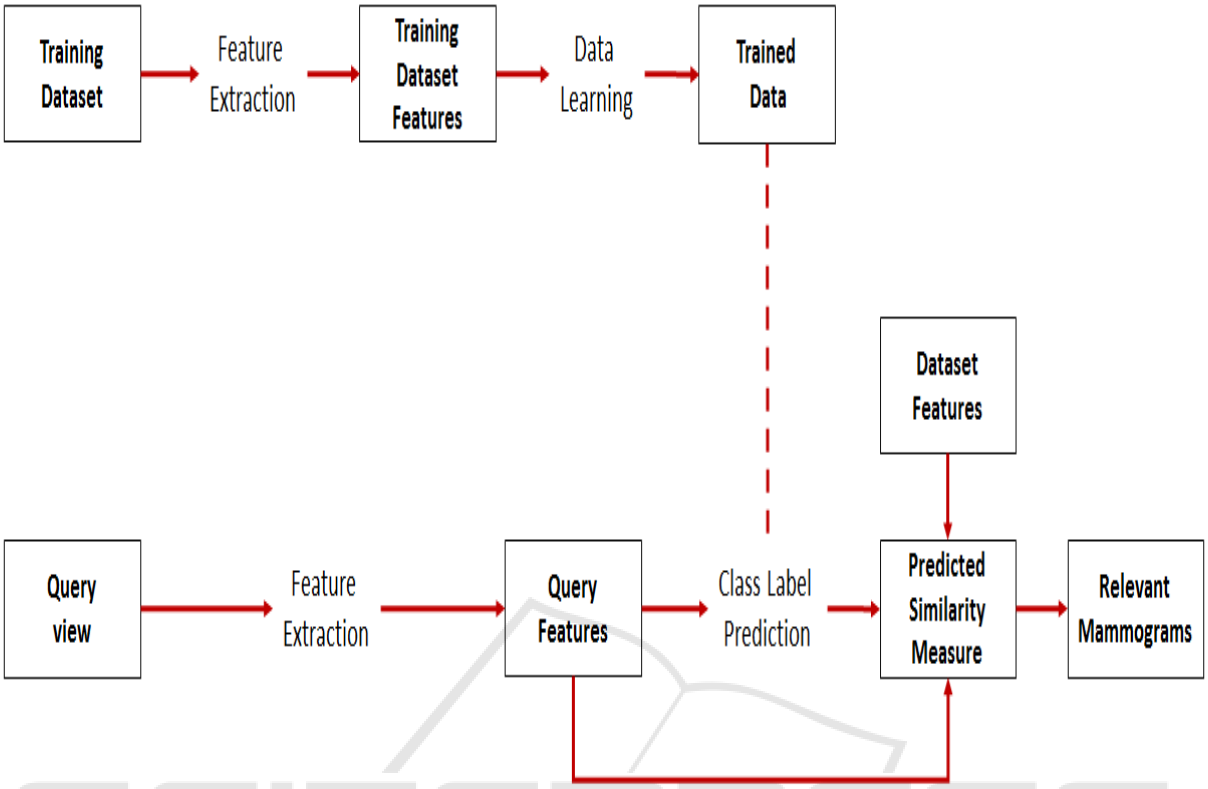


Figure 2: Overview of the proposed dynamic similarity model for each mammogram query view, including offline data learning and online similarity measure predicting.

## 2.2 Shared Information-based Late Fusion

In order to improve the final results, a late fusion module is adopted herein (Figure 3). The proposed module is based on the shared information between the both views (CC and MLO) of the same breast. In practice, the shared information concept has been investigated in various medical applications, such as the follow-up, the outcome analysis, the planning and the decision-making. Within the medical image analysis field, the concept of shared information has been successfully investigated for the image segmentation (Sbei et al., 2020), the image feature extraction (Martens et al., 2020) as well as for the image feature selection (Hao et al., 2020). In this study, we explore this concept of shared information (Krishnasamy and Paramesran, 2019) for making the final decision of the clinical case of each studied mammogram. In fact, the choice of the shared information concept in the proposed late fusion module is mainly motivated by the complementarity of the both views of the breast, what confirms the relevance of the results of the one view to the other one, since the two views illustrate the same breast. Moreover, the shared information concept has proved its efficiency in other medical image analysis works (Liu et al., 2020a), although they have not been investigated within the multi-view mammogram framework, as best as we know. In our case, after retrieving, for each breast, the sets $\Xi_{MLO}$ and $\Xi_{CC}$ of the $k$ most similar mammograms for the MLO and the CC query views, respectively, we explore the shared information in order to keep, among the mammograms within the set $\Xi_{MLO}$ (*resp.* $\Xi_{CC}$), only the set $\Xi'_{MLO}$ (*resp.* $\Xi'_{CC}$) of the $k/2$ ones that are strongly similar to the complementary CC (*resp.* MLO) view. This is performed while adopting the already identified dynamic distances for the MLO and the CC query views. Then, the final decision on the clinical case of the input query breast is defined according to those of the mammograms composing the two sets $\Xi'_{MLO}$ and $\Xi'_{CC}$. Figure 4 illustrates an example of the retrieved mammograms, relatively to a malignant right breast query, which compose the sets $\Xi_{CC}$ and $\Xi_{MLO}$ before the shared information-based late fusion, as well as the sets $\Xi'_{CC}$ and $\Xi'_{MLO}$ after the late fusion process. It is clear that the shared information allows to select the more relevant mammograms, in terms of clinical cases, for each view of the query.

