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Lesion-Based Detection of Cardiovascular Diseases Using Deep Learning and Red Deer Optimization

Ajeet singh [1] Dr. Hariom Sharan [2] Dr. C S Raghuvanshi [3]
[1] Dept of Computer Science and Engineering,
FET, Rama University
Kanpur, UP, India ;
ajeetsingh252@gmail.com
[2] Dept of Computer Science and Engineering,
FET, Rama University,
Kanpur, UP, India ;
drsharan.hariom@gmail.com
[3] Dept of Computer Science and Engineering,
FET, Rama University,
Kanpur, UP, India ;
drcsraghuvanshi@gmail.com

Abstract—Nowadays, cardiovascular disease is a very concerning health issue in human life. Medical imaging through MRI plays an important role in the detection of many diseases. Magnetic resonance imaging (MRI) is a non-invasive and sophisticated diagnostic tool for cardiovascular disease (CVD) that allows for full visualization of the heart and blood vessels. Through Magnetic resonance imaging, we get high-quality images of blood vessels, which helps in detecting various types of heart-related diseases. With the help of MRI, we can detect various types of heart-related diseases. It also gives us information about their early diagnosis and their preventive measures. Deep learning and its advanced features are proving to be very helpful in this work. Deep learning has brought many new changes in this field. The article presents the Red Deer Optimizer with Deep Learning (ACVD-RDODL) algorithm for automated cardiovascular disease identification using magnetic resonance imaging (MRI). The primary goal of the proposed approach is to use Deep Learning models on cardiac MRI to detect Cardiovascular issues. The dynamic histogram equalisation (DHE) based noise removal model is used in the given approach to pre-process the images. Additionally, the Attention Based Convolutional Gated Recurrent Unit Network (ACGRU) model is used in this approach to classify Cardiovascular disease
Keywords: Cardiovascular diseases; Magnetic resonance imaging; Red deer optimizer; Deep learning

1. INTRODUCTION

Heart disorders (CVDs) are a major global health concern that account for a significant percentage of deaths worldwide. Early and accurate diagnosis of CVDs is crucial for efficient treatment and therapy since efficient prevention has the potential to significantly improve patient outcomes and lower death rates [1]. Current image analysis methods rely on basic metrics of heart function and structure in addition to qualitative graphic evaluation of images. MRI images play an important role in the detection and analysis of cardiovascular disease in any patient [2]. Heart related diseases cause more deaths across the world than any other disease [3].

Diagnostic techniques such as echocardiography, stress testing, cardiac MRI, and coronary angiography offer important insights into the anatomy, physiology, and electrical activity of the heart. These insights enable medical practitioners to evaluate patients' cardiovascular health, spot irregularities, and establish precise diagnoses [4]. The use of Artificial Intelligence tools has now provided great help and accuracy in prediction of medical images [5]. Methods used in Machine Learning (ML) are designed to perform image-based analysis using systems that learn from prior clinical cases by identifying challenging and undiscovered imaging patterns [6]. The examination and evaluation of numerous clinical data, such as medical history, medical examination, test results, radiology investigations, and cardiovascular diagnostic procedures like electrocardiograms (ECG), are necessary for the identification of cardiovascular illness. Echocardiography stress tests, cardiac MRI, and coronary angiography. These diagnostic methods provide valuable information about the structure, function, and electrical activity of the heart, allowing healthcare professionals to assess cardiovascular health, identify abnormalities, and make accurate diagnoses.

In present article, we emphasized to develop of an Automated Cardiovascular disease detection using Red Deer Optimizer with Deep Learning technique on Magnetic radio images. The dynamic histogram equalization (DHE) model and Weiner

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filtering (WF) based noise removal are utilised in the ACVD-RDODL technique for picture pre-processing. For the categorization of CVD, we additionally employ the Attention Based Convolutional Gated Recurrent Unit Network (ACGRU) model.

