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Cardiac Disease Classification using Matrix Factorization and Machine Learning

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INTRODUCTION & AIM

Accurate classification of cardiac diseases using medical imaging is crucial for modern cardiovascular diagnosis. However, data science techniques often face challenges due to the limited availability of large, high-quality image datasets. To overcome this, various strategies have been developed, including probabilistic models, classification-based imputation, few-shot learning, and ensemble methods. Among these, data augmentation is one of the most widely used approaches to effectively increase dataset size. Common augmentation techniques include geometric transformations, elastic deformations, and statistical shape models, which have improved performance in many medical imaging tasks. Additionally, advanced methods like generative adversarial networks (GANs) and transfer learning remain popular to further enhance dataset quality and diversity.

Beyond augmentation and transfer learning, matrix, and tensor factorization techniques have shown considerable promise in medical imaging [1,2]. These classic matrix decomposition tools, combined with data-driven approaches, offer new avenues for feature extraction and dimensionality reduction.

Motivated by these advances, this work explores the use of singular value decomposition (SVD) [3], a well-known matrix factorization method, applied to echocardiography images. This analysis results in new basis for each cardiac condition, which is used to generate new images by projecting the original echocardiography images into the principal components. We then utilise the new pre-processed images to train convolutional neural networks (CNNs) for multiclass classification across five cardiac conditions, demonstrating a novel integration of matrix factorization and deep learning to improve cardiac disease diagnosis.

METHOD

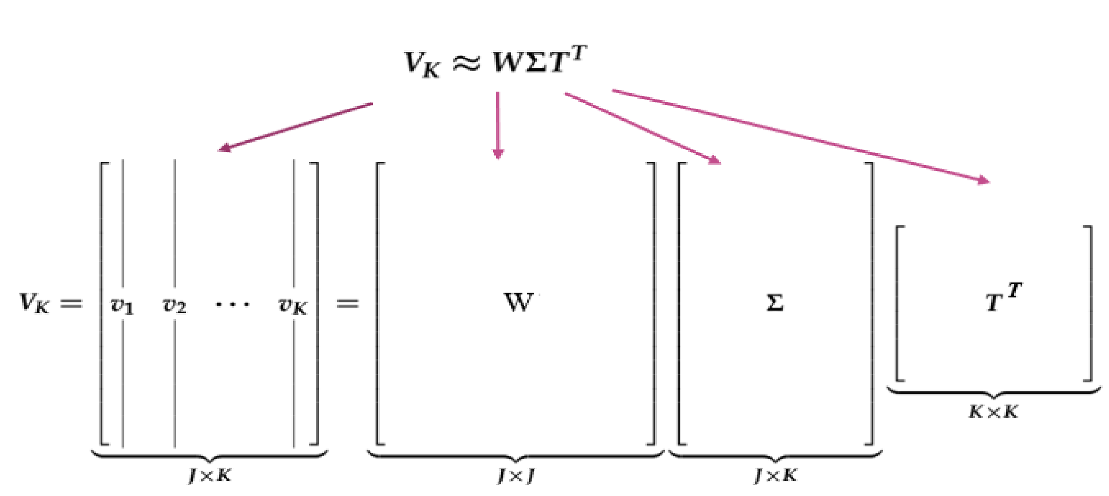
1. Singular Value Decomposition (SVD):

Singular value decomposition (SVD), which is one of the most fundamental and widely used matrix decomposition techniques is explained as follows:

Considering a data matrix $\mathbf{V}_K \in \mathbb{R}^{J\times K}$, such that: $\mathbf{V}_K = [\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_K]$,

Where $\mathbf{v}_k$ is a reshaped snapshot collected at time t_k, with $k = 1, \ldots, K$.

The SVD algorithm decomposes the matrix $\mathbf{V}_K$ into a product of three other matrix factors, as follows: $\mathbf{V}_K = \mathbf{W\Sigma T}^T$



Such that $\mathbf{W}$ and $\mathbf{T}$ are orthonormal matrices. The columns of $\mathbf{W}$ are the left singular vectors of $\mathbf{V}_K$, and the columns of $\mathbf{T}$ are the right singular vectors of $\mathbf{V}_K$. While $\mathbf{\Sigma}$, which holds the singular values, is a matrix with real, non-negative entries on the diagonal and zeros off the main diagonal.

2. Convolutional Neural Network (CNN):

The architecture of the convolutional neural network chosen in this contribution has proven to be one of the most used and robust image classification models. As a result, this structure was adapted for use in our study.