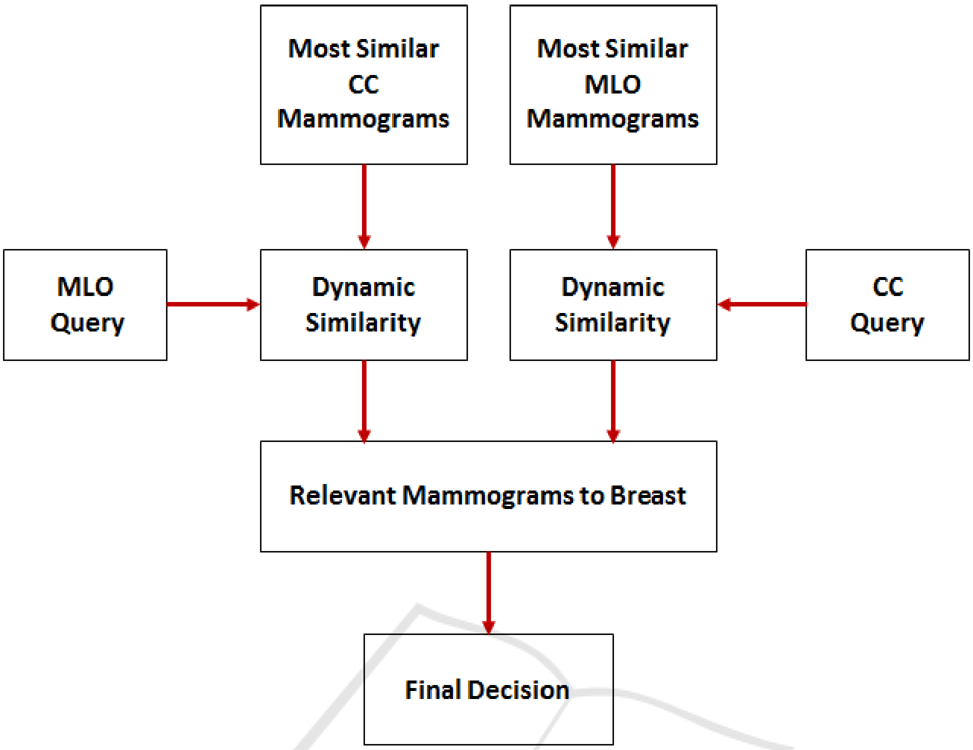


Figure 3: Overview of the proposed late fusion module, which is applied to each breast separately.



# 3 EXPERIMENTAL RESULTS

In order to validate the effectiveness of the proposed four-view CBMR method, extensive experiments on the challenging classified DDSM dataset have been conducted. In the following, we start with the description of the used mammogram dataset as well as the validation protocol. Then, we detail the implementation of the proposed four-view CBMR method. Finally, we discuss the qualitative and the quantitative evaluations of the proposed method, while comparing it against the most relevant methods from the state-of-the-art.

## 3.1 Data and Validation Protocol

The experiments have been performed on mammograms from the DDSM dataset. This dataset, which is composed of 9,852 different mammograms, is the largest publicly available resource for mammographic image analysis research (Baâzaoui et al., 2020). The construction of this challenging dataset was performed within the framework of the DDSM project (Heath et al., 1998), which comprised the Massachusetts General Hospital, the University of South Florida and the Sandia National Laboratories. Mammograms belonging to the used dataset have been classified according to their views into four sub-datasets, which are LCC, LMLO, RCC and RMLO datasets. Each of these sub-datasets contains 2,463 mammograms. Moreover, the produced mammograms are classified according to their clinical cases into normal mammograms and abnormal ones. The total number of abnormal mammograms is 3,664, whereas the total number of normal mammograms is 6,188. Besides, abnormal mammograms are classified in their turn into malignant mammograms and benign ones. Indeed, there are 1,768 benign mammograms and 1,896 malignant mammograms. It is annotated that the numbers of normal, benign and malignant mammograms are not the same in the four sub-datasets. In fact, the numbers of normal mammograms are 1,504, 1,481, 1,623 and 1,580 in LCC, LMLO, RCC and RMLO datasets, respectively. The numbers of benign mammograms are 472, 480, 398 and 418 in LCC, LMLO, RCC and RMLO datasets, respectively. The numbers of malignant mammograms are 487, 502, 442 and 465 in LCC, LMLO, RCC and RMLO datasets, respectively. An example of four-view mammograms is illustrated in Figure 5.

