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Deep Learning-Based Detection of Cardiovascular Defect Patients

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Abstract. Globally, cardiovascular diseases (CVDs) have surpassed all others as a major killer in the last few years. The symptoms of CVDs are often mild at first, but they might worsen with time. Upon beginning CVD, most people encounter a number of symptoms, including fatigue, difficulty breathing, edema in the ankles, and fluid retention. The majority of cases of CVD include arrhythmia, cardiomyopathy, mitral regurgitation, angina, and congenital heart defects (CHDs). The use of cardiac magnetic resonance imaging (CMR) for diagnosis, disease monitoring, treatment planning, and CVD prediction is on the rise among diagnostic modalities. Despite the many benefits of CMR data, doctors still have difficulties diagnosing CVDs owing to factors like poor contrast, many data slices, etc. A lot of research is being done right now to solve these problems by using enhanced deep learning (DL) techniques for the CVDs diagnosis utilizing CMR data. The research employed the Convolution Neural Network (CNN) algorithm in conjunction with MultiLayer Perceptron to further demonstrate the algorithm's efficacy. It is compared against many alternative DL techniques.

Keywords: CVD, Diagnosis, CMR, DL, Classification.

1 Introduction

Automated object recognition from diverse datasets and image segmentation has both been demonstrated to benefit greatly from DL, a branch of machine learning. Compared to conventional reporting measures, its use in cardiac imaging improves diagnostic accuracy [1]. The feature selection problem may be rapidly resolved by means of the conditional mutual information feature selection algorithm. To improve the classification accuracy as well as decrease the classification system's execution time, feature selection methods are used [2]. To test the idea that DL and machine learning (ML) could help find patients at higher risk, a Deep Neural Network (DNN) was used to forecast who would die in the hospital after having a spontaneous coronary artery dissection (SCAD) [3]. This research uses healthcare sensors and the UCI Repository dataset to make a real outline for detecting the public's heart disease (HD) risk. For the purpose of detecting, classification HD algorithms are also active to classify patient data [4]. Additionally, the literature on artificial intelligence (AI) as well as machine learning (ML) in cardiovascular care is reviewed and positioned within the framework of the possible clinical use of these methods [5]. The resolution of this research was to validate the findings on a large sample of people and determine the optimal structure of an Artificial Neural Network (ANN) and heart rate variability (HRV) parameters for non-invasively identifying patients with ischemic heart disease (IHD) [6]. Patients remained characterized as having a non-significant or considerable stenosis created on characteristics retrieved from these encodings [7].

The primary research objective was to determine which ML classifiers performed best for this kind of diagnostic task in terms of accuracy. Performance and accuracy in HD prediction were evaluated by means of many supervised machine-learning algorithms [8]. At the time of the first patient assessment, a 12-lead electrocardiogram is easily accessible; nevertheless, the accuracy of the methods based on rules is inadequate. This article details approaches that use machine learning to identify patients experiencing chest discomfort and potentially diagnose acute myocardial ischemia [9].

Despite the fact that several algorithms have been for CVD classification in the past, there are still problems with automated methods, and their accuracy is low. An enhanced DL algorithm is proposed to identify these problems in this study.

- This study used a CNN as well as multilayer perceptron (MLP) algorithm based on DL. To extract more

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comprehensive characteristics for all images, the proposed methodology uses a pre-trained CNN model also well-known as a feature generator to remove the features from the creative image.

- This research suggests a MLP classifier a deep classifier that uses the Adagrad optimizer to categorize the images.
- High classification accuracy is achieved by the proposed CNN-MLP model, according to the experimental data.

The rest of this work is planned as surveys. Section II provides an outline of some current and recent works. The proposed technique is defined in Section III. After a summary of the findings as well as analysis in Section IV, the references are provided.

2 Recent Works for Research

This part, took a look back at some of the more recent articles written on DL techniques. Table 1 summarizes the proposed DL techniques for classification development and lists their advantages and disadvantages, so it will help to find all the information you need there.