2. RELATED WORKS

CardioXNet is a novel lightweight endwise CRNN framework that was first presented through research by Shuvo, S.B. et. al [7]. The coupling of two learning stages, such as sequence residual learning and representation learning, automates this process. First, 2D-CNN-based squeeze expansion has been used to employ three parallel CNN paths. Second, the network effectively eliminated temporal features without doing any feature extraction because of the Bi-LSTM and the skip connection [10]. A network specifically designed to partition images using the efficient RAU-Net approach was proposed in [11]. Enhancing the loss function increases the system's sensitivity and specificity. Because of its ability to handle sequential data, RNNs have proven useful in identifying temporal connections in ECG signals. Popular RNN variations used in ECG analysis include Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)[9,12]. A cardiopathy diagnosis network (CDN) is used to carry out the cardiopathy detection. A DL-based model was created by Khan et al. [13]. In order to identify diseases, the designed system integrates DL-based CNN with Cardi-Net, a power spectrogram, to eliminate deep selected aspects of the PCG signal [14].

3. THE PROPOSED MODEL

in this paper, we used the red deer algorithm with deep learning methods on MRI images to provide effective functionality in CVD detection. Fig 1 shows workflow of the Red Deer Algorithm in Deep Learning.

3.1 Image Processing and Feature Extraction

The DHE and Wiener filtering (WF) for noise removal is used in pair to improve the quality of images and their contrast level. Dynamic histogram equalization (DHE) is mainly used to increase contrast and make key structures easier to see in Magnetic Radio images. Instead of measuring every modality independently, radiomics analysis can be applied to medical images from various modalities, enabling a comprehensive cross-modality examine using the potential additive value of imaging information extracted, for example, from CT, PET, and magnetic resonance imaging (MRI).

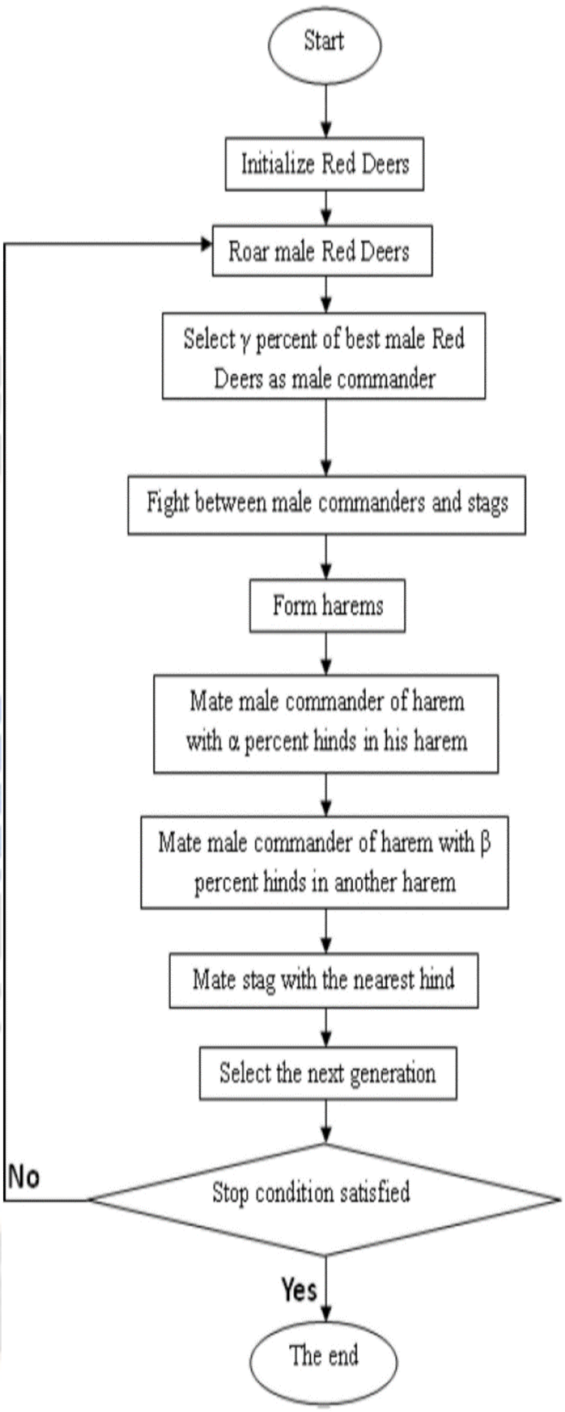

Fig1. Working of Red Deer Algorithm using Deep Learning.