Furthermore, in order to quantitatively evaluate the proposed four-view CBMR method, most

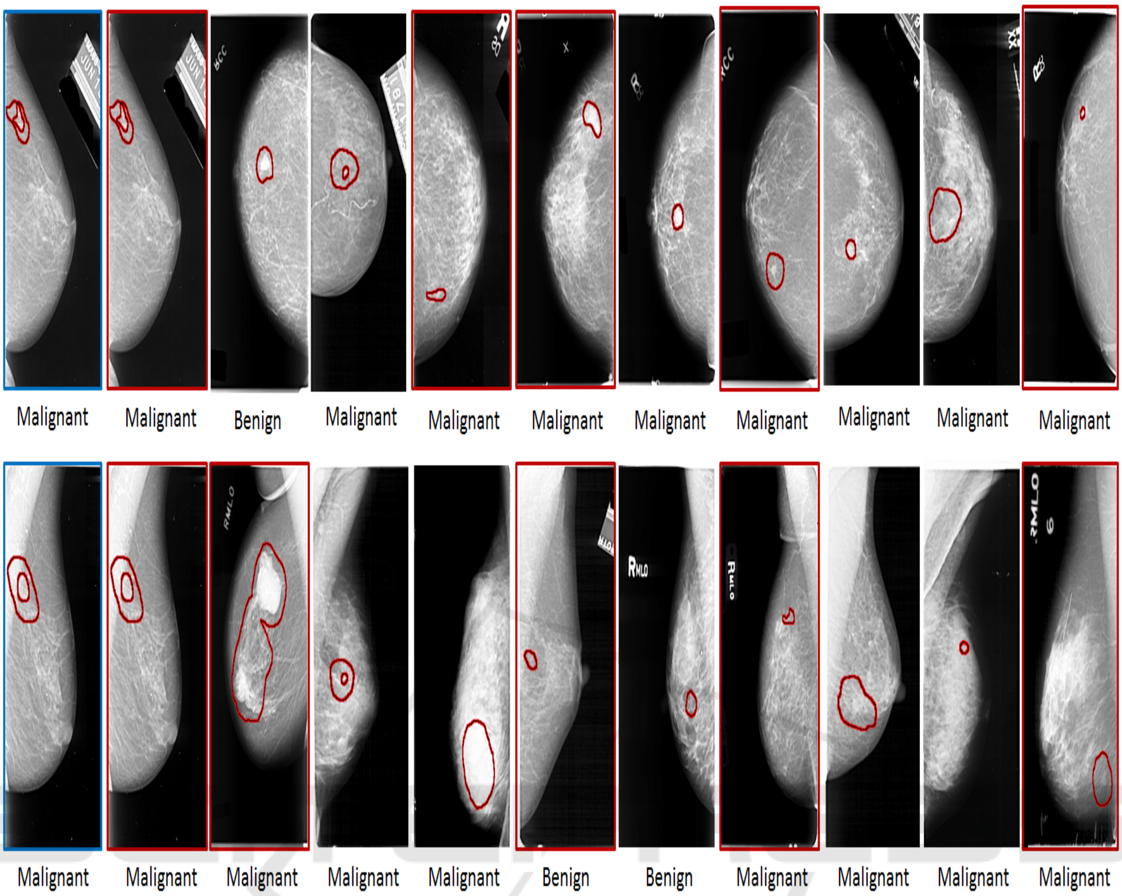


Figure 4: Example of the shared information-based late fusion for a malignant right breast. The first row illustrates the RCC query (framed in blue) with its 10 (*i.e* $k = 10$) most similar RCC mammograms ($\Xi_{CC}$). The second row shows the RMLO query (framed in blue) with its 10 most similar RMLO mammograms ($\Xi_{MLO}$). The kept mammograms ($\Xi'_{CC}$ and $\Xi'_{MLO}$) are framed in red in the both cases.

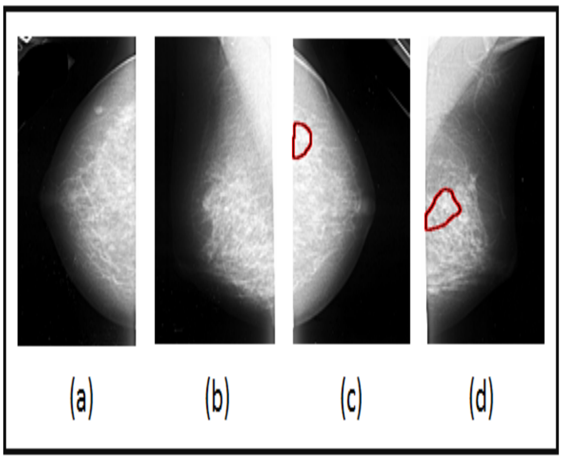


Figure 5: Example of four-view mammograms used in the experiments: Normal LCC mammogram (a), Normal LMLO mammogram (b), Malignant RCC mammogram (c), Malignant RMLO mammogram (d).

