

# Automatic Detection of Myocarditis Disease in Cardiac MRI Images using Deep Transformer Architectures and Explainable Artificial Intelligence Method

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## Abstract

Myocarditis is among the most important cardiovascular diseases (CVDs), endangering the health of many individuals by damaging the myocardium. Microbes and viruses, such as HIV, play a vital role in myocarditis disease (MCD) incidence. Lack of MCD diagnosis in the early stages is associated with irreversible complications. Cardiac magnetic resonance imaging (CMRI) is highly popular among cardiologists to diagnose CVDs. In this paper, a deep learning (DL) based computer-aided diagnosis system (CADS) is presented for the diagnosis of MCD using CMRI images. The proposed CADS includes dataset, preprocessing, feature extraction, classification, and post-processing steps. First, the Z-Alizadeh dataset was selected for the experiments. The preprocessing step included noise removal, image resizing, and data augmentation (DA). In this step, CutMix, and MixUp techniques were used for the DA. Then, the most recent pre-trained and transformers models were used for feature extraction and classification using CMRI images. Our results show high performance for the detection of MCD using transformer models compared with the pre-trained architectures. Among the DL architectures, Turbulence Neural Transformer (TNT) architecture achieved an accuracy of 99.73% with 10-fold cross-validation strategy. Explainable-based Grad Cam method is used to visualize the MCD suspected areas in CMRI images.

**Keywords:** Myocarditis, Diagnosis, Cardiac MRI, Deep Learning, Transformers, Grad CAM

## 1. Introduction

Cardiovascular disease (CVDs) prevalence has become a global public health problem [1]. According to several World Health Organization (WHO) reports, CVDs have been recognized as one of the leading causes of mortality in recent years [2-3]. The heart is responsible for the circulation of blood, carrying oxygen and nutrients throughout the body, and expelling carbon dioxide [4]. Coronary artery disease (CAD) [5], arrhythmia [6], cardiomyopathy [7], heart failure [8], congenital heart disease [9], mitral

regurgitation [10], angina [11], and myocarditis disease (MCD) [12] are among the most common CVDs. Chest, arm, and left shoulder pain, shortness of breath, nausea and fatigue, cold sweats, headache, and dizziness are the most common symptoms of CVDs [13-15]. Common causes of CVDs include hypertension, smoking, high cholesterol, diabetes, obesity, positive family history, and age [16-18]. Clinical studies have shown that avoiding causative factors of CVDs significantly reduces the risk of CVDs and guarantees human health [1-4].

In recent years, MCD has increased rapidly among people worldwide [19-22]. It is caused by inflammation of the myocardium [19]. Inflammation of the myocardium reduces the ability to pump blood throughout the body, resulting in significant health issues such as arrhythmia, chest pain, and dyspnea in MCD patients [19-20]. In some cases, myocardial dysfunction can also lead to blood clots, heart attack, stroke, heart injury, heart failure, or even death [21-22]. Clinical studies have revealed that the primary causes of MCD are SARS-CoV-2, adenovirus, and HIV [19-20]. MCD may be asymptomatic in some cases. It may often cause chest pain, heart failure, fever, palpitations, fatigue, and even sudden death [21]. Various screening methods are used for diagnosing CVDs by medical doctors. Electrocardiogram (ECG) [23], echocardiogram (Echo) [24], cardiac exercise experiment [25], CT [26], cardiac MRI (CMRI) [27], and Holter monitoring [28] are the most common methods for diagnosing CVD. Among the presented methods, experienced physicians consider CMR imaging to diagnose CVDs, including MCD. CMR imaging is a non-invasive method for analyzing different heart regions [29-31]. Specialists use CMRI images to check ventricular wall thickness, left ventricular end-systolic volume, etc. [29-31]. CMRI imaging also provides early diagnosis of cardiac dysfunction, allowing rapid and reliable diagnosis of CVDs, including MCD [29-31].

In addition to the advantages of CMRI, analyzing the images can be difficult for medical doctors in some cases. For example, accurate diagnosis of CVDs requires the acquisition of multi-slice CMRI images for each patient, the analysis of which is typically a difficult task for experienced physicians [20-21]. On the other hand, CMRI images have low resolution and may have low contrast, making it difficult to diagnose CVD [21]. Also, CMRI images show various artifacts, making it difficult for specialists for diagnosing of CVDs. To solve these existing challenges, researchers have introduced Artificial Intelligence (AI) techniques to diagnose CVDs. In AI studies, researchers have proposed various machine learning (ML) and deep learning (DL) methods for the diagnosis of CVDs from CMRI images [29-31]. This work aims to create a practical tool for diagnosing CVDs from CMRI images.

Recently, results of studies in MCD diagnosis from CMRI images using DL techniques have been published [19-21]. In a study by Sharifrazi et al. [19], the CNN-KCL model was proposed for MCD detection based on CMRI images. In this work, they performed experiments on the Z-Alizadeh dataset. The main idea of this study was to combine a 2D-CNN model using the k-means clustering method. The results of their study showed an accuracy of 97.41%. In another study by Shoeibi et al. [20], the cycle-GAN method was used with various pre-trained models to diagnose MCD. In this study, the Z-Alizadeh dataset was also used to implement the proposed model. The cycle-GAN architecture was used in the preprocessing step to develop the synthetic CMRI images. Finally, CMRI images were applied to various pre-trained models. The EfficientNet V2 method achieved an accuracy of 99.33% among the pre-trained models. The deep reinforcement learning (RL) was introduced by Moravvej et al. [21] for MCD detection using CMRI images. Next, they presented a reinforcement learning method called RLMD-PA to diagnose myocarditis. Finally, several optimization methods were assessed to increase the accuracy and efficiency of MCD diagnosis.

This paper presents a DL-based CADs for the diagnosis of MCD from CMRI images. First, the Z-Alizadeh dataset was used to implement the proposed method. Next, we applied denoising, resizing, and new data augmentation (DA) methods to generate synthetic CMRI images as preprocessing steps. The proposed DA method is based on the application of the CutMix and MixUp methods [32-33]. Then, we experimented with all transfer learning models and transformers for feature extraction and

classification. Finally, in a post-processing step, the Grad-Cam method [34] was used to visualize the suspected myocarditis regions in CMRI images. Our results demonstrate that the proposed CADS achieved successful results in MCD detection.

The main contributions of this work are given below:

- (i) CutMix, and MixUp techniques are used for DA.
- (ii) Transformers and pre-trained models are used for feature extraction.
- (iii) Explainable-based Grad Cam method is used to visualize the MCD suspected areas in CMRI images.

The rest of the paper is organized as follows. Section 3 describes the proposed method for MCD detection using CMR imaging. This section presents the details of the proposed CADS, including the dataset, preprocessing, and DL model. Section 4 represent the evaluation parameters of the proposed method. Section 5 is devoted to the results of the proposed method. Finally, the discussion, conclusion, and future work are provided in Section 6.

## 2. Material and Methods

This section proposes a CADS to diagnose MCD using CMRI images. Figure (1) shows the block diagram of the proposed method which includes dataset, preprocessing, DL model, and post-processing. First, a DL model is implemented using the Z-Alizadeh dataset. The Z-Alizadeh dataset consists of 12000 CMRI images of normal and myocarditis patients admitted to Shahid Rajaei Hospital, Tehran. In the preprocessing step, denoising, resizing, and a new DA method to generate synthetic CMRI images were performed. The CMRI images were denoised in this section and then resized to 100\*100. After a preprocessing step, synthetic CMRI data was generated using a new DA model based on the CutMix [32] and MixUp [33] methods. The proposed DA method is used for the first time in MCD detection and is the first novelty in this study. In the third step, state-of-the-art pre-trained models and transformers were used for feature extraction and classification of CMRI images. Pre-trained models included EfficientNet B3 [35], EfficientNet V2 [36], HrNet [37], Inception [38], ResNets50 [39], ResNest50d [40], and ResNet 50d [41]. Transformer models also included Beit [42], Cait [43], Coat [44], Deit [45], Pit [46], Swin [47], TNT [48], Visformer [49], and ViT [50]. The transformer model for diagnosing MCD is another novelty of this work. Finally, we visualized the CMRI images using an explainable AI-based post-processing step. The Grad Cam technique is one of the explainable AI techniques used to visualize the suspicious regions of MCD in CMRI images.

