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HD-REGNET: Heart Disease Prediction Using REGNET in Image Processing

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ABSTRACT

Abnormal functionality of the heart due to any cause is known as heart disease. It primarily affects older persons. Every year, almost six out of ten persons diagnosed with heart diseases are above the age of 65. In this paper a novel HD-RegNet have been proposed for heart disease prediction using CXR images. Initial the input CXR images are pre-processed using Adaptive Gaussian Star Filtering. Then the pre-processed images are subjected into RegNet for extracting the features. The best features are selected using Tyrannosaurus optimization Algorithm. Finally the normal and abnormal classes of heart diseases classified utilizing the Deep Neural Network (DNN). The CHD dataset are utilized to evaluate the performance of the developed work interms of performance metrics such as accuracy, recall and precision. The proposed HD-RegNet attains an accuracy rate of 99.53% in the normal class and 99.37% in the abnormal class. It achieves an overall accuracy rate 0.37%, 0.52% and 0.75% compared to the existing methods such as RFRF-ILM [12], LU-Net [17] and CNN & Bi-LSTM [18] respectively.

Keywords: Heart disease, RegNet, Adaptive Gaussian Star Filtering, Deep Neural Network

1 Introduction

One of the most serious and potentially fatal chronic diseases in the world is heart disease. As an individual has heart disease, their heart typically isn't able to pump enough blood to other parts of their body so they can function properly [1]. Coronary artery narrowing and blockage is the cause of heart failure. Coronary arteries govern how much blood the heart receives [2]. A higher risk of heart disease can be caused by a number of variables, including smoking, eating poorly, having high blood pressure and cholesterol, having fitness problems from inactivity, and other reasons. Heart attacks, strokes, and chest pain can all be symptoms of heart disease, with coronary artery disease (CAD) being the most prevalent variety [3]. Other types of heart illness include circulatory issues, congenital heart disease and congestive heart failure. Heart disease is a fatal condition that is becoming more common in both industrialized and developing nations [4]. About 20% of patients with high-risk cardiovascular disease are underdiagnosed as an outcome of risk misclassification. Conventional diagnostic approaches

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rely on the personal experiences and understanding of clinical specialists regarding the ailment; this enhances the risk of errors, postpones necessary treatment, lengthens the duration of therapy, and adds significantly to costs [5]. In order to stop the patient from suffering any further harm, a precise and appropriate diagnosis of heart disease is considered essential. According to earlier research, machine learning techniques seem to have made progress in utilizing various attributes for the purpose of predicting and categorizing patients with heart disease [6]. Recently, studies exploring models for the early identification of heart disease and comparing their accuracy have been published in the literature. These studies involve singular and group machine learning techniques. Hospitals throughout the world have been said to be in need of an intelligent system that develops databases of these patients and can aid the physician in estimating the severity of the condition [7].

The risk of diseases occurring has decreased with the development of smart devices like the Smart Cholesterol Monitoring System and the Continuous Glucose Monitor (CGM). The technologies we use on a daily basis monitor our actions and help with healthcare decision-making [8]. A majority of these developments in health departments, many people still lack awareness of the dangers and signs of chronic illnesses. As a result, the prognosis of these illnesses is currently a serious issue for humanity as a whole as well as for individuals. Long-standing illnesses are the riskiest and most significant health issues of all the diseases that affect humans [9]. The researchers were able to develop new techniques based on Machine Learning (ML) and artificial intelligence thanks to ongoing technological advancements. Big data generation has increased in tandem with the rise in health issues. In order to make usage of this big data, an automatic computer-based system that can be used to predict diseases through the deployment of machine learning algorithms that can effectively handle a variety of challenges that arise in the datasets must be developed [10]. Heart disease (CVD) is determined to be a major risk factor, along with other chronic health issues like obesity, smoking, diabetes, etc. Ageing populations are strongly associated with CVDs, particularly in industrialized nations [11]. The proposed method main contribution is as follows.

- Initial the input CXR images from CHD datasets are pre-processed using Adaptive Gaussian Star Filtering.
- Then the pre-processed images are subjected into RegNet for extracting the features.
- The best features are selected using Tyrannosaurus optimization Algorithm.
- Finally the normal and abnormal classes of heart diseases classified using the Deep Neural Network.

