Optimizing CMR-Based Diagnosis of Hypertrophic Cardiomyopathy Using Caputo Derivative and EfficientNetV2S Model

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Abstract.
Cardiac magnetic resonance imaging (CMR) is a vital non-invasive diagnostic tool in the management of hypertrophic cardiomyopathy (HCM), providing comprehensive insights into the structure and function of the heart muscle. This study evaluates and enhances the diagnostic accuracy of three deep learning models: a custom convolutional neural network (CNN) with a standard block structure, a state-of-the-art EfficientNetV2S model, and a Caputo derivative combined with a custom CNN, all trained to classify HCM using extensive preprocessing steps including image resizing, normalization, and data augmentation. The CNN achieved an accuracy of 91.51%, EfficientNetV2S achieved an accuracy of 98.61%, and the third model achieved an accuracy of 92.46%. These results confirm the effectiveness of EfficientNetV2S in the effective diagnosis of hypertrophic cardiomyopathy (HCM) and its prowess in extracting highly advanced features. While the use of fractional calculus techniques such as the Caputo derivative to improve feature extraction can be applied to simpler deep learning architectures.
Keywords: binary Classification, Caputo derivative, CMR, HCM, EfficientNetV2S.

تحسين تشخيص اعتلال عضلة القلب الضخامي القائم على التصوير بالرنين المغناطيسي القلبي باستخدام مشتق كابوتو ونموذج EfficientNetV2S

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ملخص :
التصوير بالرنين المغناطيسي للقلب (CMR) هو أداة تشخيصية غير جراحية حيوية في إدارة اعتلال عضلة القلب الضخامي(HCM) ، حيث يوفر رؤى شاملة حول بنية ووظيفة عضلة القلب. تقيم هذه الدراسة وتعزز دقة التشخيص لثلاثة نماذج للتعلم العميق: شبكة عصبية ملتوية مخصصة (CNN) ببنية كتلة قياسية، ونموذج EfficientNetV2S المتطور، ومشتق Caputo جنبًا إلى جنب مع CNN مخصص، وكلها مدربة على تصنيف اعتلال عضلة القلب الضخامي باستخدام خطوات معالجة مسبقة مكثفة بما في ذلك تغيير حجم الصورة والتطبيع وزيادة البيانات. حققت CNN دقة 91.51٪، وحقق EfficientNetV2S دقة 98.61٪، وحقق النموذج الثالث دقة 92.46٪. تؤكد هذه النتائج فعالية EfficientNetV2S في التشخيص الفعال لاعتلال عضلة القلب الضخامي (HCM) وبراعته في استخراج الميزات المتقدمة للغاية. في حين أن استخدام تقنيات حساب الكسرات مثل مشتق كابوتو لتحسين استخراج الميزات يمكن تطبيقه على هياكل التعلم العميق الأكثر بساطة .

1. INTRODCUCTION

Hypertrophic cardiomyopathy (HCM) is a disease in which the left ventricular muscle becomes thickened, leading to the risk of sudden cardiac death. Patients with HCM typically complain of shortness of breath, chest pain, fainting, heart murmurs, rapid heart rate (tachycardia), and cardiac arrhythmias [1]. The prevalence of HCM ranges from 1 in 1,000 to as high as 200 cases per 100,000 individuals with a need for rapid diagnosis to help initiate appropriate treatments, manage cardiovascular risk, and have excellent regular medical follow-up. Echocardiography or cardiac magnetic resonance imaging (CMR) are conventional diagnostic methods. Therefore, deep learning algorithms such as CNN can identify patients with HCM from CMR images using specific pathological features [2]. Cardiac MRI plays an invaluable role in the diagnosis of complex congenital heart defects. Unfortunately, 80-90 percent of HCM cases are missed, leading to high morbidity and mortality rates worldwide. Medical imaging applications have been greatly improved by recent advances in artificial intelligence, especially deep learning. Processing raw visual data with deep learning architectures such as convolutional neural networks (CNNs) can be applied to the process to acquire and classify features, in particular, cardiac magnetic resonance (CMR) imaging can detect novel phenotypic features that echocardiography may miss. Our ultimate goal is to prevent patients from sudden cardiac death by diagnosing and treating hypertrophic cardiomyopathy (HCM) at an early stage [3,4]. In this paper, we investigate the use of deep learning in the analysis of cardiac magnetic resonance (CMR) images in the diagnosis of hypertrophic cardiomyopathy (HCM). The purpose is to compare the performance of three models, each of which applies convolutional neural networks (CNNs).

