Predicting Cardiovascular Disease Risk Through Non-invasive Imaging in Precision Medicine

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Abstract. Cardiovascular disease (CVD)is the leading cause of death globally and is a significant public health problem. An echocardiogram, a non-invasive imaging technique, is crucial in diagnosing and assessing cardiovascular disease. However, the manual analysis of echocardiograms requires significant expertise and is time-consuming, prompting the need for automated approaches. Precision medicine, or personalized medicine, supports using new testing techniques and data analysis to identify and differentiate the patient's features and develop therapies according to the differences in patient characteristics. The result is improved treatment outcomes that positively impact patients' quality of life and reduce unnecessary use of medical resources. Convolutional Neural Networks, a type of deep learning model, are highly effective for image data and are employed in tasks such as segmentation, classification, and object detection. This study aims to detect the possibility of CVD through echocardiogram images using the CNN architecture. The performance model of ResNet-101 achieved an accuracy of 71%, which indicated that the model could be employed as an efficient solution for the automated analysis of echocardiograms and offers significant improvements in diagnostic accuracy and operational efficiency. This enhanced capability can lead to better diagnostic outcomes and streamlined workflows in cardiovascular medicine.

Keywords: encapsulation · deep learning · echocardiogram · precision medicine · ResNet-101

D.-J. Deng and J.-C. Chen (Eds.): SGIoT 2024, LNICST 633, pp. 183–189, 2026.
https://doi.org/10.1007/978-3-031-93825-2_16

1 Introduction

Cardiovascular disease (CVD) is the leading cause of death globally. The mortality rate stemming from CVD is estimated 18.6 million annually [13]. It comes from a combination of lifestyle, medical, genetic, and environmental factors, making it a major public health concern [6]. Diagnostic methods for CVD include invasive procedures, which are accurate but expensive and risky, and non-invasive methods, which are safer and more accessible [5]. Echocardiography - a non-invasive technique uses ultrasound to produce detailed heart images - is crucial for diagnosing and evaluating cardiac conditions [10]. More over, echocardiography offers real-time imaging, lower costs, and wide availability [2], making it ideal for comprehensive cardiac assessments [3].

Patients with CVD typically require individualized treatments that may involve lifestyle changes, medications, and sometimes surgical procedures. Precision medicine enhances this personalized approach by tailoring treatment plans to each patient's unique genetic, environmental, and lifestyle factors. This method is particularly relevant in cardiovascular care, where such customization can significantly enhance patient outcomes [12]. However, manually interpreting echocardiograms within this framework is time-consuming and requires significant expertise [11,16]. Therefore, Artificial Intelligence (AI) with its deep learning models, such as Convolutional Neural Networks (CNNs), are essential in precision medicine.

Architecture CNNs contributes in the advancement of image segmentation, classification, and detection. ResNet-101 as one of architecture CNNs offers high accuracy and efficient training but also demands significant computational resources [14]. Gao [4] employed a fused CNN architecture combining spatial and temporal CNNs on echo videos, resulting in an accuracy of 92.1%. Another researcher utilized a stacked residual-dense network, combining ResNet and DenseNet, on echo videos, achieving an accuracy of 92.27%, a specificity of 94.33%, and a recall of 92.05% [8].

One of the challenging is applying the prediction application across multi platform. Containerization approach ensures that all necessary dependencies and libraries are packaged together, allowing the application to run consistently across different platforms [15]. The purpose of this study is to classify echocardiogram analysis based on lightweight containerization of the modify ResNet-101 for support the cardiovascular precision medicine. The proposed research is organized as follows: Sect. 1 provides research background and related works. Section 2 presents materials and methods. Section 3 presents the results. Section 4 provides discussions of the results. Section 5 consists of the research conclusion and future works.

2 Materials and Methods

This section describes the data collection and methods that are used in this study. The dataset used in this study comes from the CAMUS (Cardiac

Acquisitions for Multi-structure Ultrasound Segmentation) dataset, which was specifically developed for multi-structure segmentation of cardiac ultrasound images (https://camus.creatis.insa-lyon.fr/challenge/). The dataset includes 1376 echocardiogram images with two image quality: Good and Medium. The dataset is categorized into two classes: 0 value (abnormal class), and 1 value (normal class).