relevant evaluation metrics have been considered in this work. The precisely choice of the accuracy, FP and FN rates is mainly due to the fact that they are the most used ones within the CBMR context, seen their effective ability to measure the precision of the CBMR systems. It is worth mentioning that the proposed four-view CBMR method has been implemented using MATLAB R2013a software, and all the tests were performed on a machine with 64-bit Windows operating system, over an DELL PC with $Intel(R)Core(TM)i7-6500UCPU@2.50GHz2.60GHz$ processor and $8Go$ of RAM.

### 3.2 Qualitative Evaluation

To qualitatively evaluate the implemented method, sundry tests have been performed. Examples of four-view mammograms queries with their final clinical case decisions are shown in Figure 6 and Figure 7.

In fact, the presented four-view mammogram query in Figure 6 has two abnormal breasts, and the clinical case of these two breasts is benign. The reported results of this query are very encouraging. Indeed, the accuracy rate of the left breast is equal to 90% and the accuracy rate of the right one is of 100%. Besides, the mammogram query of Figure 7 has one abnormal breast and one normal breast. The left breast contains a malignant lesion, while the right breast has no lesion. The final decision of the aforementioned query is correct. In fact, the suggested results are 90% malignant for the left breast and 100% normal for the right one. Otherwise, among the tested queries, the worst one is shown is Figure 8, where the clinical case of the presented four-view mammogram query is normal for the left breast and benign for the right one. The provided accuracy rate by the left breast is equal to 100%, while that provided by the right breast is only equal to 60%. This low rate can be explained by the irrelevant results of the separately retrieved mammograms for the RMLO view of the query and the RCC view of the query. Also, we clearly observe that the value of the accuracy rate of the right breast without fusion drops (it is equal to 40%). This is mainly due to the RCC view of the query, which provides only 20% of accuracy rate. We thus conclude that although that the right breast accuracy rate is weak, it has been improved significantly through the proposed shared information-based late fusion from 40% to 60%.

## 3.3 Quantitative Evaluation

In order to quantitatively evaluate the suggested four-view CBMR method, we firstly describe the experimental process before discussing the retrieval performance of the method. Then, we compare the proposed method with some relevant methods from the state-of-the-art.

### 3.3.1 Experimental Process

To perform the learning step, some mammograms from the DDSM dataset were tested using five different distances (Euclidean, Chi-squared, Manhattan, Canberra and Pearson Correlation Coefficient). Table 1 shows a sample of the used ground-truth for the distance metric learning. According to the final decision, the distribution of the training mammograms in five classes corresponding to the used distances metrics is detailed in Figure 9. For the number of the retrieved images, we set *k* to 10.

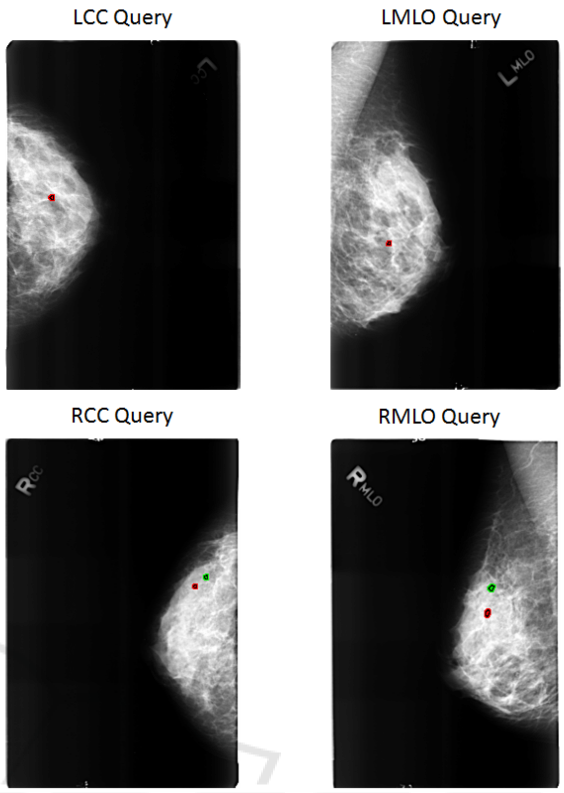


Figure 6: Example of a benign four-view mammogram query with its final decision. The first row shows the complementary views of the left breast with a final decision equals to 90% as benign and 10% as malignant. The second row illustrates the complementary views of the right breast with a final decision equals to 100% as benign and 0% as malignant.

