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Deep feature extraction, dimensionality reduction, and classification of medical images using combined deep learning architectures, autoencoder, and multiple machine learning models

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Abstract: Accurate analysis and classification of medical images are essential factors in clinical decision-making and patient care. A novel comparative approach for medical image classification is proposed in this study. This new approach involves several steps: deep feature extraction, which extracts the informative features from medical images; concatenation, which concatenates the extracted deep features to form a robust feature vector; dimensionality reduction with autoencoder, which reduces the dimensionality of the feature vector by transforming it into a different feature space with a lower dimension; and finally, these features obtained from all these steps were fed into multiple machine learning classifiers (SVM, KNN, linear DA, and ANN) for the classification purpose. The study is performed to conduct a comparative analysis, aiming to evaluate the individual impact of each step within the proposed methodology and also assess the performance of each implemented classifier in order to find a best pipeline for medical image classification. The effectiveness of the proposed approach is assessed using two different medical image datasets. The performance assessment for the classifiers implemented is achieved using overall accuracy, sensitivity, and specificity metrics. The findings show that the linear DA classifier preceded by deep feature extraction, concatenation, and dimensionality reduction reveals itself to be a very efficient pipeline for accurate classification of medical images by utilizing a very small number of features.

Key words: Medical images, classification, deep feature extraction, concatenation, dimensionality reduction, autoencoder

1. Introduction

Over the last few decades, medical imaging (MI) techniques involving endoscopy, X-rays, mammography, ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), etc. have gained extensive use in the early diagnosis, detection and treatment of diseases [1]. MI has become an indispensable resource for healthcare professionals by enabling the diagnosis and treatment of various diseases [2]. Medical image analysis and interpretation are critical in disease diagnosis and treatment.

Generally, medical image interpretation is primarily conducted by trained radiologists and physicians. However, interpreting and analyzing medical images can be challenging due to the shortage of trained specialists, increased workload, and time constraints [3]. This situation can lead to inaccurate and noneffective analysis

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and interpretation of medical images, which can have negative impacts on patient outcomes. Therefore, there is an ultimate need for tools that can assist physicians in decision-making for accurate disease diagnosis.

With the recent advances in artificial intelligence (AI) and computation techniques, developing effective and reliable methods that assist radiologists to analyze and interpret medical images for accurate disease diagnosis has become an important area of research in MI [4]. Deep learning (DL), a subset of machine learning (ML) and AI, has demonstrated significant success in medical image analysis and classification tasks in various fields of science and technology, including the medical domain [2], [5–15]. In other studies [16, 17], authors investigated different methods to extract features from images and classify them using conventional ML classifiers. In conventional ML algorithms, the process of extracting features from images are performed manually and can be difficult and time-consuming since it requires expert knowledge. However, with DL, features are automatically learned and extracted, making it faster and easier to analyze data [5]. DL has been shown to be very useful in medical image analysis since it can automatically detect important features in images without requiring manual interventions.

Extracting relevant patterns (features) from medical images is an important step for accurate disease diagnosis. In this regard, DL algorithms, especially convolutional neural networks (CNNs), have shown to have remarkable success by automatically learning and extracting features from medical images [18–23]. However, a single DL model might not be capable of capturing all the relevant features from the image. Therefore, it might be an improved approach to combine multiple DL models to extract features and then concatenate the outputs of the DL models to obtain an augmented feature vector, which will hopefully lead to more accurate and effective classification results.

Although DL models have proved successful in analyzing medical images, the high dimensionality of the extracted features from medical images is challenging and can lead to slower processing and a decrease in the performance of the classifier because of the presence of a significant number of irrelevant features [24]. Numerous techniques for dimensionality reduction, which include principal component analysis (PCA), autoencoder (AE), etc., were developed in the literature to address this issue [25–27]. PCA is a commonly utilized dimensionality reduction technique in analyzing medical images, but it has limitations due to its assumption of linear relationship between features [26], [28]. This can result in decreased classification performance as medical image datasets are complex and may not be linear [26].

Based on the aforementioned discussion, this study followed a systematic approach to address the challenge of medical image classification. Specifically, three pretrained and well-known DL algorithms including AlexNet, GoogLeNet, and VGG-16 were individually employed in this study to extract deep features from medical images of various body parts. These extracted deep features were subsequently combined through concatenation to form a comprehensive representation of the input images. Following this, an AE was utilized to minimize the dimensionality of the augmented deep feature vector extracted using the three DL algorithms. Finally, all feature vectors obtained at the output of each step were fed individually to a number of different ML classifiers for precise and accurate classification of the input medical images. The performance of the methodology summarized above was evaluated on two distinct medical image datasets. The main aim of this approach is to optimize time and computational resources while still achieving high classification performance. For this purpose, pretrained CNN architectures (such as AlexNet, GoogLeNet and VGG-16) are used to extract deep features from the medical images as feature vectors. In this way, medical images are converted into much simpler features vectors enabling the classification of these vectors by utilizing conventional ML models such as SVM, KNN, Linear DA and ANN, which are all much simpler than CNNs in terms of computational cost and time.

The remaining of the paper is arranged as follows: Section 2 gives an overview of the previous related work in the literature. Section 3 provides detailed information about the used datasets and the proposed approach. Section 4 gives the details of the experimental analyses and results. Section 5 finally provides the conclusions.