Radiomics measures features and subtle patterns in cardiac MRI scans, enabling medical professionals to examine the function and anatomy of the heart in more detail. The heart and associated structures are precisely delineated using this technique, after which a wide range of features are computed, such as texture evaluation, higher-order metrics, and contour descriptors.

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3.2 Image Classification

In this paper we use the GRU model for image classification. An unique variety of LSTM is GRU [15]. Compared to LSTM, GRU has the advantages of a shorter training period and fewer parameters. Major aspects of the GRU gate function are retained, and it may record temporal information with long-term dependencies.

. The specific parameter in the GRU structure is shown below:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (1)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (2)$$

$$\tilde{h}_t = \tanh\,(W_h x_t + U_h (h_{t-1} \odot r_t) + b_n) \quad (3)$$

$$h_t = (1 -) \odot h_{t-1} +_{-t} - \odot \tilde{h}_t \quad (4)$$

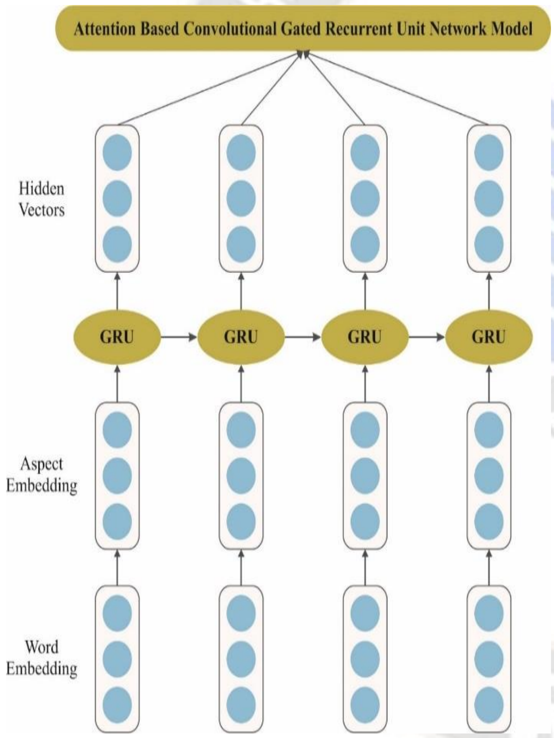

Fig. 2. Structure of ACGRU

Here, x_t and h represent the input and output of the GRU unit, respectively; Z_t and r_t represent the output of the update and reset gates, respectively; σ indicates the activation function; W and b, respectively, represent the weights and bias acquired through training; element-wise multiplication signifies ⊙.

Similar to a long short-term memory (LSTM) with a gating mechanism to input or forget specific features, the GRU has fewer parameters than an LSTM because it does not include an output gate or context vector.

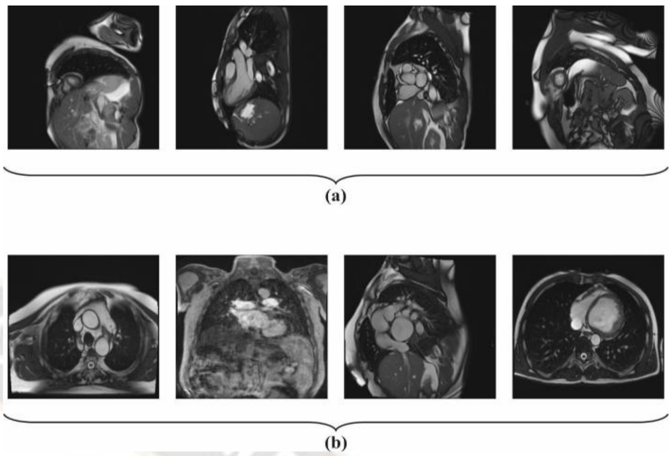

Fig. 3. (a) Normal Images b) Sick Images

It was discovered that GRU performed comparably to LSTM on a few tasks related to polyphonic sound modelling, speech signal modelling, and processing natural language. The convolution layer, recurrent unit, and attention mechanism strengths are combined in the Attention Based Convolutional Gated Recurrent Unit, an advanced neural network architecture.