### 3.3.2 Retrieval Performance

In order to assess the proposed method for CBMR, we have computed the False Positive (FP), the False Negative (FN) and the accuracy rates in all cases (normal, abnormal and overall). The reported results in Table 2 demonstrate that the provided FP and FN rates in the aforementioned cases by the proposed four-view CBMR method are quite low and the provided accuracy rate is quite high, which confirms the efficiency of the suggested method. Otherwise, in order to show the effectiveness of the proposed late fusion module, a comparison between the performance of the proposed four-view CBMR method without and with adding the late fusion module has been performed. It is clear in Table 3 and Table 4 that the proposed late fusion module improves the final results. In fact, reported results show that the accuracy increases at a rapid rate contrary to the FP and FN rates, which decrease considerably in all cases (overall, abnormal, benign and malignant). This is ensured by the shared information

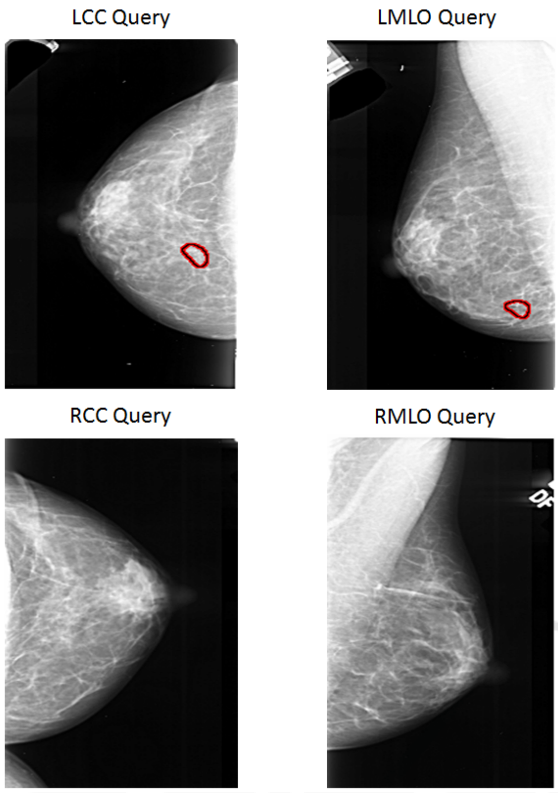


Figure 7: Example of a malignant four-view mammogram query with its final decision. The first row shows the complementary views of the left breast with a final decision equals to 10% as benign and 90% as malignant. The second row illustrates the complementary views of the right breast with a final decision equals to 100% as normal.

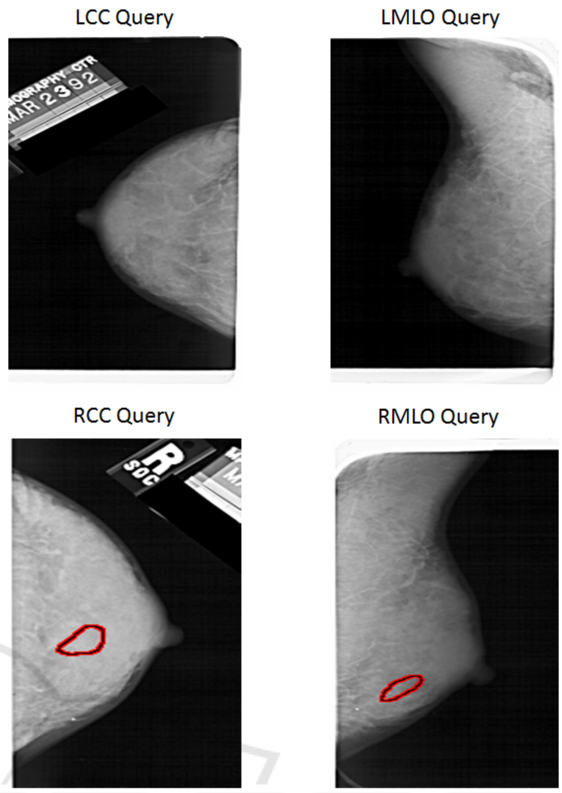


Figure 8: The worst four-view mammogram query with its final decision. The first row shows the complementary views of the left breast with a final decision equals to 100% as normal. The second row illustrates the complementary views of the right breast with a final decision equals to 60% as benign and 40% as malignant.

of complementary views of the breast, which allows to minimize the error rate by eliminating the furthest mammograms, within the studied dataset, with regard to the query mammogram.