1. Model 1: A block-based CNN architecture with five blocks, each containing different convolutional layers and skip connections, was first developed. It improves the mapping between input and output layers and improves feature extraction. A shallow ANN was then used as a binary classifier.
2. Following a transfer learning approach, Model 2 paired a shallow artificial neural network (ANN) with EfficientNetV2S—a state-of-the-art pre-trained network—to classify binary images. The presented results indicate superior performance compared to previous studies.
3. Model 3 retains the same architecture as Model 1, with one major modification: after the second block, we incorporated a Caputo-derived layer. This additional layer was built as an experimental feature aimed at enhancing the performance and accuracy of the convolutional neural network (CNN). To increase the model's ability to detect and process complex patterns in data, we sought to extend the model by incorporating the Caputo-derived one.

The best-performing model was identified through comprehensive evaluation metrics and a comparative analysis was conducted. The main contributions of this research are as follows:

• The new CNN architecture can be further improved in feature extraction and classification.
• EfficientNetV2S integration: The classification accuracy can be significantly improved by leveraging transfer learning.
• Caputo-derived layer-based CNN model: It improves the ability of our model to absorb and recognize complex designs in data.
• The proposed models are improved in performance metrics such as accuracy, precision, recall, F1 score, AUC, and MCC.

The sections of this study consist of the following: Related literature, techniques and materials, proposed models, analysis and results, and finally conclusions.

2. RELATED WORKS

This study developed two machine learning models: CNN and LSTM models were designed to be suitable for cardiac magnetic resonance (CMR) scans and electrocardiogram (EKG) data, respectively. To classify the scans into hypertrophic cardiomyopathy (HCM) and non-HCM categories, these models were designed, with CNN accuracy of 94.71%, and LSTM accuracy of 90.51%. These results may help clinicians to use both models for HCM [5]. Guo et al(2022) used a convolutional neural network (CNN) model to analyze cardiac magnetic resonance (CMR) images to assess left ventricular function in healthy individuals and patients with hypertrophic cardiomyopathy (HCM) and dilated cardiomyopathy (DCM). We show that the model performs well in diagnosing hypertrophic cardiomyopathy with an ejection fraction sensitivity of ~92.31%. This study demonstrates the potential contribution of artificial intelligence (AI) in cardiac analysis [6]. In the work of Demirbaş et al. (2024), they proposed a novel architecture called Spatial-Attention ConvMixer (SAC) for the classification of gastrointestinal diseases from the high-quality Kvasir dataset of endoscopic images. The proposed SAC model achieved an accuracy of 93.37%, outperforming the state-of-the-art ResNet50 (87.44%) and Vanilla Vision Transformer (79.52%) models. This also confirms its superior performance compared to traditional methods in medical image classification [7]. In (2024), Kim et al. presented an innovative study using deep learning to classify upper gastrointestinal anatomical landmarks using wireless capsule endoscopy (WCE). The research achieved a classification accuracy of greater than 90% by applying the

DenseNet169 model to such images [8]. In 2023, a study was conducted on how to improve their technique for classifying gastrointestinal diseases using deep learning. The researchers used the VGG-19 and ResNet-50 models. This analysis found that the ResNet50 model performed better than others, with an accuracy of 96.81%, recall of 95.28%, and precision of 95. The accuracy, recall, and precision of the VGG-19 model were 94.21%, 94%, and 94.28%, respectively. In this study, we showed that using CNN architectures, such as Resnet50 and VGG-19, can greatly help doctors obtain accurate and efficient classification of medical images to enhance diagnostic effectiveness [9].