Table 1. Literature review

Paper and Author	Method	Advantages	Limitation
Chen et al. [10]	Adaptive image-based classification	Accurate prediction	framework database should be updated with more descriptions of patients
Upton et al. [11]	Artificially intelligent	Automate strain echocardiography analysis as well as care clinician interpretation	-
Slart et al. [12]	Coronary computed tomography angiography	Improved diagnostic performance and wide implementation	Guidelines must be developed to standardize broad applications
Aggarwal et al. [13]	ANN and SVM	Diabetic prediction	Low-cost real-time prognostic system
Kumar et al. [14]	AI	Diversity of patient care as well as smart health systems	keeping the flaw mentioned earlier in consideration
Mathur et al. [15]	AI	Few applications in cardiovascular imaging, cardiovascular risk prediction, and newer drug targets	Generating correlations and do not establish causal relationships
Oikonomou et al. [16]	computed tomography	ML-based radiomic approaches can improve clinical care	There is no scientific consensus statement

Table 1 details several novel techniques. Present methods include a plethora of proposed techniques, including AI, ANN, support vector machines (SVM), computed tomography, and many more. These technologies provide an advantage, including better clinical treatment, improved diabetic diagnosis, and improved prediction in general. Nevertheless, other downsides, such as the inexpensive real-time prognostic system, are also brought up.

Chen et al. [10], creates a pooled area curve (PUC) using the ML technique for CAD prediction in the proposed algorithm. Proper prediction relies on this knowledge-based identification. Even if the pixels around it are faint, this method has a strong influence on determining variance in medical imaging. By using the occlusion and plaque of blood vessels, this pooled area creation in the ML algorithm is securing the dwindling veins as well as tissues.

Upton et al. [11] discuss the stress echocardiograms taken in a large prospective, multicenter, multivendor research project in the UK were processed using an automatic image processing pipeline that extracted geometric along with kinematic features.

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The retrieved features were used to create a machine learning classifier that can find patients with significant coronary artery disease on invasive coronary angiography. A separate study in the United States validated the model.

Slart et al. [12], implement the European Association of Nuclear Medicine (EANM) as well as European Association of Cardiovascular Imaging (EACVI) have collaborated on a position paper to discuss the current state of machine learning in cardiovascular imaging by means of nuclear cardiology (hybrid) as well as CT techniques. It give a general concepts behind ML, highlight the systems, follows along with computational models that are preferred, as well as propose novel plans to take care of the ML clinical application.

Aggarwal et al. [13] shows that nonlinear HRV characteristics may be used in diabetes prediction by means of ANN along with SVM. Both normal (n = 5) also Streptozotocin-induced diabetic (n = 5), male Wister rats with a weight of 200 ± 20 gm along with an age of 10–12 weeks remained to capture the digital lead-I electrocardiogram (ECG).

Kumar et al. [14] discusses a thorough survey using AI methods to detect a variety of ailments, including Alzheimer's disease, diabetes, cancer, stroke, chronic HD, TB, hypertension, cerebrovascular disease, skin disease as well as liver disease. An exhaustive analysis that takes into account the medical imaging dataset, feature extraction method, along with classification approach utilized for prediction.

Mathur et al. [15], detail the cardiovascular imaging, risk prediction, and the identification of novel therapeutic targets are three areas where AI-based systems have made significant strides in the field of cardiovascular medicine. This article's goal is to provide a description of several AI applications, such as DL and machine learning, as well as how they are being recycled in the arena of cardiovascular medicine. Applications powered by AI have improved our knowledge of various phenotypes of congenital HD and heart failure. Newer methods of treating various cardiovascular disorders, a fresh perspective on cardiovascular medication therapy, and postmarketing surveys of prescription pharmaceuticals have all resulted from these uses.