### 3.3.3 Comparison with Relevant Sate-of-the-Art Methods

In order to confirm the effectiveness of the proposed four view CBMR method, we compare it with some relevant MV-CBMR methods. In fact, one multi-view early fusion method and one multi-view late fusion method have been investigated. The early fusion method is based on merging the features of both views of the breast into one vector that is thereafter used for the retrieval. The score-based late fusion method is based on the fusion between the results of the CC view and the MLO view of the same breast. According to Table 5, we can observe that the proposed late fusion method outperforms the compared state-of-the-art methods (Narvaez et al., 2011; Dhahbi et al., 2015b). The provided results prove that the higher

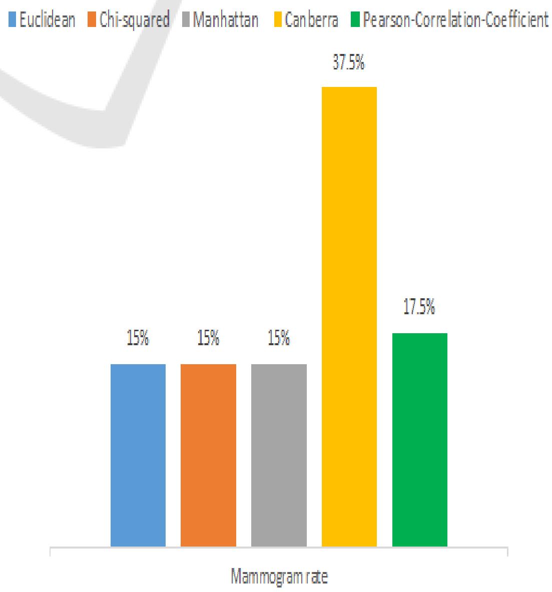


Figure 9: Distribution of the trained mammograms according to the used distance metrics.

Table 1: A sample of the proposed ground-truth that has been used for distance metric learning over the DDSM dataset.

| View | Clinical case | Adequate distance |
|---|---|---|
| LCC | Benign | Canberra |
| LCC | Benign | Manhattan |
| LCC | Malignant | Pearson-Correlation-Coefficient |
| LCC | Malignant | Manhattan |
| LMLO | Benign | Canberra |
| LMLO | Benign | Chi-squared |
| LMLO | Malignant | Euclidean |
| LMLO | Malignant | Pearson-Correlation-Coefficient |
| RCC | Benign | Canberra |
| RCC | Benign | Pearson-Correlation-Coefficient |
| RCC | Malignant | Euclidean |
| RCC | Malignant | Chi-squared |
| RMLO | Benign | Pearson-Correlation-Coefficient |
| RMLO | Benign | Chi-squared |
| RMLO | Malignant | Pearson-Correlation-Coefficient |
| RMLO | Malignant | Canberra |

Table 2: Quantitative evaluation of the proposed four-view CBMR method over the DDSM dataset.

| | Overall | Normal | Abnormal |
|---|---|---|---|
| Accuracy | 92% | 100% | 89% |
| FP | 6.92% | 0% | 12.86% |
| FN | 6% | 0% | 10% |

accuracy rate (89%) and the lower FP (12.86%) and FN (10%) rates have been obtained by the proposed CBMR method based on late fusion. This improvement can be explained by three main insights: (1) the compared MV-CBMR methods are based on two views unlike the proposed method, which is based on four views, (2) the use of the adequate similarity distance for each view of the query, which allows to increase the retrieval performance considerably, and (3) the adoption of the shared information of complementary mammogram views in the late fusion module, which permits to further enhance the final results.

# 4 DISCUSSION

Due to the fact that the use of only a single view within the framework of CBMR does not satisfy radiologists supervision and interpretation, since it does not always provide the correct decisions, the integration of the multi-view concept is becoming a great necessity in recent years. In this paper, we have proposed an effective MV-CBMR method based on the use of the four views of mammograms. Indeed, the MLO and the CC views of both breasts (left and right) of one patient are used as input in the proposed method and the relevant mammograms are displayed, for each of the four views, with their clinical cases in order to make the right decision. The main contributions of the proposed four view CBMR method resides in: (1) the use of the classified dataset, which allows to personalize each view of the query, (2) the adaptation of the dynamic distance, which allows to improve the accuracy of the retrieved mammograms for each view of the mammogram query, and (3) the proposed late fusion module, which allows to increase the decision precision rate. In fact, the classified dataset permits to perform the search of relevant mammograms for each view of the query over a sub-dataset that contains mammograms with the same view and general clinical case as the query view. This allows to avoid the search in the whole dataset, what optimizes the time cost. Moreover, the dynamic data-driven distance selection is performed in order to guarantee that the most adequate similarity, which provides the highest precision for each view of the query, will be adopted. The prediction of the used similarity distance is carried out through the random forest machine learning that proved its efficiency within the context of mammogram classification. Finally, the proposed late fusion module, which is based on the shared information, represents the most sturdiness contribution of the proposed MV-CBMR method. In fact, the shared information between the complementary views of the same breast was performed in order to select the most similar mammograms to each breast from the retrieved mammograms of the CC view and the MLO view of the breast. Experimental results on the challenging DDSM dataset show that combining the random forest algorithm, in order to predict the most appropriate distance to each view of the query, with the shared information, in order to fuse the results of both views of the same breast, allows to optimize remarkably the accuracy of the retrieved mammograms, which reaches a value equals to 92% in the overall case. As well, the FP and the FN rates are dropped to achieve 6.92% and 6%, respectively. Besides, the proposed four-view late fusion method outperforms existing multi-view late fusion methods with gain rates rounded to 26%, 34% and 15% for the accuracy, the FP and the FN rates, respectively.