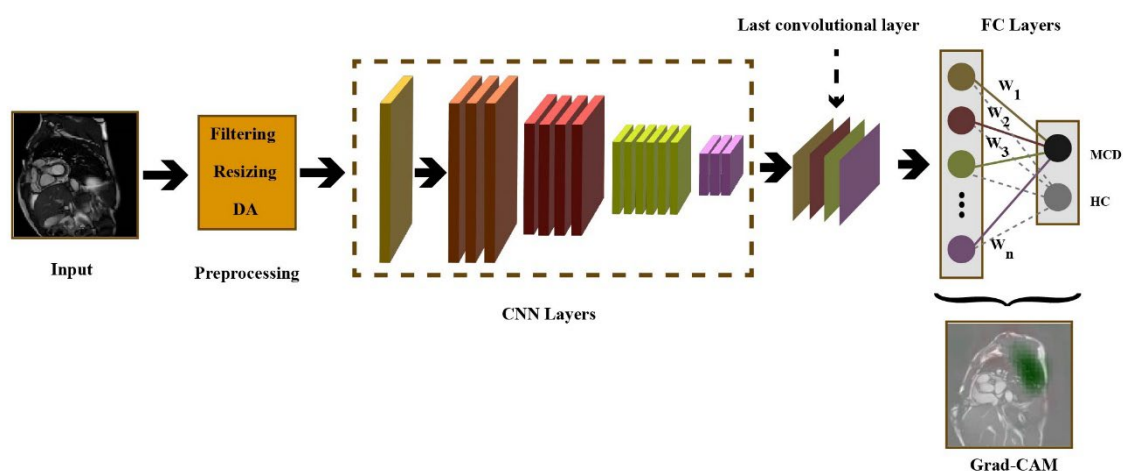


Fig. 1. Block diagram of the proposed method for diagnosis of MCD

### 2.1. Z-Alizadeh Dataset

The non-invasive gold standard for diagnosing myocarditis is the CMR imaging. Using CMRI, it is possible to assess the condition of heart accurately and perform anatomical and functional imaging. The contrast enhancement (CE-GD) confirms myocardial injury (e.g. scar, fibrosis), T2-weighted images

reveal interstitial edema, which is an integral part of inflammatory response. In addition, the presence of hyperemia/capillary leak in myocardial tissue is indicated by pre and post-contrast T1-Weighted image.

The Z-Alizadeh Sani myocarditis dataset was collected between September 2018 and September 2019 at the CMR department of OMID hospital in Tehran, Iran. The soundness of the data gathering process has been confirmed by the local ethical committee of OMID hospital. To perform CMR examination, a 1.5-T system (MAGNETOM Aera Siemens, Erlangen Germany) was used. Dedicated body coils were used to scan each patient in the standard supine position. The CMR protocols that have been complied with are listed below:

- \* CINE-segmented images and pre-contrast T2-weighted (trim) images were performed in short and long axes views.

- \* The pre-contrast T1-weighted relative images were acquired in axial views of the myocardium.

- \* After injection of Gadolinium ((DOTAREM 0/1 mmol/kg), the T1-weighted relative sequence was repeated. After 10-15 minutes, sequences of Late Gadolinium Enhancements (LGE- high-resolution PSIR) in short and long axes views were carried out.

The total number of images examined is 10425. The number of images representing healthy and myocarditis patients was 7000 and 6000, respectively. Figure (2) shows typical CMRI images obtained from the Z-Alizadeh dataset for healthy control (HC) and MCD patients.

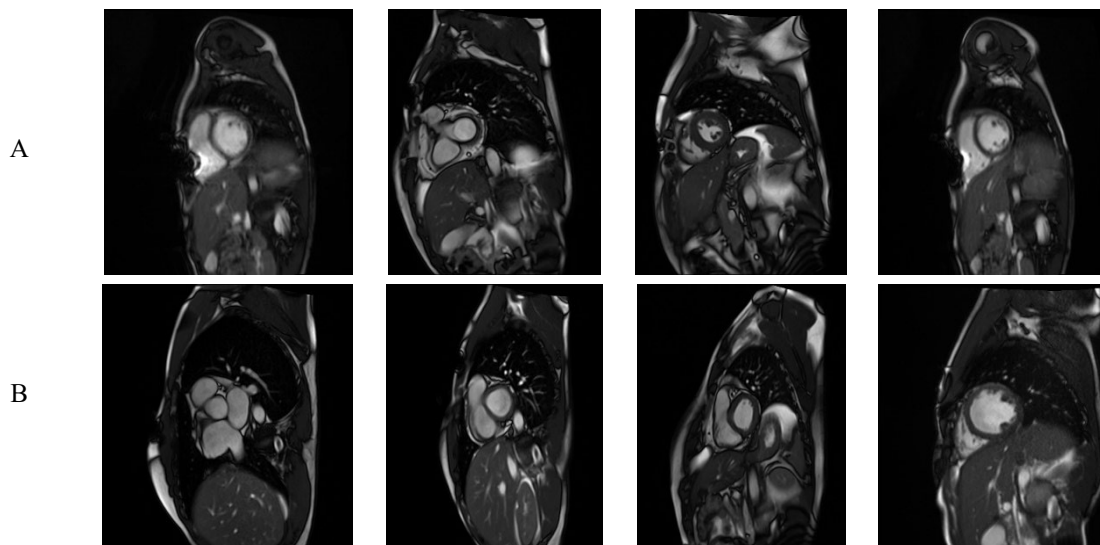


Fig 2. Sample CMR images dataset: a) Normal, and B) Abnormal.

## 2.2. Preprocessing

This section describes preprocessing steps used for CMRI images, involving denoising, image resizing, and DA. First, a Gaussian filter was used to denoise the CMRI images. Then, the CMRI images were resized to 100x100. Finally, synthetic CMRI images were generated using the proposed DA method based on CutMix and MixUp techniques. In this phase, we used the proposed DA model to increase the efficiency of pre-trained models and transformers and prevent overfitting. Details of the proposed DA method are presented below.

## 2.3. Data Augmentation

In addition to standard geometrical and colour transformations for image augmentation, we have also tested a new kind of data augmentation method based on combining the information of several images [51]. In particular, we have employed CutMix [32] and MixUp [33] techniques to produce inter-class examples. CutMix [32] replaces a portion of an image with a portion of a different image. Namely, given two random images from the dataset,  $x_i$  and  $x_j$ , and their corresponding one-hot labels,  $y_i$  and  $y_j$ , CutMix constructs a new training example  $(x,y)$  by using the following formulas:

$$x = M \times x_i + (1 - M) \times x_j$$

$$y = \lambda \times y_i + (1 - \lambda) \times y_j$$

where  $\lambda$  values are values within the  $[0, 1]$  range and are sampled from the Beta distribution, and  $M$  denotes a binary mask indicating where to drop out and fill in from two images. To sample the binary mask  $M$ , CutMix samples the bounding box coordinates  $B = (r_x, r_y, r_w, r_h)$  indicating the cropping regions on  $x_i$  and  $x_j$ . The region  $B$  in  $x_i$  is removed and filled in with the patch cropped from  $B$  of  $x_j$ . Following the approach of [32], we sampled rectangular mask  $M$  whose aspect ratio is proportional to the original image. The box coordinates are uniformly sampled according to [32]:

$$r_x \sim \text{Unif}(0, W)$$

$$r_y \sim \text{Unif}(0, H)$$

$$r_w = W \times \sqrt{1 - \lambda}$$

$$r_h = H \times \sqrt{1 - \lambda}$$

where  $W$  and  $H$  are the weight and height of the original image [32], respectively. Figure (3) shows the CutMix method applied to CMRI images.

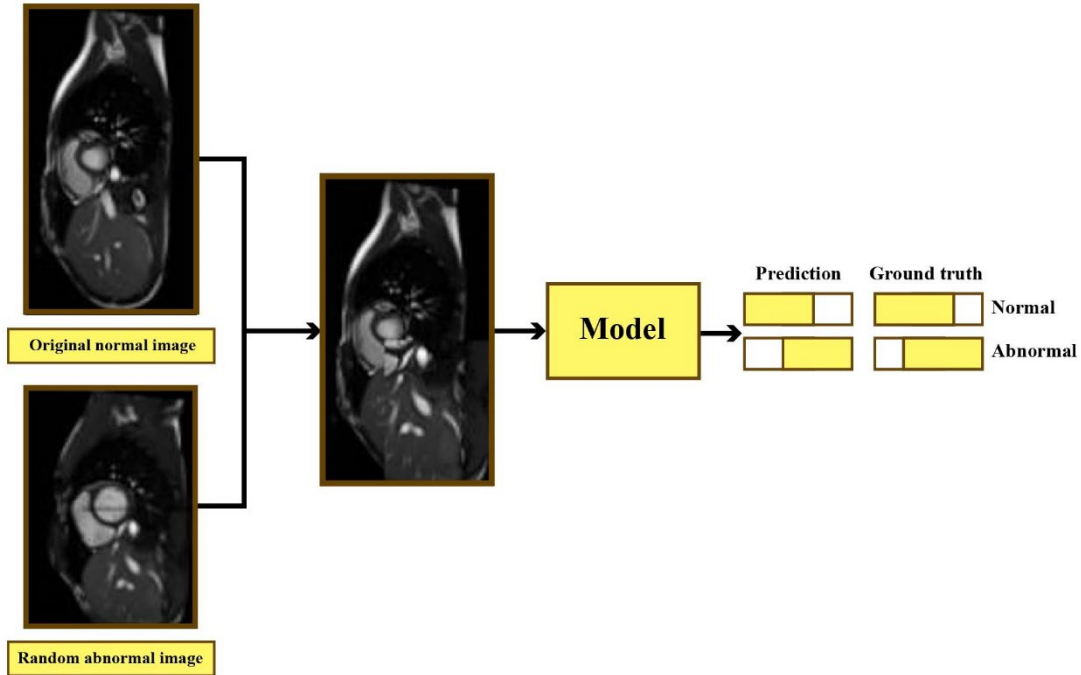


Fig. 3. Block diagram of CutMix method for DA from CMRI images.