2. Related works

Medical image analysis using DL models has gained increasing research interest in recent years. Numerous studies from literature investigated various applications of DL for classifying different types of medical images. One particular application that has been used is transfer learning (TL), where a pretrained DL model is used to perform classification tasks. Some of the studies that comprise research papers and reviews can be found in [29–35].

TL can also be applied in medical image classification by extracting deep features from images using pretrained models, which are then fed into conventional ML models for further classification. This approach can be useful to reduce the computational cost of training DL models. Dara et al. [36] investigated the use of DL models such as CNNs to perform feature extraction from medical images. In their proposed approach deep features were extracted from medical images and fed into multi-layer perceptron-based neural networks for classification. The Cancer Genome Atlas Lung Adenocarcinoma (TCGA-LUAD) dataset which comprises CT images, was used to validate the proposed method. In a study performed by Kriti et al. [37], the performances of four pretrained CNNs including VGG 19, SqueezeNet, ResNet-18 and GoogLeNet were assessed to classify tumor types using breast ultrasound images. The proposed method first extracted deep features from ultrasound images and then used the adaptive neuro fuzzy classifier (ANFC) to classify the extracted features. It was reported that the GoogLeNet based feature extraction followed by the ANFC yielded the highest classification performances. Lai and Deng [19] proposed an approach that they called Coding Network (CN) that mixes high-level features acquired by a deep CNN and features acquired using some traditional methods. The proposed approach comprised three steps. First, they trained a deep CNN as a coding network to extract deep features from images. Secondly, a group of traditional features was extracted based on background knowledge of medical images. Finally, after fusing the features obtained from these two methods a classification model based on neural networks was designed for the classification task. The proposed method was evaluated using two medical image benchmark datasets which are HIS2828 and ISIC2017.

The use of DL models for deep feature extraction can have a significant impact in reducing the computational cost since in this method the training of end-to-end DL models is not performed. However, it is worth highlighting that a single DL model might not be capable of capturing all the salient features from an image. To overcome this challenge, some studies suggested the use of feature concatenation or fusion which is performed by combining deep features extracted from multiple DL models or multiple layers of a DL model for better classification task. For instance, Saad et al. [38] concatenated deep features for the detection of cases of COVID-19 in two distinct approaches. One approach involved combining deep features extracted from X-rays and CT images utilizing their proposed CNN model. In the second approach, they implemented their proposed CNN model and two pretrained CNNs, Resnet, and GoogLeNet, for extracting deep features from CT or X-ray scans separately. The extracted features were then concatenated and fed to the classifier for further classification. In another study [39], a method for early diagnosis of brain tumors was introduced, which involved multi-level feature extraction and concatenation using two pretrained deep learning models, namely Inception-v3 and DenseNet201. In this study, two distinct scenarios were evaluated. In the first scenario, features were extracted from various Inception-v3 models and then concatenated. The resulting concatenated features were subsequently utilized as input to a softmax classifier to perform the classification task. In the second scenario, features were extracted from different DensNet blocks using the DensNet201 model. Subsequently, the extracted features from the different DensNet blocks were concatenated and later fed to a softmax classifier for the classification process. Some other studies that performed deep feature concatenation for medical image classification can be found in [40–42].

Although concatenating deep features extracted from multiple DL models or multiple layers of a DL model can be effective for classification tasks, the high dimensionality of the concatenated deep features may be challenging and lead to slower process and sometimes decrease in the performance of the classifier because of the presence of some redundant features. In order to address this issue, dimensionality reduction methods can be applied to minimize vector dimensionality of deep features by representing them in a reduced dimension for accurate classification tasks. According to this, this study proposes the use of AE methods to reduce the extracted and concatenated deep features.

3. Method

Figure 1 presents the overview of the proposed approach for classifying medical images obtained from various modalities. Initially, the proposed approach performs the identification of features from the medical images by utilizing pretrained DL models namely AlexNet, GoogLeNet, and VGG-16. Subsequently, the identified deep features are combined through concatenation to form a comprehensive feature vector. However, the high dimensionality of the concatenated feature vector can cause computational inefficiency and poor classification performance. To address this issue, an AE-based dimensionality reduction technique is applied to convert the high-dimensional feature vector into a low-dimensional one while retaining its informative features. Finally, all the features obtained after each step, i.e. extraction, concatenation, and reduction, are fed to multiple ML classification models to obtain more accurate and effective classification results and to assess the effect of each step.