Oikonomou et al. [16] use cardiac CT to show how radiomic techniques based on ML could help improve patient care and non-invasive cardiovascular imaging in AI. When you combine radiomic, machine learning, and DL methods with tissue imaging phenotyping along with tissue biology, you can make significant therapeutic connections. Focusing on cardiac imaging and CT, talk about the present evidence, strengths, limits, along with potential future directions of AI in these fields, drawing on examples from other fields if necessary.

3 Proposed Methodology

3.1 Datasets

In DL-based CVD diagnosis, datasets are crucial. So far, researchers have had access to many datasets that may be used for CVD diagnosis. The presentation of CVD detection using Left Ventricle Segmentation Challenge (LVSC) datasets is made in this part. To aid researchers, MICCAI 2011 made the LVSC dataset freely accessible. About 200 cardiac magnetic resonance images (CMRs) from various institutions' CAD and myocardial infarction patients are part of the LVSC dataset. Cine images of short-axis steady-state free precession (SSFP) make up the main sequences. There are a limited number of patients for whom long-axis SSFP cine images are offered. Scanners and imaging characteristics come in a wide range, with a wide range of spatial resolutions (0.7–2.1 mm/pixel) and matrix sizes (156–192–512, to name a few).

It is possible to classify LVSC datasets into two categories. In the first set, there will be one hundred training and testing examples with annotations. For validation purposes, the second set includes 100 samples that have not been annotated [17].

3.2 Preprocessing

The input dataset is given for preprocessing. Among the many important processes in CADS for cardiac disease diagnosis utilizing CMR images, preprocessing stands out. Using CMR images, doctors may learn crucial details about the heart's anatomy, which speeds up the diagnosis of CVDs. Various artifacts impact CMR data, notwithstanding its usefulness. Furthermore, poor contrast is sometimes seen in CMR images. As a result, expert doctors may diagnose CVDs incorrectly based on CMR images. There are a number of preprocessing strategies that aim to improve the presentation of DL-based CADS for CVD detection by addressing these concerns. In DL-based CADS, low-level and high-level processes are often used for the pre-processing of CMR images.

The main CMR images preprocessing is done using low-level techniques. Improving CADS performance in CVD detection is greatly aided by low-level preprocessing. Reduced input data severely degrades the performance of high-level preprocessing DL models. Researchers utilize data augmentation (DA) methods to expand the size of the training dataset to solve the paucity of input data and prevent overfitting. Studies for the detection of CVDs have examined many prominent DA approaches, such as horizontal flipping and affine transformation rotation [17]. Figure 1 demonstrations the architecture of CVD data as well as AI algorithm. The CNN network architecture consisted of blocks. The proposed DL-based algorithm was established using an ensemble technique linking the MLP along with CNN algorithms, for which the input is the dataset along with output is a classified.

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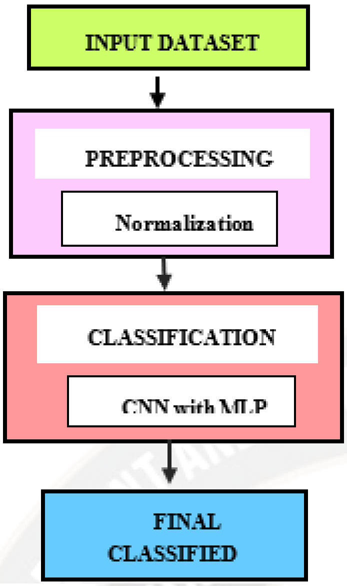

Fig 1. Architecture for CVD data and AI algorithm

3.3 Classification

The classification gets input from preprocessing. CNNs are built up of successive layers. In order to get the output map, the input map is passed through those layers. A quick overview of the layers is provided in the following subsections to illustrate the calculation formula. Let $X \in R^{h \times w \times c}$ be an RGB image where h stands for height, w stands for width, as well as c stands for the channel. Every layer receives X along with a set of parameters W as input as well as produces an original image $Y \in R^{\acute{h} \times \acute{w} \times \acute{c}}$,i.e.,$Y = f(X, W)$.