The rest of this work's sections are explained below: Section 2 reviews the research in light of existing literature. Section 3 gives a comprehensive explanation about the proposed system. The conclusion is found in Section 4, whilst the results and discussion are in Section 5.

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2 Literature Review

The detection of heart disease using deep learning techniques has been part of numerous studies in recent years. A quick summary of a few current research papers is given in the section as follows.

In 2020 Chunyan Guo et al [12] suggested method for detecting cardiac illness is the Recursion Enhanced Random Forest with an Improved Linear Model (RFRF-ILM). This work uses ML approaches to identify the salient characteristics of cardiovascular disease prediction. The heart disease prediction model helps it reach a higher degree of accuracy. The random forest and linear model properties are combined using the suggested RFRF-ILM technique. Heart disease is highly accurately predicted by RFRF-ILM.

In 2020 Martin Gjoreski et al [13] suggested that cardiac sounds be used to identify CHF. The method blends end-to-end Deep Learning (DL) with conventional ML. This method examines the variations in cardiac sounds as CHF moves from the decompensated to the decompensated phases. Equipped with a LOSO evaluation to determine the precision with which to discern between the compensated and decompensated phases.

In 2020 Mohamad ayob khan et al [14] suggested wearable extensive uses in the health monitoring system, which has fuelled the Internet of Medical Things' development (IOMT). The use of the developed study is to use ML methods to discover critical features of heart disease prediction. The MSSO-ANFIS prediction approach attains a greater accuracy with precision. In terms of the fitness value contrary to the number of iterations, the performance of the proposed LCSA method for optimal feature selection is compared with that of the current CSA.

In 2021 Tsatsral Amarbayasgalan et al [15] suggested an effective coronary heart disease risk prediction technique using two DNNs that were trained on well-organized training datasets. The opportunity to create more precise prediction models is made possible by the well-run training groups. Comparing methods with high precision and low recall or precision and high recall is challenging, though.

In 2023 Sara Ghorashi et al [16] have suggested employing ML methods to detect the essential characteristics of cardiovascular disease prediction (CVDs). The current study used DL -based regression analysis on a dataset of 2621 medical records from UAE hospitals. The optimal accuracy value for the chest has been shown to be up to 90.6%; when there is a fever, the accuracy drops to 91%. Its drawbacks may reduce its usability and accuracy for specific data sets.

In 2023 Shams Nafisa Al et al [17] suggested LU-Net, a cutting-edge deep encoder-decoder-based denoising architecture, to reduce internal and external lung sound noise. An approach for estimating signal-to-noise ratio (SNR) has been put forth for the evaluation of real-world PCG data that has been tainted by variable, transient distortions from multiple sources. The

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combination of these limited protocol flexibility and data reliance elements makes the current heart sound denoising algorithms an enormous burden for non-homogeneous real-world data.

In 2023 Shrivastava, P.K. et al [18] suggested a hybrid model that uses CNN & Bi-LSTM to predict whether or not a person has cardiac disease and to provide awareness or a diagnosis based on that prediction. The model is built on deep learning techniques. The Cleveland UCI Heart Disease dataset, gathered from Kaggle, has been the subject of experiments. The suggested method and their study of performance to provide a precise model for heart disease prediction. As a number of current approaches were looked at, the hybrid method had an accuracy rate of 96.66%.

3 Proposed Method

In this paper a novel HD-RegNet have been proposed for heart disease prediction using CXR images. Initial the input CXR images are pre-processed using Adaptive Gaussian Star Filtering. Then the pre-processed images are subjected into RegNet for extracting the features. The best features are selected using Tyrannosaurus optimization Algorithm. Finally the normal and abnormal classes of heart diseases classified using the deep neural network.