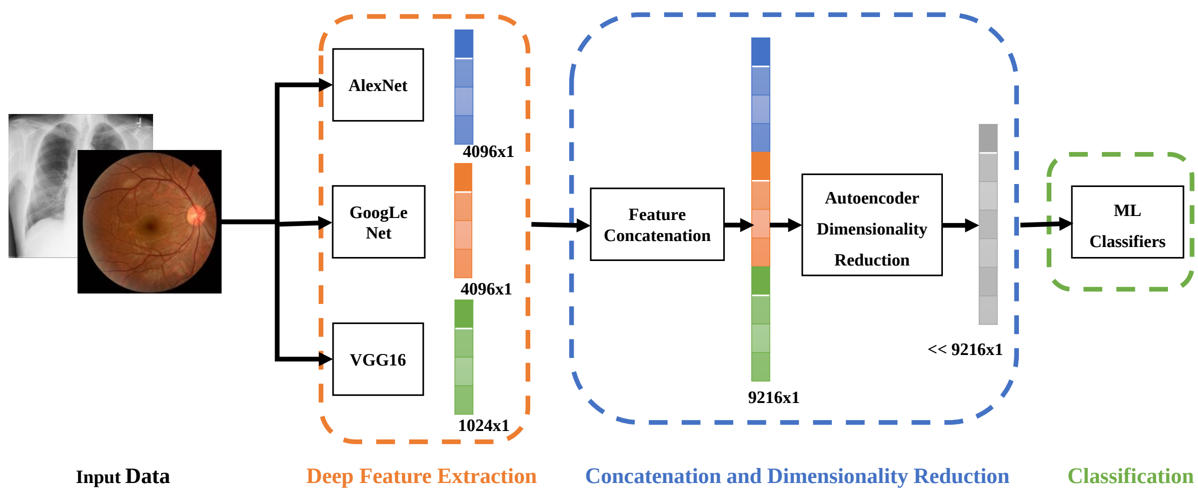

Figure 1. General flow chart of the proposed approach.

3.1. Dataset acquisition

Two distinct datasets comprising medical images of various body sections, such as chest X-ray scans and fundus images, are utilized to assess the efficacy of the proposed approach. All datasets implemented in this study are freely accessible online.

The first dataset used in this study is the chest x-ray dataset which can be found in [43, 44]. The dataset consists of 112,120 frontal-view chest X-ray images of 30,805 unique patients, annotated with 14 different categories of thoracic diseases. The categories include Pneumothorax, Pneumonia, Emphysema, Edema, Effusion, Atelectasis, Cardiomegaly, Pleural thickening, Infiltration, Consolidation, Fibrosis, Mass, Nodule and Hernia. The dataset was created by the National Institutes of Health (NIH). In this study, in order to perform binary classification, x-ray images of 1215 healthy individuals (with no finding) and 1093 individuals diagnosed with Cardiomegaly were selected and a mini dataset was created.

The ”Preprocessed eye diseases fundus images” dataset available in [45] was used as the second dataset in this study. The data used in this dataset was obtained from publicly available fundus image datasets that are widely recognized, including the High-Resolution Fundus (HRF), the Indian Diabetic Retinopathy Image Dataset (IDRiD), Ocular Disease Recognition, and Digital Retinal Images for Vessel Extraction (DRIVE). The dataset was then preprocessed by applying histogram equalization followed by image segmentation and data augmentation was applied to enhance the amount of the data. The dataset consisted of 1038 cataracts, 1098 diabetic retinopathy, 1007 glaucoma, and 1074 normal retinal images. For this study, a subset of 1074 normal retinal images and 938 images with cataracts were chosen to form a smaller dataset for binary classification.

3.2. Deep feature extraction and concatenation

The process of identifying and extracting informative features from input data (image, video, or signal) is known as feature extraction. These extracted features can be input into ML classifiers for further classification tasks. The process of feature extraction can be performed manually using traditional techniques or through DL models like convolutional neural networks (CNNs). Deep feature extraction involves using CNN models to extract informative features from input data. In this study, CNN models such as AlexNet, GoogLeNet, and VGG-16 are implemented to perform deep feature extraction from medical images for further classification.

DL is a subset of ML that utilizes algorithms derived from artificial neural networks (ANNs). These neural networks take their inspiration from the structural function of the human brain [46]. DL differs from conventional ML in how features are extracted from data. DL algorithms automatically learn and extract features from data by themselves, whereas in conventional ML algorithms, features are extracted manually before feeding into the model for classification. Various types of DL architectures exist including feedforward neural networks, recurrent neural networks, CNNs, etc. Among these DL architectures, CNNs have demonstrated effectiveness in multiple areas including image and signal processing, object detection and recognition, video analysis, etc. [47]. In this research paper, three different CNN models including AlexNet, GoogLeNet, and VGG-16 were implemented to perform deep feature extraction from medical images. The extracted deep features using different architectures were concatenated for further classification process. Details about CNNs, the implemented CNN models and the concatenation process will be provided in the upcoming sections.

3.2.1. Convolutional neural networks

CNNs are types of DL models that have similarities with conventional ANNs in that they possess neurons that are optimized through learning [48]. The main difference between CNNs and conventional ANNs is that CNNs are specifically designed for pattern recognition tasks, i.e. they automatically extract informative features from images, videos, etc. [48]. The architecture of CNNs typically involves several layers, namely, input, convolutional, pooling, fully connected, and output layers. These layers collaborate to extract meaningful features from images and perform image classification tasks. For more and detailed explanation of how CNNs work and their architectural representation, you can visit [49]. The description of these layers and their functions is as follows:

Input layer: It is the layer of CNNs responsible of receiving input data (images, videos, or signals) and passing it to other layers for processing [48].

Convolutional layer: It is the fundamental layer of CNNs that implements the convolution operation on the input data with a group of trainable kernels or filters that are able to detect and extract specific features and create a collection of output feature maps [50].

Pooling layer: In CNNs, this layer minimizes the spatial dimensionality of the output feature maps resulting from the convolutional layer by downsampling them using functions such as max or average pooling [48, 50].