ResNet (Residual Network) is a CNN architecture which can reach over 100 layers in the network depth, and it is used to overcome the gradient vanishing issue in deep neural networks [1]. The architecture of ResNet uses a combination of 1×1, 3×3, and 1×1 convolutions in its blocks, with the 1×1 convolutions adjusting the number of output channels, and the 3×3 convolutions handling the spatial dimension. ResNet-101 improves training speed and target detection accuracy while using fewer parameters. The ability of this architecture to maintain high performance in deeper networks makes it a powerful tool in computer vision [14]. During a model evaluation with k-fold cross-validation, model performance was measured using metrics such as accuracy, precision, recall, MCC, ROC AUC score, and the F1-score. Accuracy measures the overall percentage of correct predictions. Precision indicates the proportion of true positives out of all positive predictions. Recall measures the ability to detect true positives from all actual positive cases. MCC (Matthews Correlation Coefficient) provides a comprehensive evaluation of binary classification quality, taking into account true positives, false positives, true negatives, and false negatives. The ROC AUC score measures a model's ability to distinguish between positive and negative classes by examining the balance between the true positive rate and the false positive rate. The F1-Score provides a balance between precision and recall, making it useful when dealing with class imbalance.

3 Result

Table 1 outlines the performance metrics of ResNet-101 models that were employed with the normalization technique and without normalization technique. The use of normalization techniques does not always guarantee better accuracy results than without using normalization techniques. The average accuracy score between the normalized model and the non-normalized model is 0.94, whereas the non-normalized model is more accurate than the normalized model. Overall, the performance of the non-normalized ResNet-101 model was higher across all metrics than using normalization approach. However, the normalization technique influences the model training time by around 432.52 s faster compared to not using the normalization technique.

Figure 1a shows the model' curve is positioned above the diagonal line, indicating that the model has better predictive ability than random guessing. The average AUC score is above 60%, suggesting that the models' performance is moderate but not yet optimal, as the scores are still close to the diagonal line. Ideally, the further the curve is from the diagonal line, the better the model's performance. Table 2 shows the performance of the ResNet-101 model with its

Table 1. Data preprocessing results

Metric	ResNet-101	
	With Normalization	Without Normalization
Avg. Score	71.30% ± 2.25%	72.24% ± 1.87%
Avg. Specificity	0.76 ± 0.07	0.80 ± 0.03
Avg. MCC	0.43 ± 0.05	0.45 ± 0.04
Avg. ROC AUC	0.79 ± 0.02	0.80 ± 0.02
Training Time (s)	5527.95	5095.43
Precision	71%	73%
Recall	71%	72%
F1-Score	71%	72%

Table 2. Batch Size

Metric	Batch size		
	16	32	64
Avg. Score	70.86% ± 2.08%	71.30% ± 2.25%	70.20% ± 2.66%
Avg. Specificity	0.74 ± 0.05	0.76 ± 0.07	0.79 ± 0.05%
Avg. MCC	0.44 ± 0.04	0.43 ± 0.05	0.41% ± 0.05%
Avg. ROC AUC	0.79 ± 0.02	0.79 ± 0.02	0.78% ± 0.03%
Training Time (s)	6064.84	5527.95	5724.65
Precision	72%	71%	71%
Recall	72%	71%	70%
F1-Score	72%	71	70%%

different batch sizes. When the model had 32 batch size, the model achieved its highest accuracy average score at 71.30% and had the shortest training time.

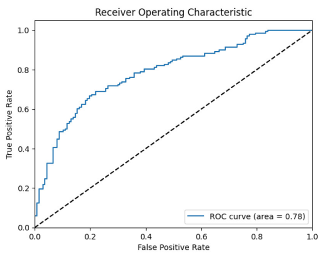
Meanwhile, when the model experienced with 64 batch size, the average score of its specificity metric got the peak at 0.79. This indicated that the model effectively identified negative cases. This high specificity is particularly valuable in medical contexts where accurately distinguishing between classes is crucial.

On the other hand, the performance of the ResNet-101 model with batch size 16 had the highest score in MCC and ROC AUC metrics. It showed its strength in classification quality. These metrics highlight batch size 16's ability to maintain robust performance in distinguishing between different classes, particularly in challenging classification tasks. However, the longer training time associated with batch size 16 could be a limitation in environments where computational efficiency is essential.

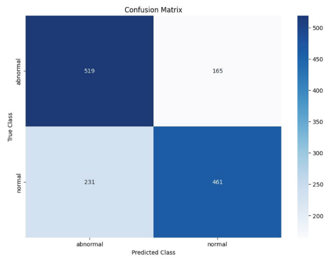
The model with 32 batch size consistently outperformed across all metrics compared to the other model's batch size. Therefore, it is chosen as the best choice configuration for training the ResNet-101 model. Through a web-based CVD risk prediction application, users can upload echocardiogram images in three image formats such as PNG, JPG, and JPEG, as illustrated in Fig. 2.