MixUp [33] also uses information from two images, but instead of implanting one portion of an image inside another, MixUp produces an elementwise convex combination of two images. Given two random images from the dataset,  $x_i$ , and  $x_j$ , and their corresponding one-hot labels,  $y_i$ , and  $y_j$ , MixUp constructs a new training example  $(x, y)$  by using the following formulas [33]:

$$x = \lambda \times x_i + (1 - \lambda) \times x_j$$

$$y = \lambda \times y_i + (1 - \lambda) \times y_j$$

where  $\lambda$  values are values within the  $[0, 1]$  range and are sampled from the Beta distribution [33]. Figure (4) shows the MixUp method applied to CMRI images.

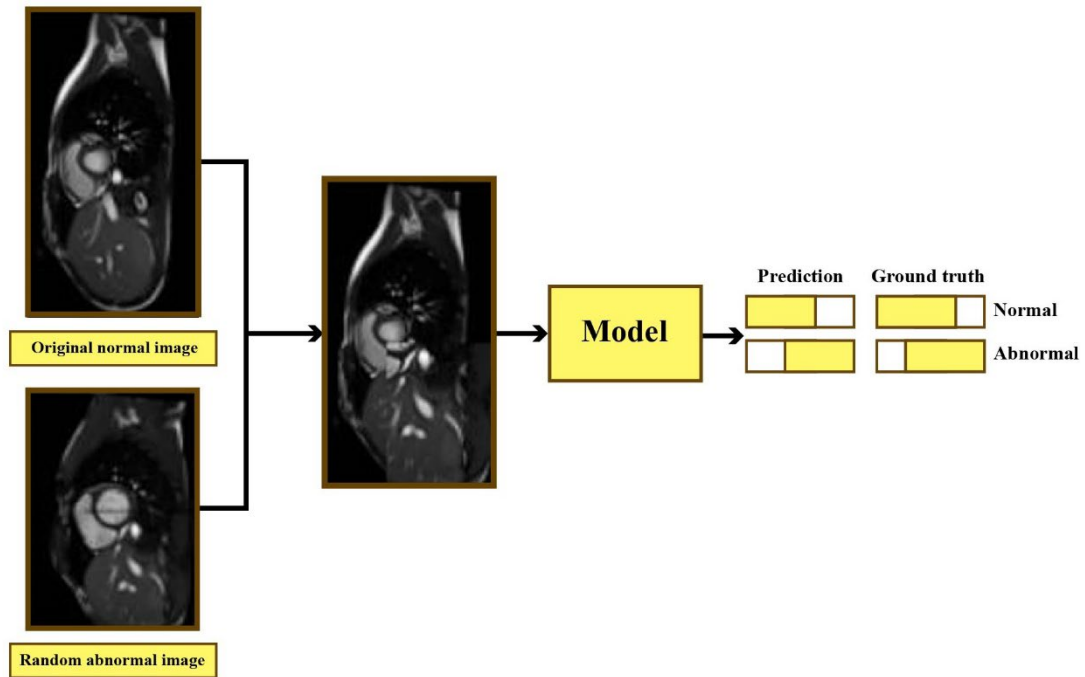


Fig. 4. Block diagram of the MixUp method used for DA using CMRI images.

CutMix [32] and MixUp [33] prevent the model from overfitting the training distribution and improve the likelihood that the model can generalize to out-of-distribution examples. In our work, we have used these data augmentation techniques using the callbacks provided by the FastAI library [52]. Figure (5) displays some of the generated synthetic CMRI images for HC and MCD classes.

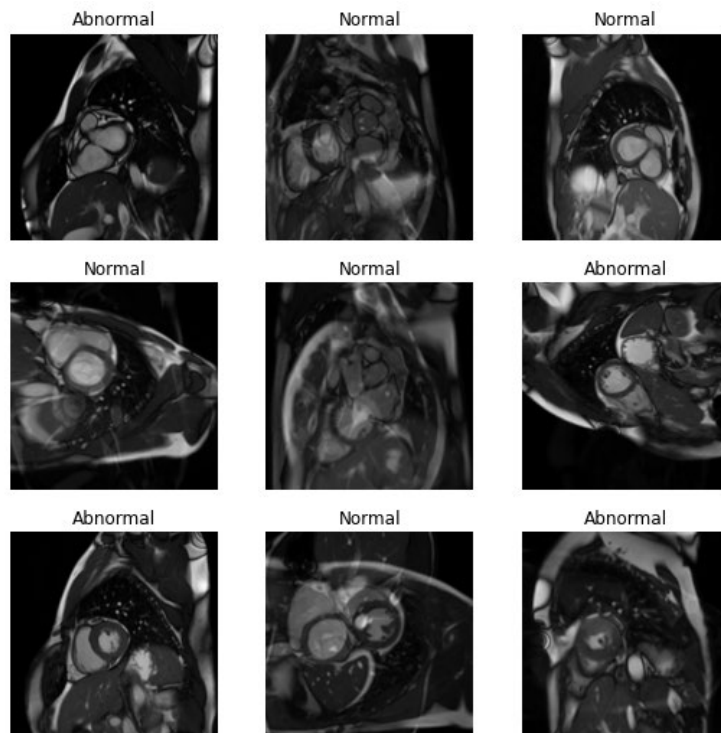


Fig. 5. Sample CMRI images generated using the proposed DA method.

#### 2.4. Deep Learning Models

DL models are used in various applications, including in medical fields [53-57]. In medical applications, DL models are widely used for diagnosing brain diseases [58-59] and CVD. DL models perform feature extraction to classification steps in deep layers. Various DL architectures have been presented; this

article uses the latest pre-trained architectures and transformers. A pre-trained model and transformer have reported acceptable performance and are used for this study. The details of the pre-trained and transformer architectures used to detect myocarditis using CMRI images are given below.

#### **2.4.1. Deep Pre-trained Models**

The pre-trained models are a class of convolutional neural network (CNN) architectures based on supervised learning. These networks are trained on the ImageNet dataset, and the weights are saved [35]. One of the challenges in the medical field is that researchers do not have access to datasets containing large numbers of subjects [60-61]. To overcome this challenge, pre-trained models have been presented for researchers for disease diagnosis. In this work, the latest pre-trained models were used for myocarditis diagnosis. New pre-trained models, including EfficientNet B3 [35], EfficientNet V2 [36], HrNet [37], Inception [38], ResNets50 [39], ResNest50d [40], and ResNet 50d [41], were applied to CMRI data for diagnosis of MCD. The rest of this section provides brief details of various pre-trained models.

##### **a) EfficientNet B3**

Authors in [35] presented a detailed discussion on scaling DL models. This work introduced a new scaling method that uniformly scales depth, width, and resolution using compound coefficients. Also, few researchers have proposed a multi-objective method for designing DL models, introducing the EfficientNets architecture [35]. The EfficientNets architecture consists of seven blocks, each with different sub-blocks. Therefore, EfficientNets architectures are denoted by the suffixes B0 to B7 and more information is presented in [35].

##### **b) EfficientNet V2**

Authors in [36] introduced a combination of neuronal architecture search (NAS) and scaling to improve the enhanced DL models, including training speed and parameter efficiency [36]. They designed a search space filled with Fused-MBConv. NAS was also used to optimize model parameters: accuracy, training speed, and size [36]. Therefore, an 8-layer EfficientNetV2 architecture was presented, which has a 4x training speed compared to the heart model [36]. Also, the size of these models was reduced by a factor of 6.8 and more information is presented in [36].