Fully connected layer: It is the layer of CNNs which comprises neurons that are relied to those in the subsequent layer, with the initial input layer receiving information from previous convolutional and pooling layers and then flattening that data, i.e. transforming it into a single vector [47, 48]. Its output layer passes through an activation function such as ReLu function to add nonlinearity to the network, enabling it to identify more complex features (patterns) [48].

Output layer: It is the final layer of CNNs that produces the prediction or output of the model. The number of classes determines how many neurons are present in the output layer.

In this study, for feature extraction purposes, three well-known CNN architectures (AlexNet, GoogLeNet, and VGG16) are implemented. These models are well-established in the field of DL and have widely been used in various computer vision applications. Readers who are interested in getting profound knowledge about how these architectures work can visit [51–54]. These CNNs were selected for their effectiveness in feature extraction and image analysis. Although deep features can be derived from any CNN layer, they are typically retrieved from the final fully connected layer that comes before the classification layer [55]. This section provides a detailed explanation of our proposed feature extraction methodology. The proposed feature extraction skill is performed by using functions from the DL software library of a commercially available software package. This package and selected functions in its DL library make it easier to customize pretrained models and conveniently tailor them for specific tasks. They enable the fine-tuning of model architectures which facilitate the quick extraction of features from designated layers. In this way, it was easily possible to customize and manage pretrained CNN models on a layer basis. We focused on specific layers in each model: 'fc7' for AlexNet, 'pool5-7x7-s1' for GoogLeNet, and 'fc7' for VGG-16. These layers have 4096, 1024, and 4096 neurons respectively. As a result, the proposed approach extracted 4096, 1024, and 4096 deep features from images. The feature extraction process can be mathematically represented and explained as follows:

Given an input image I, a DL model can be represented as a function of $M(I)$ that transforms the input image into a feature representation. For feature extraction, we select a specific layer within the model, denoted as L. The extracted features represented by Fex can be mathematically expressed as:

$$F_{ex} = M(I).L$$

The accomplishment of the feature extraction process from medical image data can be explained as follows:

1. **Model configuration:** Layer graphs of the implemented three CNN architectures were constructed, each comprising a series of layers. These layer graphs can be used to customize the pretrained models.

2. **Network creation:** For each model, a network object was created by wrapping the configured layer graphs. The network object converts the network layers to an initialized network that will represent a DL network for customized use. This allows us to choose and customize the layer that will be chosen to extract features from.

3. **Layer customization:** In order to perform the feature extraction process, each layer graph was customized by selecting specific layers conducive to our goals. For instance, "fc7" in AlexNet, "pool5-7x7-s1" in GoogLeNet, and "fc7" in VGG-16 were chosen as layers which deep features will be extracted from.

4. **Input data preparation:** The input images are in general not compatible with the pipeline and they are therefore converted into a suitable format for DL analysis.

5. **Feature extraction:** DL network models were applied to the converted input images and the deep features were extracted by using the predict function.

3.2.2. Deep feature concatenation

Deep feature concatenation is the process of concatenating (joining end-to-end) the deep feature vectors extracted from different layers of multiple neural networks into a single vector. In this study, the extraction of deep features is performed at the above-mentioned layers of the three different CNN architectures including AlexNet, GoogLeNet, and VGG-16. These vectors were then concatenated into a single feature vector to be utilized in the further classification process.

The sizes of the feature vectors extracted from each architecture were 1 x 4096, 1 x 1024, and 1 x 4096, respectively. The concatenation process involved taking each individual feature vector and stacking them horizontally to form a single larger feature vector. The resulting concatenated feature vector had a size of 1 x 9216 (4096 + 1024 + 4096).

As it was stated previously, the reason behind concatenating the extracted features is to get a more comprehensive and robust representation of the input data, leading to improved classification performance. This concatenation is also applied to compare the performance of each classifier on concatenated features to the extracted individual feature vectors.

3.3. Dimensionality reduction

The process of minimizing the number of features of the input data by transforming it to another feature space with a lower dimension is referred as dimensionality reduction. This process is applied for both reducing the computational cost and enhancing or keeping the performance of the same classifiers. Among different types of dimensionality reduction models, AE is implemented in this study to diminish the dimension of the concatenated deep features.

An AE is a type of unsupervised learning neural network that has been trained to reconstruct the input data [56]. It consists of two main parts: an encoder and a decoder. The role of the encoder is to take the high-dimensional input data and compress it into a lower-dimensional representation. On the other hand, the decoder is optimized to reproduce the original input data from the encoded representation, aiming to restore it as closely as possible to its original form. Through the process of minimizing the difference between the original input data and the reconstructed data, the AE learns a condensed representation of the input data that captures the most important features [57].

In this study, AE is applied to minimize the dimensionality of the concatenated deep features, which are extracted from medical images. The goal here is to lessen the dimension of deep features by transforming it to a different feature space with lower dimension. To achieve this, only the features obtained from the output of the encoder layer are taken and fed to the implemented classifiers. The activation function utilized in the encoder layer is the logsig (logistic sigmoid) function. Furthermore, to ascertain the optimal number of reduced features in the AE-based dimensionality reduction, the output neurons of the encoder are adjusted. This helps reduce the dimension of the input features while minimizing the computational cost and improving or keeping the same performance of the classifiers.

