FmRMR-OBL-ChefNet for Breast Cancer Histopathology Image Classification

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Abstract

Deep learning models can produce very large feature representations, making it difficult to analyze the detailed cellular and tissue information found in breast cancer histopathology images, which can aid in computer-aided diagnosis. These representations could have redundant or poorly informative features, which would raise the computational cost and complicate the classification step that follows. The hybrid deep learning and metaheuristic framework FmRMR-OBL-ChefNet is presented in this paper with the goal of obtaining a compact and discriminative feature representation for the classification of breast cancer histopathology. The suggested framework learns complementary deep features by utilizing pretrained ResNet, ResNeXt, and NASNet architectures. Fuzzy minimum redundancy maximum relevance (FmRMR), chaotic weighting, and adaptive relevance–redundancy balancing are used to refine these features. An efficient subset of the refined features is then found using an opposition-based Chef Optimization Algorithm (OBL-COA). The chosen representation is assessed using area under the curve (AUC), F1-score, recall, accuracy, precision, and specificity. The framework's goal is to minimize computational complexity and feature redundancy while preserving information that can be used to differentiate between benign and malignant breast tissue.

Keywords— breast cancer, histopathology, deep learning, ResNet, ResNeXt, NASNet, fuzzy mRMR, feature selection, opposition-based learning, Chef Optimization Algorithm.

Introduction

Breast cancer is a major clinical problem, with early and accurate diagnosis influencing treatment options and patient outcomes. Histopathological analysis is an important part of breast cancer diagnosis, offering an in-depth view of the changes in cellular and tissue architecture. However, manually analysing many biopsy images is tedious and subject to variations in human interpretation. Such difficulties gave rise to the development of computer-aided diagnostic systems with machine learning and deep learning.

Deep learning is especially helpful in the analysis of medical images since it can learn image representations directly from the data. This ability is furthered by transfer learning that allows pretrained networks to benefit from the visual insights learned from large-scale image datasets. ResNet, ResNeXt and NASNet are able to extract different levels of texture, structure and semantic details from histopathology images. Combining these representations may provide a more complete picture of breast tissue than relying on a single framework.

Deep representations are concatenated, leading to an increase in the dimensionality of the feature space. A large feature vector can include features that are correlated, redundant or uninformative. Sending all the features to a classifier increases the computational demands and may decrease the overall efficiency of the system. Thus, feature selection plays an important role in diagnosis process.

In this work, fuzzy mRMR has been used to find the features which are strongly related with the target class and are less redundant. The adaptive relevance-redundancy balancing and chaotic weighting enhance the flexibility and diversity of the selection process. The obtained candidate features are then improved by opposition based Chef Optimisation Algorithm. The whole framework is termed as FmRMR-OBL-ChefNet .

Research Problem and Questions

Deep learning models have shown great potential in the classification of cancer images, but there are still many practical challenges. Redundant features may not be meaningful for classification and high-dimensional deep features can increase processing and storage requirements. The cost of conventional search strategies can be increased as the search space size increases. Hence, a practical framework is required to integrate robust feature learning with effective feature reduction and optimization.

- How can deep learning be used to obtain reliable representations for breast cancer histopathology images?
- How can relevant features be retained while reducing redundancy in a high-dimensional deep feature space?
- How can metaheuristic optimization be used to identify a compact feature subset without relying on exhaustive search?

Research Gap and Motivation

ResNet, ResNeXt, VGG and Inception architectures have been successfully utilised in previous medical image classification studies. However, the representations learned may still be of high dimension, and the features learned by different models may be overlapping. Grid and random search strategies can require a considerable amount of computational resources for a large number of potential feature combinations. These limitations motivate a framework that integrates complementary deep feature extraction, relevance-redundancy analysis and efficient optimisation.

Our proposed framework is motivated by the following three observations. The same histopathology image can provide complementary information from different pretrained networks in the beginning. Second, fuzzy mutual information can be a flexible way to measure the relevance of features and reduce redundancy. Thirdly, an opposition-based population search can supply more candidate solutions and assist in maintaining diversity during optimisation. These ideas together constitute the basis of FmRMR-OBL-ChefNet.

Contributions

- A hybrid FmRMR-OBL-ChefNet framework is formulated for breast cancer histopathology image classification.
- ResNet, ResNeXt, and NASNet are combined to obtain complementary deep feature representations.
- Fuzzy mRMR is used to reduce redundancy while retaining features that are relevant to the target classes.
- Adaptive relevance–redundancy balancing and chaotic weighting are incorporated into the feature-selection stage.
- Opposition-based learning is integrated with the Chef Optimization Algorithm to search for an effective feature subset.
- The selected features are evaluated using accuracy, precision, recall, F1-score, specificity, and AUC.