To begin, a Convolutional Layer (CL) serves as the primary CNN layer. As a parameter of this layer, learnable filters allow the user to slide a pre-defined width and height filter across the whole input volume. So, for any given spatial region, an activation map is generated, showing how that filter reacts. Eq. (1) is used to calculate the convolution of the input X with a set of filters $W \in R^{\bar{h} x \bar{w} \times \bar{c} \times \acute{c}}$, together with a bias $\in R^{\acute{c}}$.

$$Y_{ij\acute{k}} = f\left(b_{\acute{k}} + \sum_{i=1}^{\bar{h}} \sum_{j=1}^{\bar{w}} \sum_{d=1}^{c} W_{ijd\acute{k}} \times X_{\acute{\iota}+\iota,\acute{j}+j,d}\right) \quad (1)$$

Second, by decreasing the size of the impute form, the max-pooling layer reduces the parameters as well as computation inside the network. The max-pooling layer generates its output by maximizing activation across shaped regions with dimensions (h, w). The subsampling procedure employs a $\tilde{h} \times \tilde{w}$ sub window to determine the maximum response of every picture channel Below, this may be expressed as Eq. (2).

$$Y_{\acute{\iota}\acute{j}k} = max_{1<i<\tilde{h},1<j<\tilde{w}} X_{\acute{\iota}+\iota,\acute{j}+j,k} \quad (2)$$

Lastly, a collection of layers known as fully connected layers (FCL) combine the data retrieved by earlier layers. After these layers analyze input X, the final FCL produces a one-dimensional vector with a size equal to the amount of classes.

3.3.1 MLP Classification

By including the Adagrad optimizer and a new dropout layer into our proposed improved MLP, we aim to capitalize on the benefits of MLP. Given a set of i features and k classes, it will work. In the first layer, all of the image features F_i are normalized. This normalization is a major step toward guaranteeing a uniform distribution of incoming data. The first step is to get the average of features with a size of M.

$$\mu = \frac{1}{M} \sum_{i=0}^{M} F_i \quad (3)$$

Then, variance is obtained.

$$\sigma^2 = \frac{1}{M} \sum_{i=0}^{M} (F_i - \mu)^2 \quad (4)$$

Finally, $F_i$to F_I^1 is normalized along with a very small number ϵ is added to prevent the chance of a divide by zero error.

$$F_i^1 = \frac{F_i - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (5)$$

Because of this, the convergence time during network training may be reduced. The sigmoid activation function is used to map the results of each node in the second layer between 0 and 1. This layer's output is determined by plugging F_i^1 into the subsequent equation and scales it from 0 to 1 in F_i^2.

$$F_i^2 = \frac{1}{1 + e^{-F_i^1}} \quad (6)$$

The third layer follows the authors' recommendation and uses the dropout layer. To decrease model overfitting, a regularization approach called dropout is used to stop shared modifications to the training data. Next, we'll utilize the softMax function, which receives a real-valued vector of V as input along with converts it to a distribution of V probabilities that are proportional to the exponential of the input number. The last step in gradient-based optimization is the Adagrad algorithm. During training, the primary objective is to adjust the model's learning rate according to the frequency of parameter updates [18]. Thus, the classification is done and the efficiency of the proposed technique is stated in the results section.

4 Results

The proposed method experimental results are executed in Python environment. The parameters including accuracy along with loss are used to measure the efficiency of the proposed method. The existing algorithm which are employed for comparison includes the fully convolutional network (FCN), U-Net and SegNet.

4.1 FCN

The FCN that Long et al. first proposed may be where a semantic segmentation network got its start. Using CL instead of VGG16's fully connected ones, it accomplishes pixel-level classification while preserving the feature map's spatial information. In the end, FCN restores the image using deconvolution as well as fusing feature maps, and it gives the segmentation result for each pixel using softmax.