##### **b) HrNet Model**

Authors in [37] presented a High-Resolution Net (HrNet) architecture that performs well in image classification. Recent studies have shown high efficiency in classifying gray images using HrNet architecture. Study [37] reports that HrNet is based on multiresolution fusion. Two versions of HrNet are provided: HRNetV1 and HRNetV2 [37]. An improved model of HRNetV2 called HRNetV2p was introduced with excellent performance [37]. For more information on the HrNet architecture is available in [37].

##### **c) Inception Models**

Inception v4 is an improved model of the GoogLeNet architecture [38]. Compared to Inception v3, this architecture has a more homogenous architecture with higher efficiency. The Inception v4 architecture consists of a stem block, three Inception blocks, two reduction blocks, and the average pooling/dropout/Softmax layers [38]. Given the success of residual networks, researchers [38] combined Inception and ResNets. They introduced two residual-based Inception models: Inception ResNet V1 and Inception ResNet V2 [38]. The architecture of these networks include: a stem block, three Inception-ResNets, two reduction blocks, and the average pooling/dropout/Softmax layer [38]. More information about this model is presented in [38].



**d) ResNetrs50 (ResNet RS)**

Authors in [39] examined the impact of training methods and scaling strategies using ResNet architecture. In this work, an improved training procedure was presented through an experimental investigation of training methods without modification of the model architecture [39]. Analysis of scaling strategies presented two new methods: (i) overfitting can cause model depth scaling [39] and (ii) slower scaling of image resolution compared with other previous models [39]. Using this improved training and two scaling strategies, ResNet architecture was rescaled, which is known as ResNet-RS. This new architecture uses less memory during training and faster. More information about this model is available in [39].

**e) ResNest50d (ResNeSt)**

In [40], researchers proposed a simple architecture combining the ideas of channel-wise attention strategy and multipath networks. This architecture captures cross-channel feature correlations in meta structure by maintaining independent representations [40]. A module in this architecture runs a series of low-dimensional embedding transformations and merges their outputs as a multipath network [40]. Several variables can parameterize the architecture of this network. This computational block is called a Split-Attention Block [40]. Stacking the Split-Attention Block with ResNet-style creates a new type of ResNet called a Split-Attention network (ResNeSt) [40]. The reference [40] provides more information about the ResNest50d architecture.

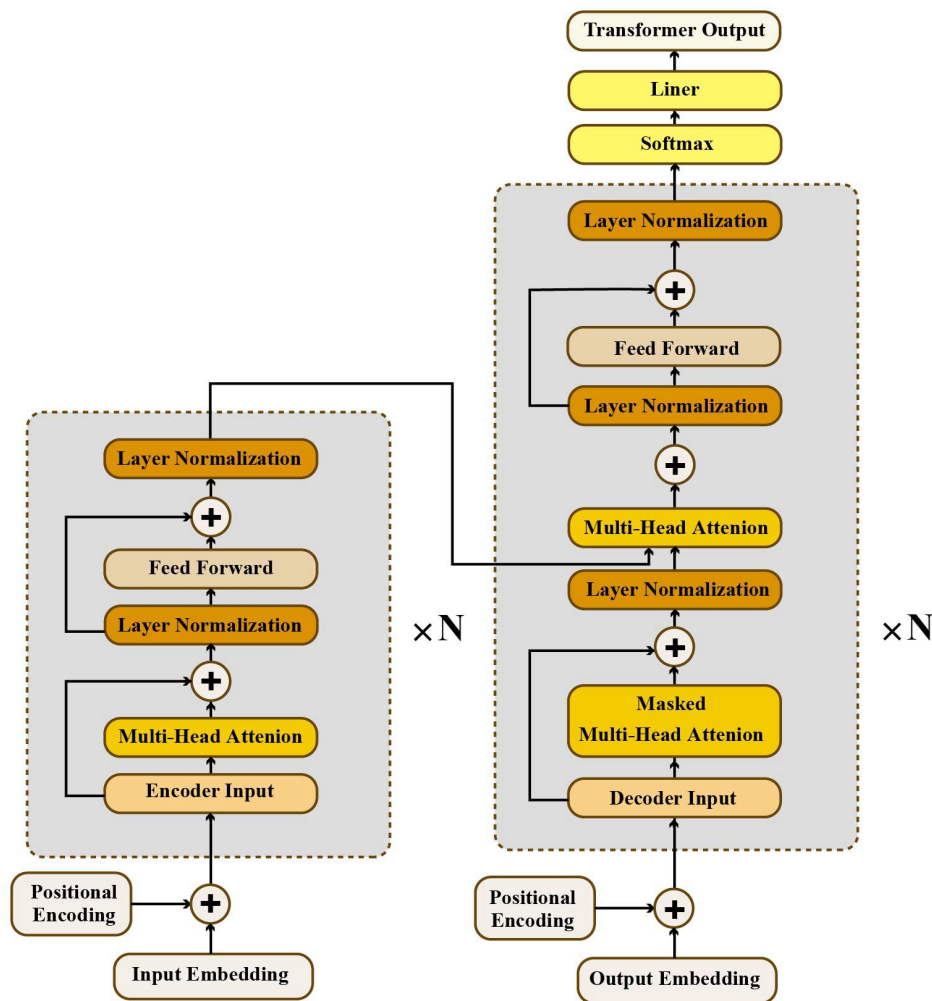


Fig. 6. General block diagram for transformers.



#### **f) ResNet 50d**

ResNet uses skip connection or Residual Connections in its architecture [41]. This layer adds the output of the previous layer to the next layer, so it might be ignored in the middle of some layers. Therefore, the vanishing gradient problem is mitigated. The family of ResNet architectures includes ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152 (numbers indicate the number of layers in each architecture) [41].

#### **2.4.2. Deep Transformer Models**

Recent works suggest that it is also possible to build successful classification models without convolutions [62], and a new family of image recognition models called transformer architecture are used. Transformers [63] were initially designed to tackle natural language processing (NLP) tasks by introducing a self-attention module that captures the non-local relationships between all input sequence elements. However, it is also used in computer vision by seeing an image as a sequence of patches and following the architectural design [63]. Figure (6) displays a general block diagram for deep transformer models. There are several transformer architectures used for computer vision. They are usually pre-trained on the ImageNet dataset as convolutional models. In this work, we have analyzed the following architectures.

##### **a) Beit**

Beit [42] is a transformer architecture that follows the design of [63], and trained in a self-supervised manner following the ideas of the language model BERT [42]. A masked image modelling (MIM) pre-training task is proposed which uses two views for each image which are image patches and visual tokens. Each image is split into a grid of patches that are the input representation of the transformer architecture. Moreover, the image is tokenized into discrete visual tokens. During pre-training, some proportion of image patches are masked, and the corrupted input is fed to the transformer. Using this approach, the model learns to recover the visual tokens of the original image. After this pre-training task, a fine-tuning process for image classification is conducted using the representations learnt during the pre-training process.

##### **b) Cait**

Cait [43] architecture was designed to increase the optimization's stability when training transformers for image classification derived from the original transformer architecture by [63], especially when the depth of the architecture is increased. In the Cait architecture, two improvements were introduced: a new layer called Layer Scale, which allows the authors to train deeper high-capacity image transformers that benefit from depth; and a class-attention layer is devoted to extract the content of the processed patches into a single vector so that it can be fed to a linear classifier.

##### **c) Coat**

Coat [44] is a transformer-based image classifier with co-scale and conv-attentional mechanisms. The co-scale mechanism maintains the integrity of transformers' encoder branches at individual scales while allowing representations learned at different scales to communicate with each other effectively. The conv-attentional mechanism provides a relative position embedding formulation with an efficient convolution-like implementation.

##### **d) Deit**

In general, transformers do not generalize well when trained on insufficient data, this drawback was addressed by [45]. The Deit architecture is based on the Vit architecture [50] but uses a training that considers strategies for hyper parameter optimization, data augmentation, and regularization, allowing the authors to learn vision transformers in a data-efficient manner. Moreover, a teacher-student strategy that is specific for training transformers was also proposed in this work.

#### **e) Pit**

The authors of Pit [46] proposed a pooling-based vision transformer using the original ViT model [50]. The Pit architecture is a transformer architecture combined with a pooling layer that enables the spatial size reduction in the ViT structure as in the ResNet convolutional network [46]. This architecture tries to mimic the approach followed in CNNs, which starts with a feature of large spatial sizes and a small channel size which gradually increases the channel size while decreasing the spatial size.

#### **f) Swin**

The Swin [47] transformer was designed to address the challenges in adapting transformers from language to vision due to the differences in these two domains. The differences are mainly the large variations in the scale of visual entities and the high resolution of pixels in images compared to words in text. To address these differences, the Swin architecture is a hierarchical transformer whose representation is computed with shifted windows is employed.