3. MATERIALS AND METHODS

The approach used to create the classification network, along with details regarding the database and its processing, is explained in this section of the paper.

3.1 Dataset Description

59267 cardiac CMR images of cardiomyopathy from Kaggle with 37421 healthy images and 21846 HCM patient images [10]. The data were collected from Omid Hospital, Tehran between 2018 and 2020 and classified by three cardiac imaging experts. The mean age of the participants was 48.2 years (SD 19.5 years) and (53%) female. Images of five healthy individuals and five individuals with HCM from the dataset are shown in Figure 1.

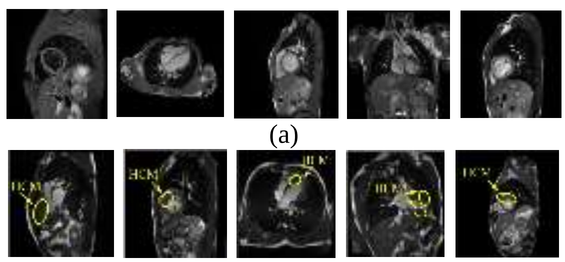

FIGURE 1: Sample CMR images: (a) healthy subjects, (b) HCM patients.

3.2 Convolution Neural Network

Semantic segmentation, object detection, and classification are just a few of the many tasks that can be accomplished by neural networks (NNs) known as convolutional neural networks (CNNs). Multiple convolutional layers, fully connected layers, and pooling layers are common components of CNNs[11,12]. Figure 2 shows a CNN in action during image classification.

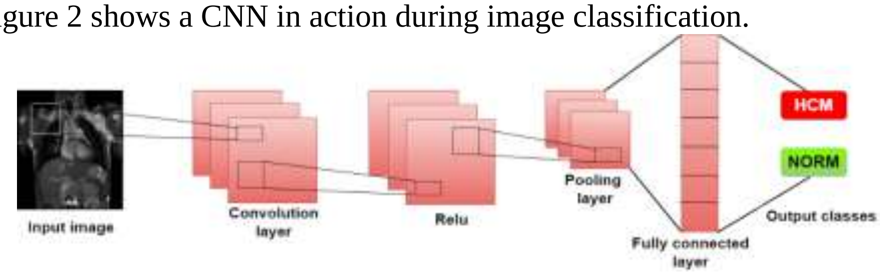

FIGURE 2: CNN architecture for image classification.

3.3 Transfer learning

Transfer learning (TL), the reuse of pre-trained CNN models, is a promising approach to address the problems caused by scarcity of small datasets and limited computational resources. Using pre-trained

CNN models in conjunction with transfer learning can significantly reduce this cost while enhancing the effectiveness of CNNs in medical imaging diagnosis [14,15].

3.3.1 EfficientNetV2S

EfficientNetV2 represents a significant improvement over EfficientNetV1 in all aspects. According to the authors, EfficientNet models have several drawbacks:

•The training process slows down significantly when using large image sizes.

•The use of deep convolutions causes delays in the first layers.

•Constant scaling is not recommended at all stages.

The EfficientNetV2 family of networks was developed to address these issues. To improve accuracy, speed, and parameter size during training. In the EfficientNetV2 family, there are three main models: EfficientNetV2S, EfficientNetV2M, and EfficientNetV2L [16,17].

3.4The proportional Caputo derivative

Caputo's derivative is a fractional calculus technique that enhances the performance of neural networks, especially in image classification tasks. The purpose of using fractional derivatives is to improve the generalization ability of the model and enhance stability during training.

$$C\ D^{\alpha}{}_{a}f(t) = \frac{1}{\Gamma(n - \alpha)}\int_{a}^{t}\frac{f^{(n)}(x)}{(t-x)^{\alpha-n+1}}dx \qquad (1)$$

for $\alpha \in (n-1, n]$, $n \in$ N.