4.2 U-Net

To build the encoder-decoder assembly in semantic segmentation, U-Net uses the principle of FCN deconvolution to recover image size along with features. By continually merging the layers to extract feature data, the encoder progressively lowers the spatial dimension. The decoder component, using this feature information, gradually reestablishes the desired detail along with spatial dimension. Downsampling refers to the encoder's step in progressively decreasing the image size, whereas upsampling describes the decoder's step in progressively lowering the image features and size. To separate the feature maps before upsampling the encoder and downsampling the decoder, the U-Net upsampling method employs the concatenate operation. Once the feature map has been concatenated, it is deconvolved. In order to maximize the use of the downsampling encoder's characteristics for upsampling, U-Net utilizes the skip connection splicing approach. This approach uses this method to shallow feature data of every sizes to complete an improved reduction impact and a more refined reduction.

4.3 SegNet

A deep semantic segmentation network developed by Cambridge University using the encoder-decoder architecture, SegNet , aims to address problems in intelligent robotics and autonomous driving. There are thirteen CL in SegNet's decoder and encoder. The encoder's CL is analogous to VGG16's first thirteen CL. Unpooling is used by the decoder's upsampling section. SegNet saves the element positions from the maximum pooling operation during encoder downsampling and uses them to recreate the image during decoder sampling. SegNet upsampling using this method doesn't need learning, and training SegNet is quicker and more accurate than FCN. We evaluated many popular DL networks, such as FCN, Unet, SegNet, and MCNN, for hippocampal segmentation. In addition, the dice coefficient is used as a metric. High accuracy in hippocampus segmentation is achieved using MCNN. Meanwhile, we found that Unet has a far smaller impact compared to SegNet [20].

4.4 Analysis

The accuracy and loss comparison are tabulated in table 2 and is picturized in figure 2.

Table 2. Comparison methods of accuracy and loss

Methods	Accuracy	Loss
FCN	96.22	0.1995
Unet	98.60	0.0906
SegNet	99.02	0.0714
MCNN	99.31	0.0542

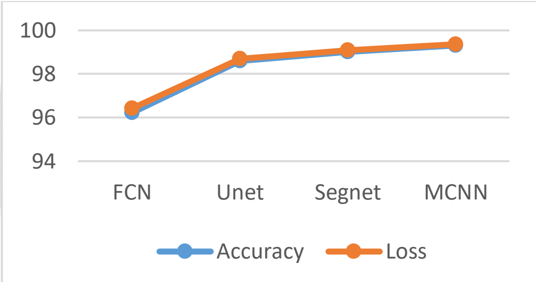

Fig 2. Accuracy and Loss Comparison Graph

From the table and graph it is evident that the proposed algorithm shows better results than the existing methods. Compared to other models like FCN, Unet, SegNet and MCNN, the proposed model seems to perform better across all parameters. On the LVSC dataset, the proposed model has an accuracy of about 99%. With a performance gap of 3.09%, this model beats FCN, 0.71% Unet, 0.29% Segnet. Simultaneously the proposed model has a loss of about 0.0542%. With a performance gap of 0.14%, this model beats FCN, 0.03% Unet, 0.017% Segnet. Additionally, Figures 2 show the comparison graph for these models.

5 Conclusion

A CNN-MLP model, a successful DNN, suggests very high-resolution (VHR) image scene categorization using image characteristics. The proposed model makes use of an improved MLP based on the Adagrad optimizer to boost classification accuracy. It plays a role in the stage of categorization. The proposed approach employs data augmentation methods to rise the number of pictures in each class. It then uses a pre-trained CNN model to extract features from the images. To classify the features, it uses improved MLP. Using the LVSC datasets, an assessment of the CNN-MLP model is carried out. The results demonstrate that the model achieves high classification accuracy of 99.31%, respectively. To further enhance accuracy, future research should look at more advanced ways for modifying the MLP layers.

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