#### **g) Turbulence Neural Transformer (TNT)**

Vision transformers first divide the input images into several local patches and then calculate both representations and their relationship. However, due to the high complexity with abundant details and color information of natural images, the granularity of the patch dividing is not fine enough for excavating features of objects in different scales and locations. In the TNT architecture [48], the local patches are seen as "visual sentences," and they are further divided into smaller patches as "visual words". Features of both visual words and sentences are aggregated to enhance the representation ability of this architecture.

#### **h) Visformer**

The authors of Visformer [49] deal with the over-fitting problem in vision transformers when the training data is limited. To this aim, the authors studied the transition from the Deit transformer model [45] to the ResNet convolutional network [49]. This architecture uses the advantages of transformers and discards the disadvantages of obtaining a model that outperforms both Deit and ResNet.

#### **i) ViT**

Vit [50] was the first fully-transformer network for image classification. In this work, images were split into fixed-size patches; subsequently, those patches were linearly embedded, combined with positional embedding, and finally fed to a standard transformer encoder that follows the design of [63]. An extra learnable "classification token" is added to the sequence of linearly embedded patches to perform classification. The Vit models were trained by combining three datasets: ILSVRC-2012 ImageNet, ImageNet-21k, and JFT.

### **3. Statistical Metrics**

This section presents the evaluation metrics for demonstrating the efficacy of the proposed method. A k-fold cross-validation with k=10 was used to evaluate the classification results. The advantage of the k-fold method is its application to train and experiment data. Evaluation metrics, including specificity (Spec), sensitivity (Sens), accuracy (Acc), and F1 score, were calculated for each of the DL models. Table (1) shows the evaluation metrics used and their relationships. For each evaluation parameter, true positives (TP), false negatives (FN), true negatives (TN), and false positives (FP) are obtained from the confusion matrix [64].

Table 1. Description of the performance metrics used in this work.

| Parameter Name | Formula                                   |
|----------------|---|
| Accuracy       | $Acc = \frac{TP + TN}{FP + FN + TP + TN}$ |
| Sensitivity    | $Sens = \frac{TP}{FP + TP}$               |
| Specificity    | $Spec = \frac{TN}{FP + TN}$               |
| Precision      | $Prec = \frac{TP}{TP + FP}$               |
| F1-score       | $FS = \frac{2TP}{2TP + FP + FN}$          |

#### 4. Experiment Results

This section presents the results obtained for MCD diagnosis with pre-trained and transformed models. All simulations were run on a hardware system with 16 GB RAM, CPU Core i7, and NVidia GeForce 2080. Also, the proposed CADs was implemented using TensorFlow 2 [73], Keras [74], FastAI [52], and Scikit-learn [75], and PyTorch [76] tools. In the beginning of this section, the results of pre-trained models are discussed, including EfficientNet B3 [35], EfficientNet V2 [36], HrNet [37], Inception [38], ResNets50 [39], ResNest50d [40], and ResNet 50d [41]. Table (2) shows the results of the pre-trained models for MCD diagnosis using CMRI images. Table (2) shows that the Inception ResNet v2 model was more successful in MCD diagnosis than other pre-trained models. The ResNet 50d model also achieved good results.

Table 2. Results of pertained models for diagnosis of MCD from CMRI images

| Models              | ACC          | Prec          | NPY          | Rec           | Spec          | F1           | AUROC        | Cohen         |
|---------------------|--------------|---------------|--------------|---------------|---------------|--------------|--------------|---------------|
| EfficientNet B3     | 99,52 (3,48) | 99,47 (17,87) | 99,55 (6,43) | 99,14 (30,96) | 99,72 (17,85) | 99,3 (24,07) | 99,96 (8,15) | 98,94 (13,9)  |
| EfficientNet V2     | 99,54 (2,58) | 99,19 (15,64) | 99,72 (4,39) | 99,47 (20,46) | 99,57 (6,89)  | 99,33 (21,2) | 99,98 (7,97) | 98,98 (13,95) |
| HrNet               | 99,04 (0,28) | 98,11 (0,31)  | 99,54 (0,27) | 99,12 (0,51)  | 99 (0,16)     | 98,61 (0,41) | 99,95 (0,05) | 97,88 (0,63)  |
| Inception ResNet V2 | 99,66 (0,18) | 99,31 (0,49)  | 99,85 (0,1)  | 99,71 (0,18)  | 99,64 (0,26)  | 99,51 (0,26) | 99,99 (0,01) | 99,26 (0,4)   |
| Inception V4        | 99,30 (0,32) | 98,46 (1,08)  | 99,75 (0,34) | 99,52 (0,66)  | 99,18 (0,59)  | 98,99 (0,46) | 99,98 (0,01) | 98,45 (0,71)  |
| ResNest 50d         | 99,23 (0,4)  | 99,69 (0,44)  | 98,99 (0,37) | 98,06 (0,72)  | 99,84 (0,23)  | 98,87 (0,58) | 99,93 (0,09) | 98,28 (0,88)  |
| ResNet 50d          | 99,62 (0,14) | 99,51 (0,27)  | 99,68 (0,2)  | 99,39 (0,38)  | 99,74 (0,14)  | 99,45 (0,2)  | 99,99 (0,01) | 99,16 (0,3)   |
| ResNets 50          | 99,42 (0,33) | 99,04 (0,69)  | 99,63 (0,54) | 99,29 (1,03)  | 99,49 (0,37)  | 99,16 (0,48) | 99,96 (0,08) | 98,72 (0,72)  |

The following results of the pre-trained model are presented along with the proposed DA method. The proposed DA model is based on CutMix [32] and MixUp [33] techniques. To the best of our knowledge, we are the first group to use it for the MCD diagnosis. In this section, the proposed DA method was used to generate an artificial CMRI image and then applied the original artificial CMRI image to the input from a pre-trained model. Table (3) shows the results obtained by combining the DA model with the pre-trained architectures for MCD diagnosis. Table (3) shows the performance of the pre-trained architectures obtained using new DA method. It can be noted from the table that the inception\_v4 model performed better than the other pre-trained architectures. Furthermore, the inception of ResNet V2 and efficientnetv2 architectures also achieved satisfactory results. Figure (7) shows the accuracy results for pre-trained models trained with DA method for diagnosis of MCD.

Table 3. Results (%) obtained using pertained models with the new DA method for diagnosis of MCD with CMRI images

| Models              | ACC          | Prec         | NPY          | Rec          | Spec         | F1           | AUROC        | Cohen        |
|---------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| EfficientNet B3     | 99,55 (0,27) | 99,23 (0,44) | 99,72 (0,25) | 99,47 (0,47) | 99,59 (0,23) | 99,35 (0,39) | 99,97 (0,03) | 99,01 (0,6)  |
| EfficientNet v2     | 99,66 (0,22) | 99,35 (0,48) | 99,83 (0,16) | 99,67 (0,31) | 99,66 (0,25) | 99,51 (0,33) | 99,95 (0,06) | 99,25 (0,5)  |
| HrNet               | 99,10 (0,52) | 97,98 (1,76) | 99,72 (0,25) | 99,47 (0,47) | 98,91 (0,96) | 98,71 (0,74) | 99,95 (0,05) | 98,02 (1,14) |
| Inception ResNet v2 | 99,68 (0,24) | 99,47 (0,49) | 99,79 (0,21) | 99,59 (0,41) | 99,72 (0,26) | 99,53 (0,34) | 99,99 (0,02) | 99,29 (0,52) |
| Inception v4        | 99,70 (0,18) | 99,44 (0,3)  | 99,84 (0,14) | 99,69 (0,26) | 99,71 (0,16) | 99,57 (0,25) | 99,94 (0,1)  | 99,34 (0,39) |
| ResNest 50d         | 99,33 (0,3)  | 99,02 (0,52) | 99,49 (0,46) | 99,02 (0,89) | 99,49 (0,28) | 99,02 (0,44) | 99,94 (0,06) | 98,51 (0,67) |
| ResNet 50d          | 99,58 (0,19) | 99,47 (0,23) | 99,64 (0,36) | 99,31 (0,7)  | 99,72 (0,12) | 99,39 (0,28) | 99,99 (0,02) | 99,07 (0,43) |
| ResNets 50          | 99,43 (0,18) | 98,75 (0,62) | 99,79 (0,13) | 99,59 (0,25) | 99,34 (0,33) | 99,17 (0,26) | 99,98 (0,02) | 98,73 (0,4)  |

The rest of this section presents the results of the transformer models for MCD diagnosis. Recently, transformer models have been introduced and have been successfully used in various imaging applications, including medical imaging. In this work, the most recent transformer models have been investigated and compared for MCD diagnosis using CMRI images. Transformer models used in this article include Beit [42], Cait [43], Coat [44], Deit [45], Pit [46], Swin [47], TNT [48], Visformer [49], and ViT [50]. Table (4) shows the results of the transformer models for MCD diagnosis. According to Table (4), Coat and TNT models have achieved successful results in MCD diagnosis from CMRI images.