Of particular interest are the properties that Caputo's derivative indicates, especially when integrated into a CNN framework for medical image classification. The key points are:

Control of model behavior, we show that Caputo's derivative reduces overfitting, improved stability, and computational efficiency. This makes Caputo's derivative a preferred tool for developing robust and efficient neural network models for medical image classification tasks [13].

4. PROPOSED MODEL

This work introduces two novel models based on convolutional neural networks (CNNs) and transfer learning architecture. It presents a convolutional neural network model that includes the Caputo derivative, before creating this architecture, the proposed system includes the following common steps:

1- Reading the image dataset.

2- Generating class labels for the images based on their index.

3- Using the TensorFlow package in Python to:

• Read the image files.

• Decode the images (convert the content of the image file to a 3D tensor: height, width, and color channels where color channel = 3).

4- Preprocessing steps:

• Resizing the images to a fixed square size of 300 × 300.

• Zooming the image using two methods: flipping the image randomly horizontally and vertically.

Other methods cannot be used to ensure the authenticity of the image and generate images without changing the structure or content, as they are medical images and any change affects the prediction decision.

5- Generating training and testing datasets using an 80:20 split.

6- Build the proposed model architectures separately.

7- Assemble the model and fit it to the training data as part of the training process.

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8- Use the trained model to make predictions and evaluate the model's accuracy, recall, precision, F1 score, MCC and AUC metrics.

The proposed classification model will be built entirely based on the CNN architecture, which will be built from a CNN feature extractor and an additional ANN as a classifier, as shown in Figure 3. Figure 4 shows the entire proposed classification model using block-based CNN, Figure 5 shows the second proposed classification model based on efficientNetV2S, and Figure 6 shows the architecture of the proposed convolutional neural network with Caputo derivative.

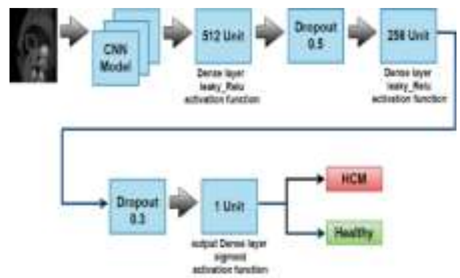
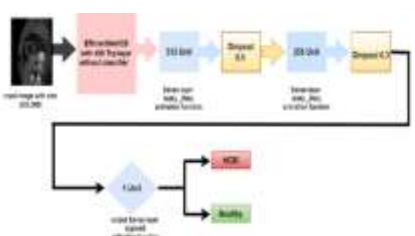


Figure 3 : Proposed CNN architecture. **Figure 4 :**Entire proposed classification model using block-based CNN.



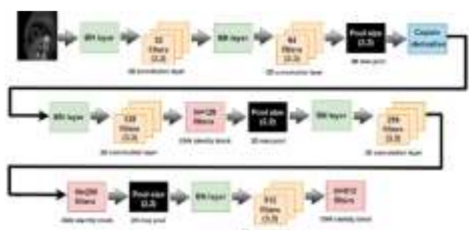


Figure 5 : Second proposed classification model based on **Figure 6 :** The proposed convolutional neural network architecture efficientNetV2S. with Caputo derivative.

5. RESULTS AND DISCUSSION

Table 1 presents the results of all proposed models and serves as a comparative analysis aimed at identifying the most effective model. Upon review, it is evident that the second model, EfficientNetV2S, stands out as the best-performing model across all evaluation criteria utilized in this study.

Table 1: Summary of comparative analysis of all proposed models.

Model	Accuracy	Precision	Recall	F1 Score	AUC	MCC
CNN	91.51	90.24	86.36	88.26	90.44	81.66
EfficientNetV2S	98.61	98.43	97.80	98.11	98.44	97.02
CNN+Caputo	92.46	93.47	85.58	89.35	91.04	83.74

5.1 Analysis and Comparison With Other Work

This section presents a comparative study of the proposed classification models and previous research on muscle hypertrophy detection. It discusses the classification accuracy and the classifiers used, Table 2 illustrates this.