Dataset

The BreakHis dataset is used as the benchmark dataset in the proposed framework. It contains microscopic breast tumor images acquired at four magnification levels: 40×, 100×, 200×, and 400×. The presentation specifies a total of 7,909 RGB images, including 2,480 benign images and 5,429 malignant images. The benign group contains adenosis, fibroadenoma, phyllodes tumor, and tubular adenoma, whereas the malignant group contains ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma. The images are stored in PNG format at a resolution of 700 × 460 pixels.

Magnification	Benign	Malignant
40×	625	1370
100×	644	1437
200×	623	1390
400×	588	1232
Total	2480	5429

Table 1. Magnification-wise distribution of the BreakHis dataset.

Proposed FmRMR-OBL-ChefNet Framework

6.1 Deep Feature Extraction

In the first stage, pretrained ResNet, ResNeXt and NASNet models are employed to extract deep representations from the input histopathology images. These networks are able to reuse the visual patterns learned from large image collections and adapt them for medical imaging tasks via transfer learning. Instead of a single architecture, the proposed framework merges the features of all the three networks, to create a more complete feature space with complementary information about the tissue.

6.2 Fuzzy mRMR Feature Selection

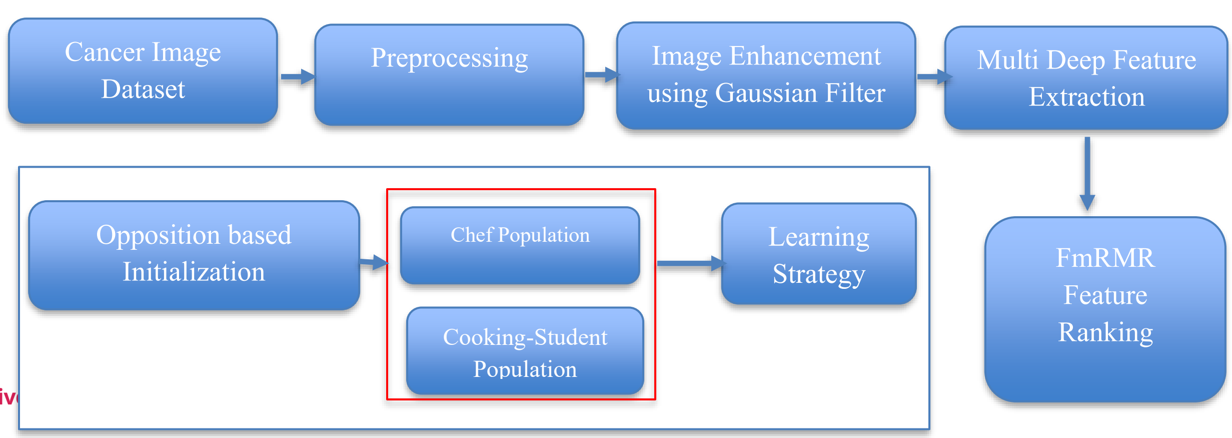
It is probable that the combined deep feature space will contain features of varying degrees of relevance to the benign and malignant classes. FmRMR improves this representation by rewarding features that are informative for the target classification problem, and penalizing features that duplicate information already provided by selected features. The fuzzy formulation provides the ability to easily deal with complex feature relationships. Chaotic weighting is applied to bring in diversity to the selection process. Adaptive relevance–redundancy balancing is used to balance the two objectives appropriately.

6.3 Opposition-Based Chef Optimization Algorithm

The optimized candidate feature set is optimized by using the Chef Optimization Algorithm. The optimizer is inspired by the learning process in culinary training where students improve their skills by being taught, observing, imitating, practicing and learning from better solutions. In the proposed feature-selection problem, each candidate solution is a possible subset of features, and the fitness is the quality of that subset in classifying the data.

Opposition based learning is employed to improve population diversity and to produce alternative candidate solutions. This allows more chances for the search process to explore different parts of the solution space. Thus, the optimizer tries to minimize the number of selected features and simultaneously balance the exploration and exploitation. The last solution is the feature subset that provides a practical trade-off between computational efficiency and discriminative information.