Table 4. Results (%) obtained using transformer models for diagnosis of MCD with CMRI images.

| Models    | Acc           | Prec          | NPY           | Rec           | Spec          | F1            | AUROC         | Cohen         |
|-----------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Beit      | 75,98 (75,98) | 65,32 (65,32) | 82,23 (82,23) | 65,86 (65,86) | 81,26 (81,26) | 65,09 (65,09) | 82,01 (82,01) | 46,88 (46,88) |
| Cait      | 79,3 (79,3)   | 68,24 (68,24) | 86,02 (86,02) | 74,08 (74,08) | 82,03 (82,03) | 70,89 (70,89) | 87,43 (87,43) | 54,89 (54,89) |
| Coat      | 99,68 (99,68) | 99,55 (99,55) | 99,74 (99,74) | 99,51 (99,51) | 99,77 (99,77) | 99,53 (99,53) | 99,68 (99,68) | 99,28 (99,28) |
| Deit      | 84,68 (84,68) | 83,12 (83,12) | 85,4 (85,4)   | 69,66 (69,66) | 92,53 (92,53) | 75,72 (75,72) | 91,15 (91,15) | 64,66 (64,66) |
| Pit       | 97,41 (97,41) | 95,02 (95,02) | 98,76 (98,76) | 97,67 (97,67) | 97,27 (97,27) | 96,3 (96,3)   | 98,96 (98,96) | 94,31 (94,31) |
| Swin      | 96,9 (96,9)   | 96,27 (96,27) | 97,22 (97,22) | 94,61 (94,61) | 98,1 (98,1)   | 95,43 (95,43) | 98,34 (98,34) | 93,09 (93,09) |
| TNT       | 99,68 (99,68) | 99,47 (99,47) | 99,79 (99,79) | 99,59 (99,59) | 99,72 (99,72) | 99,53 (99,53) | 99,94 (99,94) | 99,28 (99,28) |
| Visformer | 98,23 (98,23) | 96,63 (96,63) | 99,15 (99,15) | 98,37 (98,37) | 98,16 (98,16) | 97,46 (97,46) | 99,43 (99,43) | 96,11 (96,11) |
| ViT       | 75,98 (75,98) | 65,32 (65,32) | 82,23 (82,23) | 65,86 (65,86) | 81,26 (81,26) | 65,09 (65,09) | 82,01 (82,01) | 46,88 (46,88) |

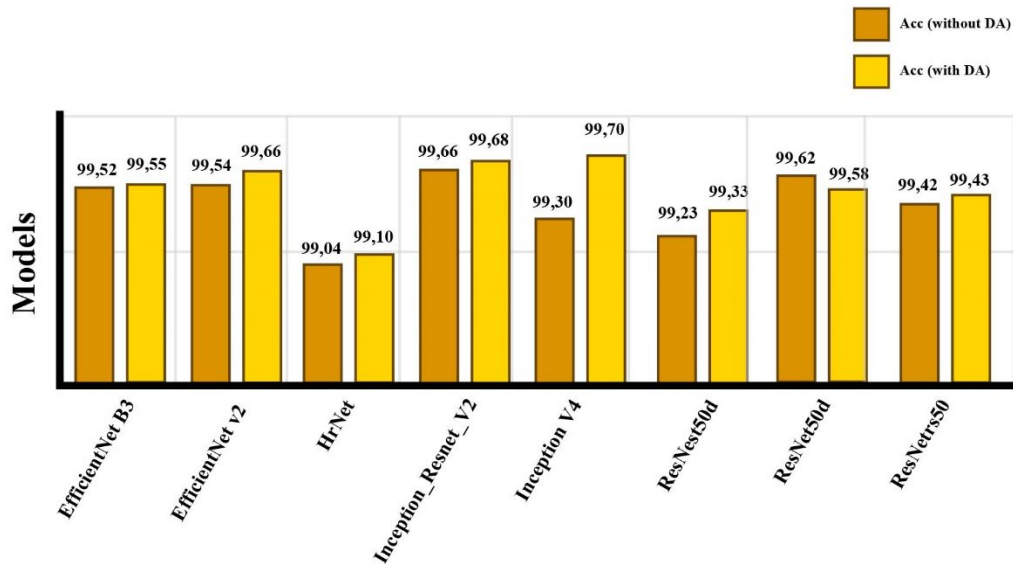


Fig. 7. Accuracy (%) obtained using various pre-trained models.

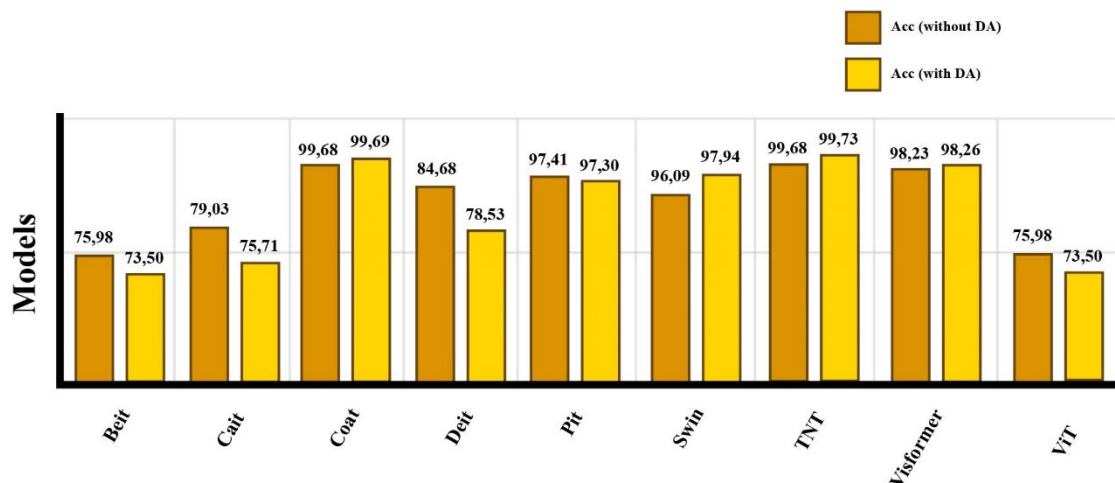


Fig. 8. Accuracy (%) obtained using various transformer models.

Finally, the results(%) of the transformers models trained with the new DA method are provided in Table (5). The proposed DA method helps to improve the results (%) using artificial CMRI images. The composite and original CMRI images are used as the input to the transformer models. Table (5) shows the results of the transformer architecture alongside the proposed DA method. As shown, the DA technique and transformer architecture improved the efficiency of the proposed CADs for MCD diagnosis. Table (5) shows that the TNT architecture achieved superior results compared to other transformers and pre-trained methods. Figure (8) shows the accuracy results obtained for deep transformer models without and the DA method for MCD diagnosis. In addition, Figures (9) and (10) show the ROC curves for transformers with DA.

Table 5. Results of transformer models with new DA for diagnosis of MCD from CMRI images

| Models    | Acc          | Prec          | NPY          | Rec           | Spec         | F1           | AUROC        | Cohen        |
|-----------|--------------|---------------|--------------|---------------|--------------|--------------|--------------|--------------|
| Beit      | 73,5 (2,25)  | 64,3 (6,73)   | 78,33 (2,19) | 55,74 (8,66)  | 82,78 (6,3)  | 58,89 (3,04) | 77,17 (3,37) | 39,63 (2,46) |
| Cait      | 75,71 (3,66) | 69,41 (10,18) | 79,81 (3,57) | 58,02 (12,82) | 84,95 (9,55) | 61,69 (5,98) | 81,48 (4,03) | 44,38 (6,93) |
| Coat      | 99,69 (0,18) | 99,39 (0,61)  | 99,65 (0,27) | 99,32 (0,51)  | 99,68 (0,32) | 99,35 (0,26) | 99,89 (0,09) | 99,02 (0,39) |
| Deit      | 78,53 (0,94) | 70,53 (3,26)  | 82,45 (1,69) | 64,97 (5,32)  | 85,62 (3,22) | 67,43 (2,04) | 85,13 (1,31) | 51,49 (2,13) |
| Pit       | 97,3 (2,13)  | 94,12 (4,84)  | 99,18 (0,9)  | 98,47 (1,65)  | 96,69 (2,78) | 96,21 (2,95) | 99,1 (0,53)  | 94,12 (4,61) |
| Swin      | 97,94 (1,77) | 96,72 (3,25)  | 98,6 (0,97)  | 97,35 (1,81)  | 98,25 (1,77) | 97,03 (2,52) | 99,46 (0,64) | 95,45 (3,88) |
| TNT       | 99,73 (0,17) | 99,19 (0,45)  | 99,89 (0,08) | 99,8 (0,14)   | 99,57 (0,24) | 99,49 (0,25) | 99,94 (0,07) | 99,22 (0,38) |
| Visformer | 98,26 (0,63) | 96,78 (0,69)  | 99,06 (0,7)  | 98,2 (1,35)   | 98,29 (0,36) | 97,48 (0,92) | 99,4 (0,53)  | 96,16 (1,4)  |
| ViT       | 73,5 (2,25)  | 64,3 (6,73)   | 78,33 (2,19) | 55,74 (8,66)  | 82,78 (6,3)  | 58,89 (3,04) | 77,17 (3,37) | 39,63 (2,46) |