TABLE 2: The comparison between the proposed classification models and previous works.

Ref.	**Year**	**Classifier**	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**AUC**	**MCC**
6	2022	Deep CNN	/	/	78.05	/	0.695,	/
9	2023	CNN/T.L(VGG-19 . ResNet-50)	(94.21, 96.81)	(94.28, 95.00)	(94.00, 95.28)	(94.00, 94.85)	/	/
5	2024	CNN	94.71	96.97	91.21	94.85	/	/
7	2024	CNN/T.L	93.37	93.66	93.37	93.42	/	/
8	2024	CNN	/	/	/	/	94.06	/
Proposed Model	CNN-block		91.51	90.24	86.36	88.26	90.44	81.66
	EfficientNetV2S		98.61	98.43	97.80	98.11	98.44	97.02
	CNN with Caputo		92.46	93.47	85.58	89.35	91.04	83.74

6. CONCLUSION

This research paper focuses on the classification of hypertrophic cardiomyopathy using cardiac magnetic resonance imaging (CMR). A deep learning architecture was used to develop and evaluate the system. The preprocessing phase included image scaling, normalization, and data augmentation techniques to improve the quality of the dataset. Three basic models were used to classify cardiac CMR images for cardiomyopathy: the EfficientNetV2S-based model, the Caputo derivative-based model, and the CNN-based model. The improved Caputo CNN model was found to outperform the standard CNN model.
This work demonstrates the potential of using fractional arithmetic, such as the Caputo derivative, to enhance the performance of deep learning models for medical image classification. The EfficientNetV2S-based model demonstrated exceptional overall performance, outperforming both CNN-based variants.
Future directions for this research include generalizing CNNs to other medical imaging modalities, such as X-ray, echocardiography, computed tomography, and electrocardiography, and improving the results using Caputo derivative developments to enhance the versatility and applicability of the models to a wider patient population. Furthermore, true integration of these models with electronic health records and other diagnostic tools is proposed to enable comprehensive patient assessment. The work will also be expanded to include additional types of cardiomyopathy (e.g., dilated and restrictive cardiomyopathy).

REFERENCES

1- D. Sharifrazi, R. Alizadehsani, N. Hoseini Izadi, M. Roshanzamir, A. Shoeibi, F. Khozeimeh, F. Alizadeh Sani, Z. Alizadeh Sani, C. Harlapur, A. Khosravi, and S. Nahavandi, "Hypertrophic cardiomyopathy diagnosis based on cardiovascular magnetic resonance using deep learning techniques," *Colour Filtering*, Res Sq, Oct. 26, 2021. [Online]. Available: https://doi.org/10.21203/rs.3.rs-1005999/v1.

2- V. Sangha, L. S. Dhingra, E. Oikonomou, A. Aminorroaya, N. V. Sikand, S. Sen, H. M. Krumholz, and R. Khera, "Identification of hypertrophic cardiomyopathy on electrocardiographic images with deep learning," *medRxiv*, Dec. 28, 2023. [Online]. Available: https://doi.org/10.1101/2023.12.23.23300490.

3- H. Wu, Z. Huang, J. Liu, J. Dai, Y. Zhao, and W. Luo, "The predictive value of deep learning-based cardiac ultrasound flow imaging for hypertrophic cardiomyopathy complicating arrhythmias," *Eur. J. Med. Res.*, vol. 28, no. 1, p. 36, Jan. 19, 2023. [Online]. Available: https://doi.org/10.1186/s40001-022-00975-7.

4- R. K. Hughes, H. Shiwani, S. Rosmini, J. B. Augusto, L. Burke, Y. Jiang, I. Pierce, G. Joy, S. Castelletti, M. Orini, and P. Kellman, "Improved diagnostic criteria for apical hypertrophic cardiomyopathy," *J. Cardiovasc. Imaging*, vol. 17, no. 5, pp. 501–512, May 1, 2024. [Online]. Available: https://doi.org/10.1016/j.jcmg.2023.07.012.