3.4. Classification and performance evaluation metrics

To assess the effectiveness of the proposed approach, which extracts deep features from medical images, concatenates them and reduces their dimensionality using AE, multiple ML models are implemented through an extensive comparison. The comparison includes the execution of these models to both the concatenated deep features without dimensionality reduction and the dimensionality-reduced deep features. In this study, four well-established ML models known for their effectiveness in classification tasks are selected: support vector machines (SVM), k-nearest neighbors (KNN), linear discriminant analysis (linear DA), and artificial neural networks (ANN).

Performance evaluation metrics are utilized to evaluate a model's performance on different applications. There are several commonly used performance evaluation metrics for assessing the performance of ML classifiers. These metrics include overall accuracy, specificity, sensitivity (recall), and more. In this study, overall accuracy, sensitivity, and specificity are utilized to evaluate the performance of each implemented classifier. The mathematical representation of these evaluation metrics is as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad Sensitivity = \frac{TP}{TP+FN}, \quad Specificity = \frac{TN}{TN+FP}$$

where TP, TN, FP and FN represent true positive, true negative, false positive and false negative, respectively.

4. Results and discussion

It is well known that CNNs are mainly developed for image classification tasks. However, their main disadvantage is the computational cost and time needed for their training. Our aim here is to optimize time and computational resources while still achieving high classification performance. We achieved this goal by using pretrained CNN architectures (such as AlexNet, GoogLeNet and VGG-16) to extract deep features from the medical images as feature vectors.

We also evaluated the possible advantages of jointly using multiple pretrained CNN models for feature extraction. The main motivation for using multiple pretrained models for feature extraction is to benefit from their different training processes. For this purpose, we attempt to concatenate individual feature vectors coming from different pretrained models to obtain a single augmented feature vector. However, the dimension of this augmented feature vector is much larger than the dimension of the individual feature vectors. Therefore, this augmented feature vector is further processed by the AE block to generate a new feature vector with a lower dimension. The AE block is used in our study to effectively reduce the dimensionality of the input feature vector in all experimental cases.

It should be observed that the conversion of medical images into much simpler feature vectors enables the classification of these feature vectors by utilizing conventional ML models such as SVM, KNN, Linear DA, and ANN, which are all much simpler than CNNs in terms of computational cost and time.

The aim of this study was to evaluate the effectiveness of deep feature extraction and dimensionality reduction on diverse medical image datasets for precise classification with several ML models. To achieve this, several sets of experiments were conducted in order to assess the effectiveness of the implemented ML classifiers after deep feature concatenation and dimensionality reduction. First, we evaluated the performance of the classifiers using only the features derived from the medical images by the three CNN models, with no dimensionality reduction. This allowed us to determine which architecture performed better for each dataset. Subsequently, the performance of the classifiers was assessed after using an AE to minimize the dimensionality of the deep features extracted by each CNN model separately. To examine the impact of reducing the features on the computational cost and the effectiveness of the classifiers, the dimension of deep features was decreased to 50%, 25%, 10%, and 5%. Following that, the extracted deep features were concatenated to form a single feature vector, and the impact of concatenation on the performance of the classifiers was evaluated. Finally, we assessed the performance of the classifiers on the dimensionality-reduced version of concatenated deep features obtained at the output of the AE. These experiments aimed to investigate the most effective approach for utilizing deep features to achieve precise and accurate classification of medical images.

Tables 1-4 provide a comprehensive summary of the results obtained from applying the classifiers to the NIH Chest X-ray Dataset. The purpose of these experiments was to classify cardiomegaly and normal X-ray images and make a comparative analysis of the implemented classifiers using the proposed method. The tables present the experimental findings of the classifiers applied to the deep features with and without dimensionality reduction. The dimensionality reduction was applied at different rates of 50%, 25%, 10%, and 5% of the deep features. Tables 1, 2, and 3 illustrate the results of the classifiers when applied to classify the deep features extracted by the AlexNet, GoogLeNet, and VGG-16 deep learning models, respectively. Table 4 presents the accuracy results of the classifiers applied to the concatenated deep features.

Among all the ML classifiers applied to perform the classification task, the linear DA surpasses the others in terms of accuracy after reducing the dimensionality of the deep features. While its performance has increased, the computational cost has significantly decreased after performing the dimensionality reduction. For the other classifiers, however, the performance did not improve, but the computational cost significantly decreased in all cases. For instance, using deep features extracted by the AlexNet model, linear DA achieved an accuracy of 85.0% with the full feature set (100%). Remarkably, this accuracy increased to 88.5% when reducing the feature set to 25%, while also experiencing a significant reduction in computational cost. Importantly, even at a 10% reduction rate, accuracy remained high at 85.9%, and at an extreme 5% reduction rate, it recovered to 86.0%. This analysis highlights that the linear DA classifier can work well with different feature sizes. It can also be seen that reducing the number of features can make classification better, with only a slight drop in accuracy, for example in 50% rate, when compared to using all the features.

Table 1. Performance metrics results of the implemented classifiers applied to the NIH Chest X-ray dataset for the evaluation of the proposed approach using only features extracted by AlexNet model.