## 5. Post Processing using Explainable AI

One of the main drawbacks of machine learning and deep classification models is their black-box nature, which hinders the usage and trust of these models. An approach to tackle this issue is the application of model interpretability techniques [65]. Interpretable machine learning methods extract relevant knowledge from a machine learning model concerning relationships either contained in data or learned by the model [66]. A particular case of interpretability methods is explainability techniques, which provide explanations of individual predictions of a given model [67].

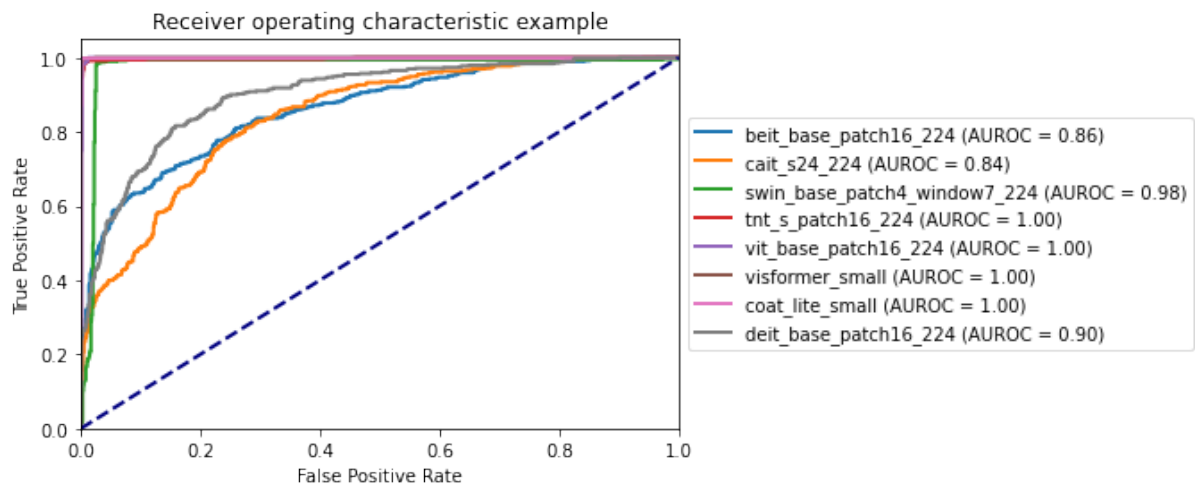


Fig. 9. ROC curves for transformer models in the diagnosis of MCD using CMRI images.

Following the taxonomy [68], we distinguish two kinds of interpretability methods: intrinsic and post hoc. Intrinsic methods refer to machine learning models considered interpretable due to their simple structure, such as short decision trees or sparse linear models. The post hoc interpretability refers to applying interpretation methods after model training. Due to the nature of deep learning models, interpretability methods for deep learning techniques are mainly post hoc methods. In the context of interpretability methods for deep image classification models, we can find several techniques, such as LIME [69], saliency maps [70], or integrated gradient attribution [71].

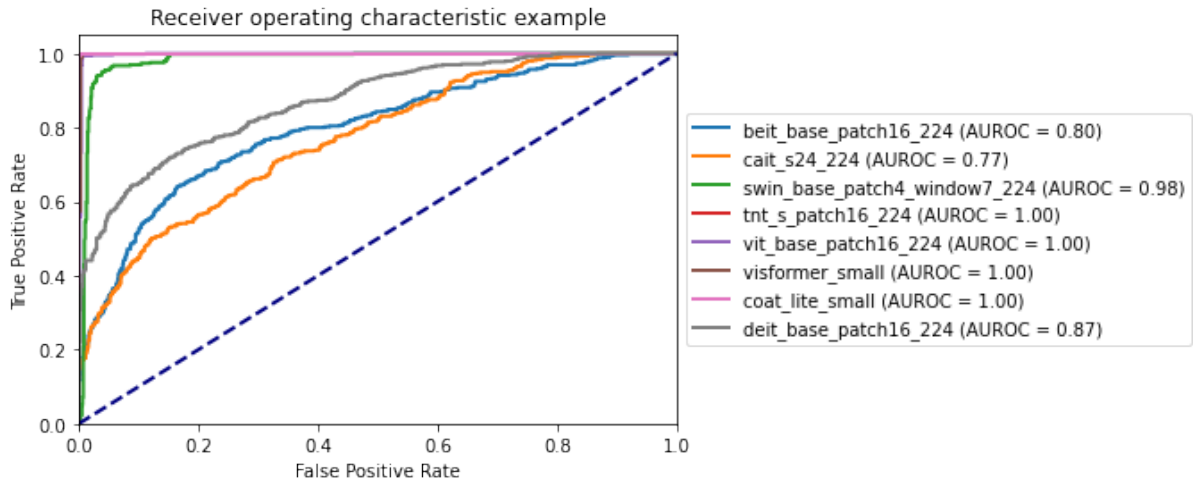


Fig. 10. Roc curves for transformer models trained with new DA techniques in diagnosis of MCD from CMRI images

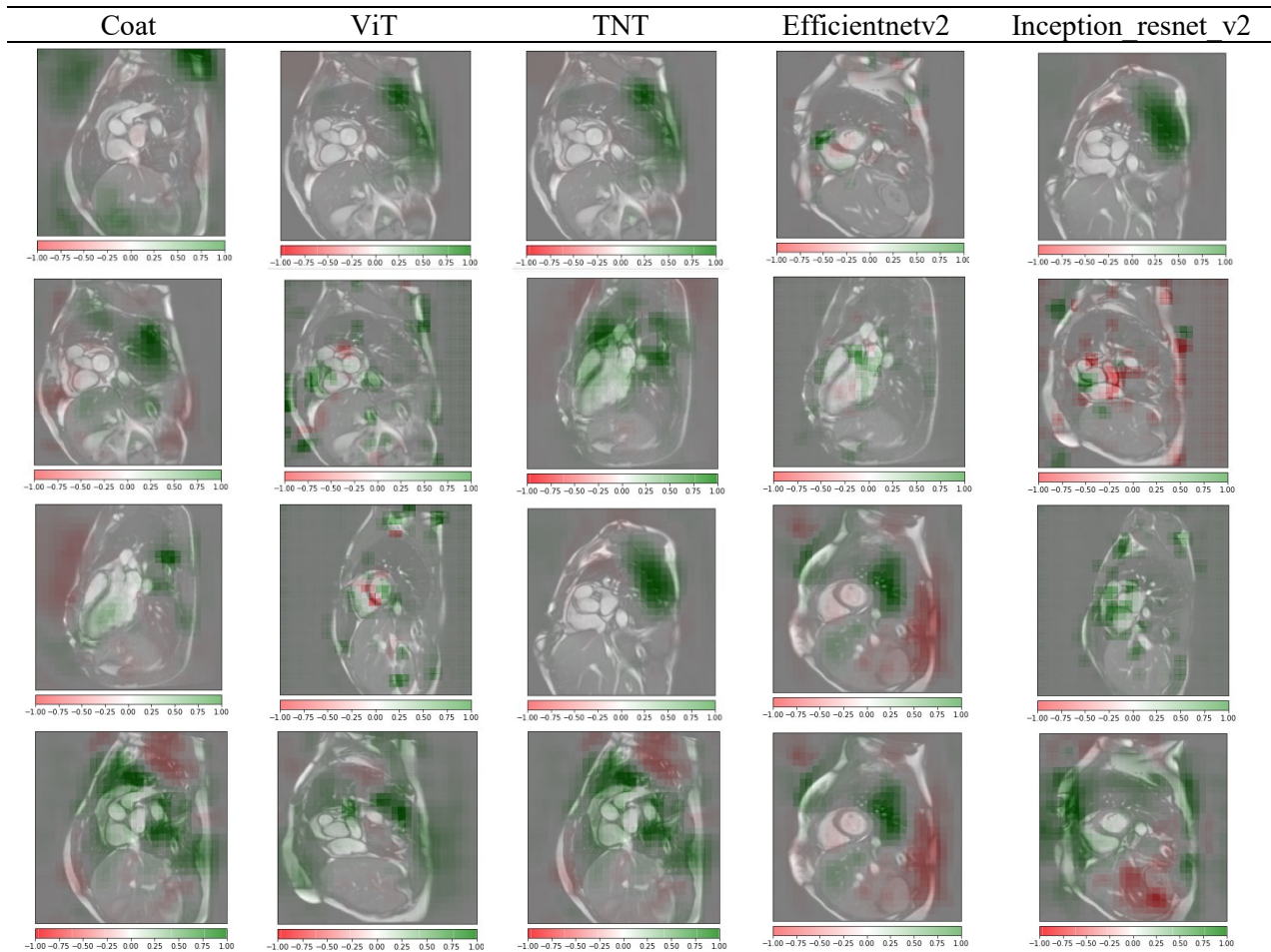


Fig. 11. Plot Grad-Cam for the best transformer and pre-trained models based on the new DA method