The final tuning resulted in the following: a CNN architecture consists of three convolutional layers with (3 × 3) kernels, each followed by a (2 × 2) max-pooling layer. A flattening layer is applied next, followed by two fully connected dense layers. The dense layers use the Rectified Linear Unit (ReLU) and softmax activation functions, respectively. Figure 1 illustrates the CNN's architecture.

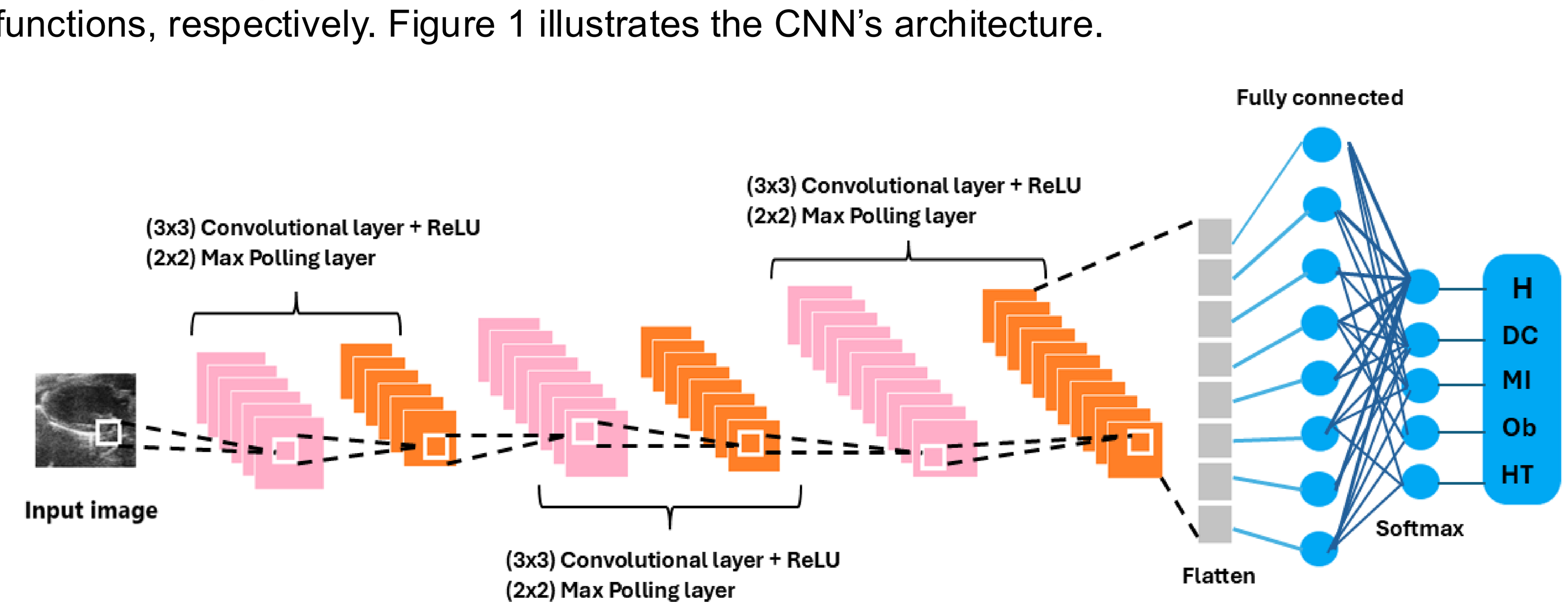


Fig.1: A sketch illustrating the architecture of the employed CNN.

Data and preprocessing

1. Original Echocardiography data:

This study employs 260 echocardiography datasets (videos) acquired from two different imaging views: the long-axis (LAX) and short-axis (SAX) views (illustrated in Fig.2). The video loops are taken from mice with five different cardiac conditions: healthy (H), diabetic cardiomyopathy (DC),myocardial infarction (MI), obesity (OB) and TAC hypertension (TAC).

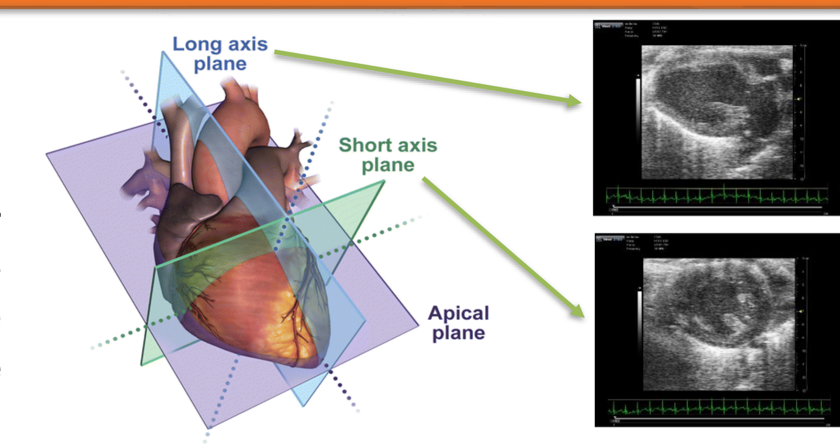


Fig.2: Imaging planes of the heart: the long axis and the short axis.