Table 3: Comparison of the performances of the proposed four-view CBMR method with and without the use of the late fusion over the DDSM dataset.

| Case | Overall | | Normal | | Abnormal | |
|---|---|---|---|---|---|---|
| Late fusion | Without | With | Without | With | Without | With |
| Accuracy | 88% | 92% | 100% | 100% | 83% | 89% |
| FP | 11.23% | 6.92% | 0% | 0% | 20.86% | 12.86% |
| FN | 8.07% | 6% | 0% | 0% | 13.45% | 10% |

Table 4: Comparison of the performances of the proposed four-view CBMR method with and without the use of the late fusion in the benign and malignant cases over the DDSM dataset.

| Case | Benign | | Cancer | |
|---|---|---|---|---|
| Late fusion | Without | With | Without | With |
| Accuracy | 79.14% | 87.14% | 86.55% | 90% |

Table 5: Comparison of the performance of the proposed method against two relevant MV-CBMR methods from the state-of-the-art.

| Abnormal case (Benign vs. Malignant) | Early fusion method (Narvaez et al., 2011) | Score-based late fusion method (Dhahbi et al., 2015b) | Proposed shared information-based late fusion method |
|---|---|---|---|
| Accuracy | 56.4% | 63.2% | 89% |
| FP | 48,4% | 46,33% | 12.86% |
| FN | 38.4% | 25.6% | 10% |

## 5 CONCLUSION

In this paper, we proposed a four-view CBMR method based on the use of a classified dataset. Indeed, the proposed method takes as input a four-view query mammogram and conjointly retrieves the most similar mammograms for each query view in order to provide radiologists with a source that allows them to make the right decision. The retrieved mammograms for each view of the query are selected from its relevant sub-dataset that contains mammograms with the same view and general clinical case. Moreover, the dynamic similarity assessment was effectively integrated within the proposed four-view CBMR method. This data-driven distance selection is mainly based on the random forest machine learning, which allows to predict dynamically the similarity measure that should be applied for each view of the query. The appropriate similarity can be either a standard similarity measure or a statistic similarity measure. Furthermore, in order to increase the right decision rate, a late fusion module has been proposed. This module is principally based on the shared information between both views of the same breast. It consists of retrieving the most similar mammograms to each breast with their clinical case (normal, malignant, benign) and suggesting the final decision. Produced results using the classified DDSM dataset show the relevance of the proposed four-view CBMR method. As well, the effectiveness of the proposed late fusion module has been proved by the increase of the accuracy rate from 88% to 92% in the overall case and from 83% to 89% in the abnormal case. As future work, we aim to propose a late fusion approach, based on the Dempster-Shafer theory, that will be adapted in the case of bilateral analysis of mammograms.

## REFERENCES

Arora, R., Rai, P. K., and Raman, B. (2020). Deep feature–based automatic classification of mammograms. *Medical and Biological Engineering and Computing*, 58:1199—-1211.

Baâzaoui, A., Abderrahim, M., and Barhoumi, W. (2020). Dynamic distance learning for joint assessment of visual and semantic similarities within the framework of medical image retrieval. *Computers in Biology and Medicine*, 122:103833.

Boudraa, S., Melouah, A., and Merouani, H. F. (2020). Improving mass discrimination in mammogram-cad system using texture information and super-resolution reconstruction. *Evolving Systems*, 11:697—-706.

Dhahbi, S., Barhoumi, W., and Zagrouba, E. (2015a). Breast cancer diagnosis in digitized mammograms using curvelet moments. *Computers in Biology and Medicine*, 64:79–90.

Dhahbi, S., Barhoumi, W., and Zagrouba, E. (2015b).

Multi-view score fusion for content-based mammogram retrieval. In *Proceedings of SPIE 9875, Eighth International Conference on Machine Vision*, page 987515.

Gao, X., Mu, T., Goulermas, J. Y., Thiyagalingam, J., and Wang, M. (2020). An interpretable deep architecture for similarity learning built upon hierarchical concepts. *IEEE Transactions On Image Processing*, 29:3911–3926.

Gu, Y., Vyas, K., Yang, J., and Yang, G.-Z. (2017). Unsupervised feature learning for endomicroscopy image retrieval. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 64–71.

Hao, X., Bao, Y., Guo, Y., Yu, M., Zhang, D., Risacher, S. L., Saykin, A. J., Yao, X., Shen, L., and for the Alzheimer's Disease Neuroimaging Initiative (2020). Multi-modal neuroimaging feature selection with consistent metric constraint for diagnosis of alzheimer's disease. *Medical Image Analysis*, 60:101625.

Heath, M., Bowyer, K., Kopans, D., Jr, P. K., Moore, R., Chang, K., and Munishkumaran, S. (1998). Current status of the digital database for screening mammography. *Digital Mammography Computational Imaging and Vision*, 13:457—-460.