Among the available explainability techniques for image classification models, we employed the occlusion-based attribution algorithm [72], supported by the Captum library [73]. Using this algorithm, we estimated areas of the image that are critical for the classifiers' decision by occluding them and quantifying how the decision changed. We run a sliding window of size  $15 \times 15$  with a stride of  $8$  along both image dimensions. At each location, we occluded the image with a baseline value of  $0$ , corresponding to a black patch.

Figure (11) presents grad cam results obtained for the best pre-trained and transformer models for MCD diagnosis. Hence, the grad cam method could successfully identify suspicious regions of MCD on CMRI images. This post-treatment phase helps cardiologists to diagnose MCD in the early stages which is one of the novelties of this article.

## 6. Limitations of Study

All experiments were performed on the Z-Alizadeh dataset, as described in the previous section. The Z-Alizadeh dataset contains 4000 CMRI images of MCD patients and 4100 HC images. Hence, this dataset contains limited CMRI images of MCD and HC. This challenge limits the development of advanced DL models for MCD diagnosis. Another challenge of this dataset is providing CMRI images for MCD diagnosis. Providing multimodal datasets such as X-rays and CMRI may provide more information for MCD diagnosis using DL models. However, the Z-Alizadeh dataset is provided for MCD diagnosis and not for determining disease severity. Therefore, this dataset is unsuitable for the prediction of severity of MCD. The Z-Alizadeh dataset consists of two classes: MCD and HC. In future, a multiclass DL model can be used to diagnose different types of CVDs.

## 7. Discussion, Conclusion, and Future Works

The myocardium is one of the most critical parts of the heart, responsible for contraction, pumping, and supplying blood throughout the body. Damage to myocardial tissue leads to MCD, which causes many complications for patients due to devastating effects on the heart muscle and electrical system [19]. On the other hand, the disease severely reduces the blood pumping ability of the heart, causing arrhythmias. MCD can lead to blood clots in the heart, causing strokes and heart attacks [20-21]. Viral and bacterial infections, heart surgery, rheumatic fever, and some drugs or toxins [19-22] play an important role in people with MCD.

To date, medical professionals have introduced several screening methods for CVD diagnosis [22-28]. CMRI images provide important information regarding heart tissue, which physicians use for CVD diagnosis in the early steps [29]. Along with the advantages of CMR imaging, it also presents challenges for medical professionals. For example, MCD diagnosis mandates high-slice CMRI images [29-31]. Analyzing high-slice CMRI images can be time-consuming for specialists [31]. In such cases, factors such as eyestrain can lead to misdiagnosis of MCD by medical doctors. For this purpose, several investigations have been performed to diagnose CVDs, such as MCD, using DL techniques [16-19]. This article proposes a new DL-based CADs for MCD diagnosis from CMRI images. The proposed method includes acquisition of dataset, preprocessing, feature extraction and classification using DL models, and finally, post-processing. The Z-Alizadeh Sani myocarditis dataset was used in this work. In the preprocessing step, denoising, resizing, and DA was employed to generate an artificial CMRI images. In the third step, the latest pre-trained and transformers models were investigated and experimented for feature extraction and classification of CMRI images. Simulation results showed that combining the TNT architecture with the proposed DA method help to achieve the highest performance. The explainability-based grad cam method was also used in the post-processing step to indicate MCD suspicious regions in CMRI images. This section implemented the grad cam method on pre-trained and transformer models. Table (6) compares the results of the proposed method with various research works done on automated CVD detection.

Table 6. Comparison of the proposed method with related works.

| Ref  | Application                               | Dataset                                  | Preprocessing   | DNN     | Performance (%)     |
|------|---|--|-----------------|---------|---------------------|
| [80] | Myocardial                                | MICCAI 2009                              | ROIs Extraction | CNN     | Acc=86.39<br>Sen=90 |
| [81] | End-Diastole and<br>End-Systole<br>Frames | Free-Breathing CMR<br>Data<br>STACOM2011 | DA              | 2D-CNN  | Acc= 76.5           |
| [82] |   | Clinical                                 | DA              | NF-RCNN | AUC: 0.98           |



|                 |  |   |  |                                |                                      |
|-----------------|--|---|--|--------------------------------|--------------------------------------|
|                 | Heart and right ventricle                          | York University                             |  |                                | recall: 0.96                         |
| [83]            | Detection  | Shenzhen Maternal and Child Health Hospital | ROI detection  | 2D-CNN                         | Acc=94.84<br>Sen=92.73<br>Spec=94.27 |
| [84]            | Classification of MYO Delayed Enhancement Patterns | Clinical                                    | --   | GoogLeNet, AlexNet, ResNet-152 | Acc=79.5                             |
| [85]            | Classification and Prediction                      | Clinical                                    | --   | deeplabV3<br>InceptionResnetV2 | Different Results                    |
| [86]            | Cardiac view                                       | Clinical                                    | --   | Autoencoder                    | Acc: 96.7                            |
| [87]            | LV   | Clinical                                    | ROI extraction   | AE                             | Acc=:97.5<br>Sens:84.2<br>Spec:98.6  |
| [88]            | MYO  | Clinical                                    | --   | CNNEC                          | Acc: 95.3                            |
| [89]            | Cardiac Contraction                                | UK Biobank                                  | --   | cGAN                           | DM: 0.89                             |
| [90]            | Myocardial   | MICCAI 2020 EMIDEC                          | Different Methods  | U-Net                          | --                                   |
| [91]            | Myocardial   | Clinical                                    | Standard Preprocessing   | 2D-CNN                         | Acc= 96.70                           |
| [92]            | Myocardial   | MICCAI 2020 EMIDEC                          | Normalization, Resampling, Segmentation, Applying Three-order Spline Interpolation | 2D U-Net                       | Acc= 92.00                           |
| [93]            | Myocardial   | Clinical                                    | Resampling, Cropping, CLAHE, LV Localization, Filtering Methods                    | ResNet-56                      | --                                   |
| [94]            | Myocardial   | Clinical                                    | Standard Preprocessing   | GoogLeNet, AlexNet, ResNet-152 | Acc= 79.50                           |
| [19]            | Myocarditis  | Z-Alizadeh Sani myocarditis dataset         | Standard Preprocessing   | CNN-KCN                        | Acc= 97.41                           |
| [20]            | Myocarditis  | Z-Alizadeh Sani myocarditis dataset         | Standard Preprocessing   | RLMD-PA                        | Different Results                    |
| [31]            | Myocarditis  | Z-Alizadeh Sani myocarditis dataset         | Filtering, Image Resize, Cycle GAN   | EfficientNet V2                | Acc= 99.33                           |
| Proposed Method | Myocarditis  | Z-Alizadeh Sani myocarditis dataset         | Filtering, Image Resize, New DA method   | TNT transformer Model          | Acc = 99.71                          |

Table (6) shows that the proposed method achieved superior results compared to related works. In the future, the method proposed in this article can be used as an MCD diagnostic software in healthcare centers and specialized clinics. Also, the proposed CADs will be available for use in CVD surgical centers. Of note, adding some advanced DL architectures for the proposed CADs in this paper is vital. In future, we intend to validate our model with a huge CMRI dataset obtained from more subjects for MCD diagnosis. Moreover, the new DA model, including simple copy and paste of CMRI data, may be used in MCD diagnosis in our future works. Also, new DL models, such as graph CNNs [77-78] and compact size CNNs [79], can be used to improve the performance of CADs for MCD diagnosis with CMRI images.

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