		100%			50%			25%			10%			5%		
Classifier \ Metric		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	86.7	82.2	90.9	79.7	77.3	81.8	78.2	76.8	79.4	77.0	76.0	77.9	66.4	49.9	81.2
	Quadratic	86.8	82.5	90.6	80.8	78.0	83.3	79.2	76.8	81.5	77.6	73.3	81.5	73.8	60.9	85.4
	Cubic	83.6	80.5	86.4	78.0	76.9	79.1	79.6	76.6	82.3	59.9	69.6	51.2	65.3	62.8	67.5
KNN	Cosine	81.7	76.1	86.7	68.6	72.2	65.3	68.4	70.7	66.3	64.9	66.4	63.5	58.9	62.7	55.6
	Cubic	80.5	75.1	85.3	66.6	69.1	64.4	68.7	68.4	68.9	57.9	63.8	52.7	57.2	60.2	54.6
	Weighted	81.1	72.5	88.9	67.2	60.4	73.3	69.1	61.9	75.5	60.2	55.4	64.6	57.0	51.9	61.6
DA	Linear	85.0	78.3	91.0	83.8	82.7	84.8	88.5	85.0	91.7	85.9	84.0	87.7	86.0	84.8	87.2
ANN	Bilayered	83.6	82.3	84.8	79.9	78.4	81.2	79.2	74.7	83.2	78.8	76.4	81.0	78.6	78.9	78.4

Tables 5-8 provide the outcomes of the implemented ML classifiers on the retinal images dataset to differentiate between images with cataracts and normal retinal images, with and without dimensionality reduction

Table 2. Performance metrics results of the implemented classifiers applied to the NIH Chest X-ray dataset for the evaluation of the proposed approach using only features extracted by GoogLeNet model.

		100%			50%			25%			10%			5%		
Metric / Classifier		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	86.8	84.4	89.1	77.6	77.6	77.7	75.6	76.2	75.0	72.0	72.5	71.5	80.5	79.5	81.4
	Quadratic	87.3	83.1	91.2	80.3	79.3	81.2	79.9	77.5	82.1	74.1	74.2	74.1	81.6	81.2	82.0
	Cubic	86.7	83.6	89.5	77.9	83.2	73.2	76.7	82.9	71.1	54.9	69.9	41.4	68.2	75.7	61.5
KNN	Cosine	78.3	80.4	76.4	69.7	74.0	65.8	70.1	75.5	65.3	69.7	75.0	64.9	70.1	76.2	64.5
	Cubic	79.3	78.2	80.2	68.9	70.0	68.0	66.3	69.1	63.9	67.5	69.5	65.6	68.6	71.4	66.2
	Weighted	79.3	74.4	83.8	68.8	64.0	73.0	66.9	62.6	70.8	67.6	63.5	71.3	68.6	63.9	72.8
DA	Linear	83.1	81.2	84.9	84.2	82.3	85.9	86.2	83.5	88.6	84.8	83.2	86.3	83.3	82.0	84.4
ANN	Bilayered	83.0	82.1	83.8	81.5	78.9	83.8	85.9	81.3	90.3	73.5	71.3	75.5	81.3	79.9	82.6

Table 3. Performance metrics results of the implemented classifiers applied to the NIH Chest X-ray dataset for the evaluation of the proposed approach using only features extracted by VGG-16 model.

		100%			50%			25%			10%			5%		
Metric / Classifier		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	86.0	83.1	88.6	64.6	53.9	74.2	63.4	50.0	75.5	63.0	45.5	78.8	71.7	65.5	77.3
	Quadratic	86.1	83.9	88.1	55.0	49.5	60.0	58.4	30.6	83.5	55.4	53.8	56.8	59.7	85.1	36.9
	Cubic	84.7	83.1	86.1	49.9	65.8	35.6	47.2	57.7	37.7	52.6	28.2	74.7	49.6	34.6	63.0
KNN	Cosine	79.2	77.8	80.5	61.6	63.3	60.1	61.1	60.1	62.1	60.0	59.1	60.7	63.1	62.1	64.0
	Cubic	78.2	76.1	80.1	58.8	64.6	53.6	60.1	64.2	56.3	57.2	61.8	53.1	57.2	64.2	50.9
	Weighted	79.3	73.4	84.7	56.8	53.2	60.1	60.3	55.9	64.2	54.3	50.5	57.8	57.6	54.7	60.2
DA	Linear	79.7	79.1	80.2	85.2	83.0	87.2	81.4	80.5	82.2	83.9	82.6	85.1	85.3	82.2	88.1
ANN	Bilayered	82.7	80.1	85.0	71.1	65.1	76.5	72.2	69.0	75.1	66.6	63.9	69.1	76.3	73.9	78.4

Table 4. Performance metrics results of the implemented classifiers applied to the NIH Chest X-ray dataset for the evaluation of the proposed approach using concatenated features extracted by AlexNet, GoogLeNet, and VGG-16 DL models.