6.4 Block Diagram of the Proposed Framework



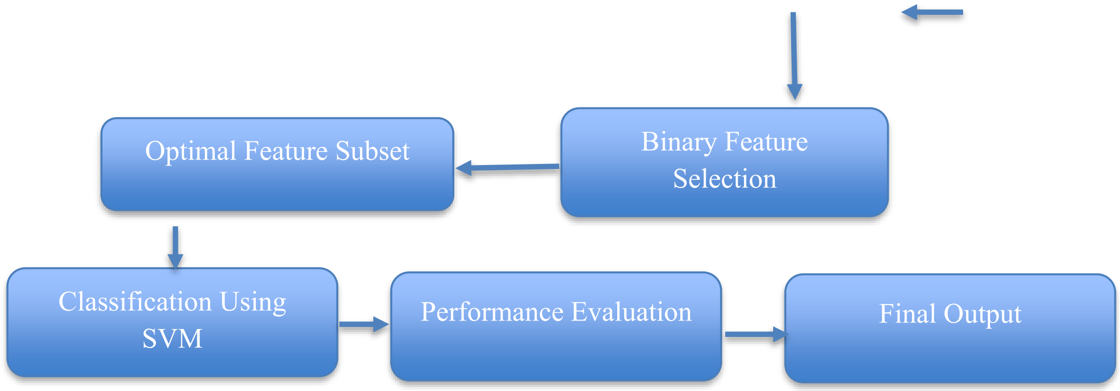


Fig. 1. Architecture of the proposed FmRMR-OBL-ChefNet framework.

The work we propose uses a full processing pipeline presented in Figure 1. First, the input histopathology image is passed through the pretrained deep feature extraction stage. The resulting representation is fed to the fuzzy mRMR-based feature-selection stage, that considers relevance, redundancy, adaptive balancing, and chaotic weighting. then, the optimized features are optimized by the OBL-improved Chef Optimization Algorithm. Finally, the selected feature subset is given to the classification stage. The trained model is evaluated on the given performance indicators.

Classification and Evaluation

The experimental protocol splits the optimized feature subset into training and testing parts. In the next step, the selected features are used in the classification stage to differentiate between benign and malignant histopathology images. The aim of this step is not to optimize a single number, but to see whether the reduced feature representation still contains enough information to allow for a reliable classification.

Accuracy is the proportion of samples that are correctly classified. Recall or sensitivity is the ability to correctly identify malignant samples. Precision is the proportion of samples predicted as malignant that are actually malignant. The F1-score gives a concise measure of the trade-off between recall and precision. Specificity is the measure of how well benign cases are detected. The AUC summarizes the discrimination of the classification at different decision thresholds. It is more informative to evaluate a medical classification model by considering these measures together.

Discussion

The core idea of FmRMR-OBL-ChefNet is not to assume that all deep features are equally useful. The use of three pretrained architectures provides a rich representation, but the later selection stages are essential for managing the representation. FmRMR provides an information guided reduction stage, while OBL-COA performs a more focused search for a useful feature subset. The goal of this combination is to retain the discriminative features of breast tissue while reducing redundancy and computational cost at the same time.

Moreover, the proposed design makes a clear distinction between feature optimization and representation learning. The metaheuristic stage takes care of the search for the final subset. Relevance and redundancy evaluation is performed by FmRMR. Deep networks are responsible for learning visual patterns. The division allows for a simpler conceptual understanding of the framework and opens up many possibilities for future development.

Research Significance and SDG Alignment

The proposed framework is intended to enhance the efficiency of computer-aided diagnosis of breast cancer by reducing the size of deep feature representations. A compact representation could alleviate the computational burden of the subsequent classification and make the workflow more practical for real-world deployment. The research is also in line with Sustainable Development Goal 3 (Good Health and Well-Being) with a specific focus on its wider goal of harnessing technology to support detection and management of NCDs.

Conclusion and Future Work

In this paper, we present FmRMR-OBL-ChefNet, a hybrid framework of metaheuristic feature optimization, fuzzy relevance-redundancy analysis and pretrained deep learning for breast cancer histopathology classification. ResNet, ResNeXt and NASNet respectively learn complementary deep representations. FmRMR is then used to reduce redundancy and select informative candidates. Then the compact feature subset is determined by the OBL-enhanced Chef Optimization Algorithm. The resulting representation is evaluated in terms of accuracy, precision, recall, F1-score, specificity and AUC.

The framework is based on the distribution of the dataset BreakHis mentioned in the conference presentation and maintains the 4 magnification levels that do not affect the class counts reported. Future work includes adding more clinical datasets to the evaluation, exploring explainable AI methods, and testing the robustness of the selected features in wider experimental settings.

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