4. RESULT OF PROPOSED MODEL

This portion of paper uses the cardiac MRI database from the Kaggle .com [16] to analyse the CVD detection result of the CVD-Red Deer Algorithm technique [17]. There are two classes in the dataset: normal and sick. The Python 3.10.5 tool is used to mimic the CVD-Red Deer Algorithm technique. The sample of healthy and sick photos is shown in Fig. 3 which is used as dataset in the performance evaluation of the method.

Table 1 Accuracy outcome of proposed system with other models

Methods	$Accu_y$ (%)
HRFLM Model	88.40
DNN Model	86.50
ANN Model	77.00
SVM Model	90.00
LSTM-RNN	93.00
Proposed model	94.00

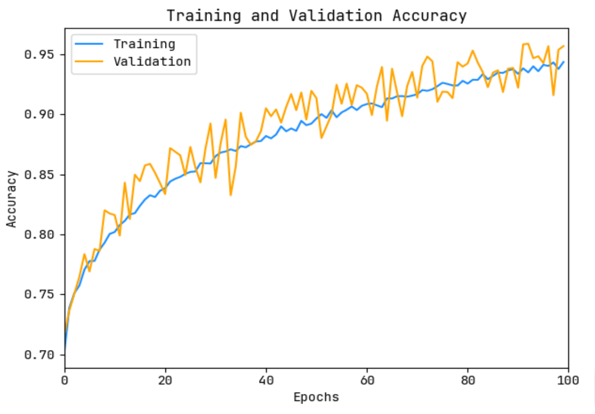

Fig. 4. Accuracy curve of proposed system

The comparison in the different models of processing in shown in Table 1 [22, 24]. In table 1 it clearly shows that the result of the given model using Red Deer optimization is better than the other models like RF, ANN, SVM and LSTM. The performance outcome of HRFLM,DNN and ANN is comparatively poor while the performance outcome of the SVM and LSTM -RNN is slightly better but the proposed model outcome with Red Deer optimization is having the highest outcome.

Fig. 5. Loss curve of ACVD-RDODL algorithm

To determine the efficacy of the proposed system, accuracy curves are constructed for the training phase (TRPH) and testing phase (TSPH), as illustrated in Fig. 4. This curve offers important information about how well the model is learning to generalise. As we increase the number of epochs, we can clearly see an improvement in the accuracy curves for both the TR and TS. This demonstrates the model's ability to accurately identify patterns in the TR and TS data.

A brief explanation of the ACVD-RDODL algorithm and the loss values during training are also shown in Fig. 5. The model progressively increases its weights to minimise the predicted errors on TR and TS data, as seen by the decreasing tendency in TR loss over epoch. This loss curve displays the model's fit to the training set.

5. CONCLUSION

In current paper we have developed a new cardiovascular -RD model based on the magnetic Resonance images. With the help of this proposed model we can automate the detection of cardiovascular disease. The WF-based noise removal and DHE model are utilised for image pre-processing at the proposed approach. Our research demonstrates the potential of integrating the Red Deer Optimizer with deep learning techniques for the automated detection of cardiovascular diseases from Magnetic Resonance Imaging (MRI) data. The results obtained in this study are promising, as they show that our proposed approach can effectively aid in the early and accurate diagnosis of cardiovascular diseases. By harnessing the power of deep learning algorithms and the optimization capabilities of the Red Deer Optimizer, we were able to achieve high accuracy and precision in detecting various cardiovascular conditions, including heart disease, cardiac anomalies, and arterial blockages.

In conclusion, the fusion of Red Deer Optimizer and deep learning on MRI data shows great promise in the field of automated cardiovascular disease detection. As technology continues to advance, our approach has the potential to revolutionize the way we diagnose and manage cardiovascular diseases, ultimately improving patient outcomes and healthcare efficiency.

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