5- Kolluri, S., & Hathwar, S. (2024). Diagnosing hypertrophic cardiomyopathy using machine learning models on CMRs and EKGs of the heart. *Journal of Emerging Investigators, 7*, 1-7. https://doi.org/10.59720/23-209

6- Guo, J., Lu, H., Chen, Y., Zeng, M., & Jin, H. (2022). Artificial intelligence study on left ventricular function among normal individuals, hypertrophic cardiomyopathy, and dilated cardiomyopathy patients using 1.5T cardiac cine MR images obtained by SSFP sequence. *British Journal of Radiology, 95*(1133), Article 20201060. https://doi.org/10.1259/bjr.20201060.

7- Demirbaş, A. A., Üzen, H., & Fırat, H. (2024). Spatial-attention ConvMixer architecture for classification and detection of gastrointestinal diseases using the Kvasir dataset. *Health Information Science and Systems, 12*(32). https://doi.org/10.1007/s13755-024-00290-x

8- Kim, H.-S., Cho, B., Park, J.-O., & Kang, B. (2024). Color-transfer-enhanced data construction and validation for deep learning-based upper gastrointestinal landmark classification in wireless capsule endoscopy. *Diagnostics, 14*(591). https://doi.org/10.3390/diagnostics14060591.

9- Mary, X. A., Raj, A. P. W., Evangeline, C. S., Neebha, T. M., Kumaravelu, V. B., & Manimegalai, P. (2023). Multi-class classification of gastrointestinal diseases using deep learning techniques. *The Open Biomedical Engineering Journal, 17*(1), Article e187412072301300. https://doi.org/10.2174/18741207-v17-e230215-2022-HT27-3589-11

10- D. Sharifrazi and R. Alizadeh, "Hypertrophic Cardiomyopathy Dataset," Kaggle, 2021. [Online]. Available: https://www.kaggle.com/danialsharifrazi/hypertrophic-cardiomyopathy-dataset.

11- K. C. Tan and D. Tao, *Machine Learning: Foundations, Methodologies, and Applications*. Springer, 2021. [Online]. Available: https://link.springer.com/bookseries/16715.

12- L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J. Big Data*, vol. 8, p. 53, Dec. 2021. [Online]. Available: https://doi.org/10.1186/s40537-021-00444-8.

13- A. Hosna, E. Merry, J. Gyalmo, Z. Alom, Z. Aung, and M. A. Azim, "Transfer learning: a friendly introduction," *J. Big Data*, vol. 9, no. 1, p. 102, Oct. 22, 2022. [Online]. Available: https://doi.org/10.1186/s40537-022-00652-w.

14- 22. P. Grd, I. Tomičić, and E. Barčić, "Transfer Learning with EfficientNetV2S for Automatic Face Shape Classification," *JUCS*, vol. 30, no. 2, Feb. 1, 2024. [Online]. Available: https://doi.org/10.3897/jucs.104490.

15- I. Pacal, O. Celik, B. Bayram, and A. Cunha, "Enhancing EfficientNetV2 with global and efficient channel attention mechanisms for accurate MRI-based brain tumor classification," *Clust. Comput.*, May 20, 2024, pp. 1–26. [Online]. Available: https://doi.org/10.1007/s10586-024-04532-1.

16- D. Chicco and G. Jurman, "The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation," *BMC Genomics*, vol. 21, pp. 1–3, Dec. 2020. [Online]. Available: https://doi.org/10.1186/s12864-019-6413-7.

17- Kumar, M., Mehta, U., & Cirrincione, G. (2023). *Enhancing neural network classification using fractional-order activation functions*. *AI Open,* 5, 10–22. https://doi.org/10.1016/j.aiopen.2023.12.003.