		100%			50%			25%			10%			5%		
Metric / Classifier		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	88.6	85.9	91.1	76.5	74.8	78.0	75.0	70.4	79.3	72.0	72.6	71.4	75.7	73.7	77.4
	Quadratic	88.6	86.0	91.0	62.0	63.4	60.7	61.1	36.8	83.0	76.9	74.1	79.5	61.6	37.0	83.8
	Cubic	87.6	85.5	89.5	51.6	61.8	42.4	46.8	45.8	47.7	66.4	69.1	64.0	44.8	75.8	17.0
KNN	Cosine	83.6	82.4	84.7	71.0	74.6	67.7	64.0	63.3	64.6	62.0	66.2	58.3	66.8	68.4	65.3
	Cubic	84.1	81.9	86.2	62.7	67.2	58.6	60.1	64.9	55.7	62.4	68.4	57.0	57.2	60.4	54.3
	Weighted	84.7	78.2	90.5	64.3	59.5	68.7	59.1	55.1	62.7	61.2	58.4	63.7	60.8	54.6	66.3
DA	Linear	82.7	82.1	83.3	85.0	83.7	86.1	83.4	82.4	84.2	80.2	77.3	82.8	86.0	84.2	87.7
ANN	Bilayered	86.3	84.8	87.7	82.5	80.1	84.7	80.0	77.9	82.0	80.5	79.0	82.0	78.7	77.6	79.8

applied at different rates. The accuracy results of each classifier were presented for deep features extracted by different DL models, including AlexNet, GoogLeNet, and VGG-16 and the concatenated deep features.

In the second dataset, similar findings were obtained as observed in the first dataset, with the Linear DA classifier demonstrating superior performance following the dimensionality reduction of deep features. This trend remained consistent for features extracted by AlexNet and the concatenated features. However, when using deep features extracted by GoogLeNet and VGG-16, there was a slight change. For instance, with GoogLeNet extracted features, initially, with all the feature set (100%), liner DA had an accuracy of 80.9%. But, after reducing the number of features, the accuracy dropped by about 3%. While this drop is noticeable, it does not greatly affect the classifier's performance. This shows that linear DA can handle different types of features, and reducing feature dimensionality can generally improve its performance, even if there is a slight drop in accuracy as seen with GoogLeNet extracted features.

Table 5. Performance metrics results of the implemented classifiers applied to the retinal images dataset for the evaluation of the proposed approach using only features extracted by AlexNet model.

		100%			50%			25%			10%			5%		
Classifier \ Metric		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	78.5	72.5	83.8	63.8	35.9	88.2	66.9	44.3	86.6	63.9	36.2	88.1	63.1	33.6	88.9
	Quadratic	82.1	78.8	84.9	55.9	46.1	64.5	69.8	42.4	93.8	61.3	48.6	72.3	64.4	37.5	87.9
	Cubic	80.8	79.1	82.2	56.9	38.9	72.5	62.0	26.8	92.8	61.1	39.4	80.1	47.4	62.6	34.2
KNN	Cosine	74.8	83.5	67.2	59.8	62.5	57.4	61.3	67.6	55.9	58.5	62.9	54.7	60.3	65.5	55.8
	Cubic	76.1	79.0	73.6	65.7	63.9	67.3	69.2	68.4	69.9	67.6	65.4	69.6	66.2	63.0	69.0
	Weighted	79.8	79.4	80.1	62.8	55.0	69.6	67.8	61.2	73.6	63.7	55.8	70.7	61.1	52.5	68.5
DA	Linear	76.4	74.5	78.0	80.5	78.4	82.4	78.7	76.9	80.4	77.9	74.2	81.1	78.6	75.3	81.5
ANN	Bilayered	79.1	78.9	79.3	71.1	60.2	80.5	73.9	67.6	79.3	71.3	62.0	79.4	69.5	58.7	78.9

Table 6. Performance metrics results of the implemented classifiers applied to the retinal images dataset for the evaluation of the proposed approach using only features extracted by GoogLeNet model.

		100%			50%			25%			10%			5%		
Classifier \ Metric		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	79.1	73.3	84.1	69.6	48.5	88.1	62.5	32.0	89.1	71.1	51.0	88.6	65.5	38.3	89.3
	Quadratic	81.9	78.7	84.6	68.8	42.5	91.8	68.4	47.0	87.2	69.4	50.0	86.3	71.8	50.7	90.1
	Cubic	79.7	75.7	83.1	50.6	60.1	42.4	56.9	11.2	96.8	48.5	74.3	26.0	49.3	67.0	33.8
KNN	Cosine	73.7	86.6	62.4	63.8	76.4	52.8	61.7	72.5	52.2	67.4	79.3	57.1	62.4	69.8	56.0
	Cubic	76.7	77.3	76.2	69.7	70.3	69.3	64.9	61.5	67.9	67.3	64.2	70.0	68.5	67.4	69.6
	Weighted	78.9	75.9	81.6	69.5	63.3	75.0	63.5	55.9	70.2	67.6	60.0	74.3	66.0	59.1	72.1
DA	Linear	80.9	77.5	83.8	76.2	73.7	78.4	78.7	74.9	82.0	79.0	73.6	83.8	75.6	68.3	81.9
ANN	Bilayered	77.8	77.5	78.1	77.6	75.7	79.3	70.2	63.2	76.3	76.1	72.0	79.8	75.9	71.9	79.5

Table 7. Performance metrics results of the implemented classifiers applied to the retinal images dataset for the evaluation of the proposed approach using only features extracted by VGG-16 model.