2. Processed images: For the generation of the new data, the following first pre-processing step is performed: first, all images for each cardiac condition are reshaped into column vectors and grouped into a data matrix for that condition as shown in Fig. 3. The mean image of each condition is computed and subtracted from its matrix to centre the data. SVD is then applied separately to each mean-subtracted matrix, yielding matrices of singular vectors whose columns represent the principal components for that condition. These components form a new basis in which original images are approximately represented through projection. The projected images, now expressed in the reduced-dimensional space, are used as input to train the convolutional neural network for classification

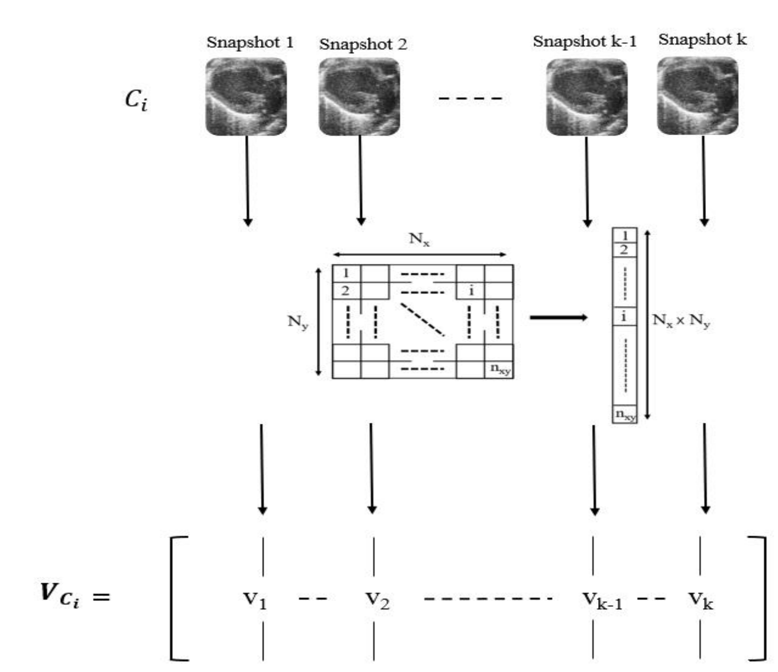


Fig.3: Schematic illustration of the process for preparing data matrices of the cardiac conditions.

RESULTS & DISCUSSION

As shown in Table 1, classification results using the original images revealed high training accuracy of 99% for LAX and 100% for SAX, but more modest testing accuracy, with 81% for LAX and 76% for SAX. Prediction accuracy on unseen data was considerably lower, reaching only 50% for LAX and 43% for SAX.

In contrast, when using the newly generated images, classification accuracy improved significantly across all phases. Training accuracy remained consistently high at 100% for both LAX and SAX. Testing accuracy also showed marked improvement, increasing to 97% for LAX and 94% for SAX. Most notably, prediction accuracy on unseen data experienced the greatest enhancement, with approximately a 50% increase compared to the original images, achieving 98% for LAX and 85% for SAX.

Accuracy	Original images		Pre-processed images	
	LAX	SAX	LAX	SAX
Validation	0.99 ± 0	1 ± 0	1 ± 0	1 ± 0
Testing	0.81 ± 0.058	0.76 ± 0.13	0.97 ± 0.027	0.94 ± 0.030
Prediction (Unseen data)	0.5 ± 0.041	0.43 ± 0.077	0.98 ± 0.021	0.85 ± 0.047

Table 1: Accuracy results summary for LAX and SAX data. The results are displayed as average accuracy ± standard deviation.

CONCLUSION

This study explored combining singular value decomposition (SVD) with convolutional neural networks (CNNs) to classify five cardiac conditions. When trained on the original images, the CNN achieved high training accuracy but showed poor generalization, with notable declines in testing and prediction accuracy on unseen data. By contrast, using the SVD-generated images led to consistently better and more stable performance. The CNN achieved perfect training accuracy, while testing accuracy improved significantly to 97% for LAX and 94% for SAX. Prediction accuracy also increased substantially, reaching 98% for LAX and 85% for SAX. Overall, this hybrid approach substantially enhanced classification accuracy, demonstrating approximately a 50% improvement compared to training on the original images.

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