4 Discussion

The dataset includes patients' echocardiogram images and a configuration file that stores various parameters, including image quality and EF (Ejection Fraction) values, which are essential indicators of heart function. EF values are used to determine normal and abnormal class labels, with an EF of 40 or less is categorized as abnormal, indicating potential heart dysfunction [7,9], while an EF above 40 is considered normal. The pre-trained models run with an NVIDIA L4 GPU, Linux version 6.1.85+, and Python 3.10.12. To increase the variation of training data, data augmentation was employed using Keras's ImageDataGenerator to apply multiple transformations. This function converts images to NumPy arrays and then normalizes pixel values using the 2nd and 98th percentiles, and then scales them to a range from 0 to 1. This ensures a consistent intensity range across images and preserves image contrast and detail. The MinMax normalization was also performed to reduce noise and create more consistent images for training. To provide a comprehensive performance evaluation, the echocardiogram images were split into training and testing sets- with a ratio 80% for training and 20% for testing- using a 5-fold cross-validation. Using 5-fold cross-validation provides a more accurate estimate of model performance compared to a single train-test split because it reduces the variance associated with the random sampling of the training and test data, leading to more reliable and robust performance metrics. Each fold contained four subsets with 275 images and one subset with 276 images. This approach maximized data utilization by ensuring that each image was used for both training and validation in five-times iterations.



(a) ROC ResNet-101 normalization



(b) Confusion matrix ResNet-101 normalization

Fig. 1. ROC diagram and confusion matrix of ResNet-101 model evaluation

After all iterations, the performance metrics from each fold were averaged to provide a comprehensive evaluation of the model's performance. This method maximizes data utilization, reduces overfitting, and provides more reliable and robust performance metrics.

To enhance its performance in the classification task, the ResNet-101 models were structured with 101 convolutional layers and 1 fully connected layer. However, the last 10 layers were non-trainable. The ReLu activation function with Dense layer parameters were set at 256, 128, and 64, respectively. A Dropout rate of 0.5 to prevent overfitting. The final Dense layer also employed the softmax activation function for multi-class classification, with the model trained using the Adam optimizer and a learning rate of 0.0003. After training the model, its performance was evaluated using various metrics, including accuracy, precision, recall, MCC, AUC ROC score, and F1-score. Matplotlib and Seaborn libraries were used to visualize the results, making them easier to understand.

To ensure that the CVD risk prediction application runs consistently across platforms and environments, encapsulation techniques are used. A container package consists of the best-performing model and all its dependencies in a file container, simplifying deployment across platforms. A web-based application that uses the model trained allows users to upload echocardiogram images for analyzing the predictions.

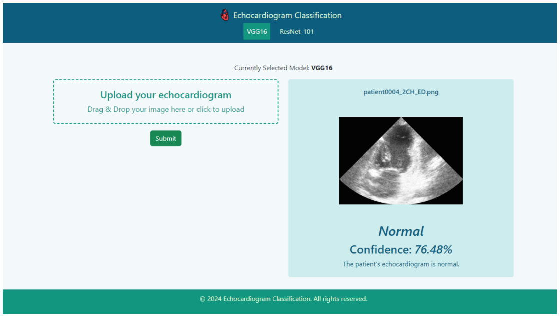


Fig. 2. User interface for echocardiogram classification

5 Conclusion

The advancement of AI, especially the ResNet-101 model, enables personalized treatments designed by medical professionals through medical image analysis. The layer's architecture of ResNet-101 captures complex data patterns essential for tailored care. Normalization techniques in preprocessing influence the training time, promising low-cost prediction. The performance model of ResNet-101 achieved its accuracy at 71% which indicated that the model could be employed as an efficient solution for the automated analysis of echocardiograms, offering significant improvements in diagnostic accuracy and operational efficiency. Users are also facilitated with the flexibility, user-friendliness, and portability of prediction applications through the encapsulation approach. This enhanced capability can lead to better diagnostic outcomes and streamlined workflows in cardiovascular medicine. Such an application significantly supports Future research that should explore combining additional parameters, such as End Diastole (ED) and End Systole (ES), with EF for a more comprehensive analysis. To improve model generalization and accuracy, it is recommended that the dataset size be increased, other CNN architectures like DenseNet, EfficientNet, or U-Net evaluated, and computational efficiency be optimized. These strategies will enhance echocardiogram analysis and support personalized cardiovascular treatments.

Acknowledgement. This research is supported by the National Science and Technology Council research project grant, project number 113-2622-E-029-003 and 113-2221-E-029-028-MY3.

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