Jouirou, A., Baâzaoui, A., and Barhoumi, W. (2019). Multi-view information fusion in mammograms: A comprehensive overview. *Information Fusion*, 52:308–321.

Jouirou, A., Baâzaoui, A., Barhoumi, W., and Zagrouba, E. (2015). Curvelet-based locality sensitive hashing for mammogram retrieval in large-scale datasets. In *12th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA)*, pages 1–8. IEEE.

Khan, H. N., Shahid, A. R., Raza, B., Dar, A. H., and Alquhayz, H. (2019). Multi-view feature fusion based four views model for mammogram classification using convolutional neural network. *IEEE Access*, 7:165724–165733.

Kiruthika, K., Vijayan, D., and R, L. (2019). Retrieval driven classification for mammographic masses. In *International Conference on Communication and Signal Processing*, page 18619401. IEEE.

Krishnasamy, G. and Paramesran, R. (2019). Multiview laplacian semisupervised feature selection by leveraging shared knowledge among multiple tasks. *Signal Processing: Image Communication*, 70:68–78.

Liu, Q., Dou, Q., Yu, L., and Heng, P. A. (2020a). Ms-net: Multi-site network for improving prostate segmentation with heterogeneous mri data. *IEEE Transactions on Medical Imaging*, 39(9):2713–2724.

Liu, W., ran Wei, Y., and qian Liu, C. (2020b). Mammographic mass retrieval using multi-view information and laplacian score feature selection. In *Proceedings of the 2nd International Conference on Intelligent Medicine and Image Processing*, pages 75–79.

Liu, W., Xu, W., Li, L., Li, S., Zhao, H., and Zhang, J. (2011). Mammographic mass retrieval based on multi-view information. In *5th International Conference on Bioinformatics and Biomedical Engineering (iCBBE)*, page 12072452.

Martens, R. M., Koopman, T., Lavini, C., Ali, M., Peeters, C. F. W., Noij, D. P., Zwezerijnen, G., Marcus, J. T., Vergeer, M. R., Leemans, C. R., de Bree, R., de Graaf, P., Boellaard, R., and Castelijns, J. A. (2020). Multi-parametric functional mri and 18f-fdg-pet for survival prediction in patients with head and neck squamous cell carcinoma treated with (chemo)radiation. *European Radiology*, https://doi.org/10.1007/s00330-020-07163-3.

Narvaez, F., Diaz, G., and Romero, E. (2011). Multi-view information fusion for automatic bi-rads description of mammographic masses. In *Proceedings of SPIE 7963, Medical Imaging 2011: Computer-Aided Diagnosis*, pages 84—-89.

Rasheed, A. S., Zabihzadeh, D., and Al-Obaidi, S. A. R. (2020). Large-scale multi-modal distance metric learning with application to content-based information retrieval and image classification. *International Journal of Pattern Recognition and Artificial Intelligence*, https://doi.org/10.1142/S0218001420500342.

Rayen, S. and Subhashini, R. (2020). An efficient mammogram image retrieval system using an optimized classifier. *Neural Processing Letters*, https://doi.org/10.1007/s11063-020-10254-3.

Sapate, S., Talbar, S., Mahajan, A., Sable, N., Desai, S., and Thakur, M. (2020). Breast cancer diagnosis using abnormalities on ipsilateral views of digital mammograms. *Biocybernetics and Biomedical Engineering*, 40(1):290–305.

Sbei, A., ElBedoui, K., Barhoumi, W., and Maktouf, C. (2020). Gradient-based generation of intermediate images for heterogeneous tumor segmentation within hybrid pet/mri scans. *Computers in Biology and Medicine*, 119:103669.

Singh, V. P., Srivastava, S., and Srivastava, R. (2018). Automated and effective content-based image retrieval for digital mammography. *Journal of X-Ray Science and Technology*, 26(1):29–49.

Soudani, A. and Barhoumi, W. (2019). An image-based segmentation recommender using crowdsourcing and transfer learning for skin lesion extraction. *Expert Systems with Applications*, 118:400–410.

Wei, G., Cao, H., Ma, H., Qi, S., Qian, W., and Ma, Z. (2017). Content-based image retrieval for lung nodule classification using texture features and learned distance metric. *Journal of Medical Systems*, 42(13):1–7.

Wu, W., Tao, D., Li, H., Yang, Z., and Cheng, J. (2020). Deep features for person re-identification on metric learning. *Pattern Recognition*, 110:107424.

Yang, L., Jin, R., Mummert, L., Sukthankar, R., Goode, A., Zheng, B., Hoi, S. C., and Satyanarayanan, M. (2010). A boosting framework for visuality-preserving distance metric learning and its application to medical image retrieval. *IEEE Transactions On Pattern Analysis And Machine Intelligence*, 32(1):30–44.