		100%			50%			25%			10%			5%		
Classifier \ Metric		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	74.9	66.1	82.6	58.6	20.8	91.6	60.7	30.5	87.2	64.6	43.1	83.4	65.0	43.9	83.4
	Quadratic	76.0	72.1	79.4	51.6	47.0	55.6	51.0	28.5	70.7	54.5	46.4	61.6	58.0	15.9	94.7
	Cubic	75.4	72.0	78.5	50.4	72.3	31.3	48.9	66.2	33.7	48.2	63.1	35.1	52.4	38.0	65.1
KNN	Cosine	74.3	77.1	71.8	66.1	67.7	64.6	63.7	68.2	59.7	68.6	68.0	69.1	66.6	69.0	64.4
	Cubic	73.3	73.7	72.9	64.0	66.0	62.3	63.3	65.4	61.5	68.7	71.3	66.5	63.8	66.5	61.5
	Weighted	74.9	72.2	77.2	60.0	54.1	65.3	61.3	54.7	67.0	66.0	62.7	68.9	62.9	59.1	66.2
DA	Linear	77.6	71.4	83.1	73.7	64.1	82.1	76.9	70.3	82.8	75.6	67.4	82.9	74.4	67.1	80.7
ANN	Bilayered	74.8	73.3	76.1	67.0	65.6	68.2	67.7	64.5	70.5	70.1	63.6	75.8	69.3	61.8	75.8

Table 8. Performance metrics results of the implemented classifiers applied to the retinal images dataset for the evaluation of the proposed approach using concatenated features extracted by AlexNet, GoogLeNet, and VGG-16 DL models.

		100%			50%			25%			10%			5%		
Classifier \ Metric		ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC	ACC	SENS	SPEC
SVM	Linear	81.2	74.3	87.2	64.5	43.1	83.1	65.6	43.9	84.5	63.1	38.2	84.8	64.1	40.0	85.1
	Quadratic	82.8	79.9	85.3	58.3	28.8	84.0	60.2	36.9	80.5	59.3	20.0	93.7	59.6	20.3	93.9
	Cubic	81.3	79.6	82.8	52.2	37.7	64.9	52.1	37.1	65.3	56.3	80.6	97.9	47.1	60.1	35.7
KNN	Cosine	77.0	83.6	71.3	67.1	74.7	60.5	70.7	75.6	66.4	65.0	69.3	61.2	66.8	71.5	62.7
	Cubic	76.8	78.0	75.8	65.0	63.3	66.5	69.7	71.3	68.3	67.0	64.1	69.6	64.2	63.2	65.1
	Weighted	79.7	78.8	80.5	63.0	55.1	69.9	68.8	64.5	72.6	63.8	58.5	68.3	64.7	59.2	69.6
DA	Linear	76.5	65.9	85.8	82.1	77.9	85.7	79.4	71.7	86.0	79.9	72.8	86.0	79.2	76.8	81.4
ANN	Bilayered	79.3	78.8	79.7	68.8	61.7	75.0	74.0	75.2	73.0	66.8	60.0	72.7	70.6	67.5	73.4

It should be noted from the outcomes obtained in this study that the linear DA classifier achieved superior performance compared to the other classifiers, even when utilizing only 25% or 10% of the total features. It is also worth noting that, while the performance improvements obtained from the other classifiers using the proposed approach are usually not significant in most cases, there was a significant reduction in computational cost in all cases. The main objective of this study was to determine the most effective pipeline for automatically classifying medical images using a minimal number of features. The results showed that, after performing deep feature extraction, concatenation, and dimensionality reduction, the linear DA classifier emerged as a very good choice for the purpose. Based on these observations and remarks the linear DA classifier preceded by deep feature extraction, concatenation, and dimensionality reduction reveals itself to be a very efficient pipeline for the accurate classification of medical images by utilizing a very small number of features.

5. Conclusion and future work

This paper investigates a novel comparative method for the analysis and classification of medical images using deep feature extraction, concatenation, and dimensionality reduction techniques. The process of extracting deep features was performed using three pretrained and well-known DL algorithms which extracted meaningful features from the medical images. These features were then combined through concatenation to form a new feature vector. In order to enhance the classification performance, an AE was utilized to lessen the dimensionality of the concatenated feature vector by transforming it to a different feature space with a lower dimension. The proposed approach was evaluated using different medical image datasets of different parts of the body, including the chest and eyes. For the performance evaluation of the proposed framework, four well-known ML classifiers were implemented including SVM, KNN, linear DA, and ANN. Accuracy, sensitivity, and specificity were chosen as the performance metrics to assess the effectiveness of these classifiers. The findings obtained from the proposed approach showed that the dimensionality reduction process positively affected the linear DA classifier by improving its performance, which led it to outperform the other classifiers. While the performance of the remaining classifiers did not show a significant increase, the computational cost was significantly decreased after applying the dimensionality reduction process. This suggests that the proposed approach not only improves classification accuracy but also enhances the computational efficiency of the implemented classifiers. Considering these observations and comments, it can be concluded that the combination of deep feature extraction, concatenation, and dimensionality reduction followed by the linear DA classifier is an exceptionally effective approach for the precise classification of medical images. This pipeline demonstrates remarkable efficiency even with a minimal number of features. As future work, this approach can extend to be conducted on large and more diverse medical image datasets.

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