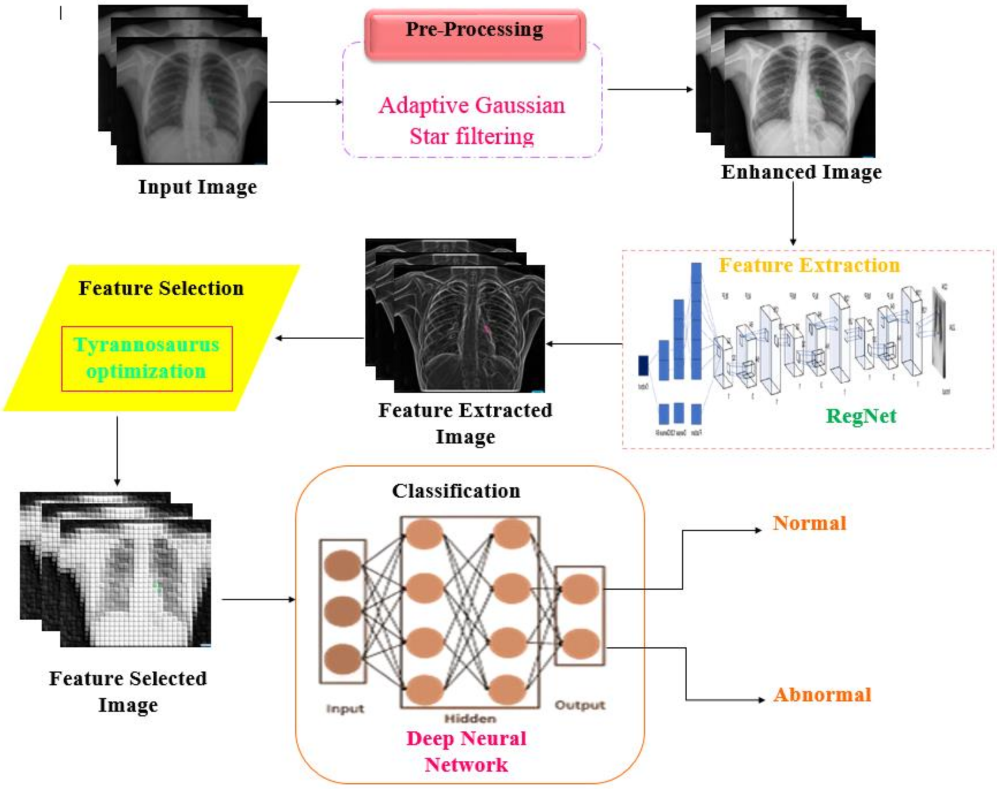

Figure 1: *Block Diagram of the developed HD-RegNet approach*

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3.1 Data Pre-processing using Adaptive Gaussian Star Filtering

Adaptive Gaussian Star filtering is then used to pre-process the occluded images are divided into frames. This section describes an image enhancement technique that modifies the intensity ranges by locally adjusting the contrast stretches inside sub-blocks. The CAGF is divided into two sections. Histograms with modified levels and increased contrast. Every initial intensity value is changed throughout this denoising phase, and a locally adjusted contrast-stretching adjustment is used to compare the histograms. Using a variable transfer function based on the attributes of the input images, the new level is allocated to each pixel.

$$Range = |R_{max-}R_{min}| \tag{1}$$

When R the input image and the intensity range of the input is calculated to determine the range. The highest values of the input image at the new intensity are denoted by R_{max} and R_{min}respectively. At the moment, every pixel equation gets an additional intensity from

$$X_j = \begin{cases} R_{M-}\sigma_M & ,if\ R_M = R_{max} \\ R_{M+}\sigma_M & ,if\ R_M = R_{min} \end{cases} \tag{2}$$

$$q_m = N - \sqrt{(range} - N)^2 \tag{3}$$

When N varies from 0.01 to 0.02 and the aforementioned formulae are used to modify the value of each pixel. This enhances image quality while lowering image noise. Periodic noise in an amplitude spectrum is typically seen as a star.

3.2 RegNet for Feature Extraction

RegNet is implemented in the feature extraction process to extract statistical properties from images, including average, median, variance, normalized entropy, standard deviation, and kurtosis. RegNet is a lightweight and efficient foundation for the graphical function. RegNet uses a series of similar units and advances in four steps with progressively less pixels. The module output is shown in the next section, E^m and the feature map for the nth module is presented in E^{m-1}. Feature systems often employ the pooling method to accomplish the necessary analysis and minimize the total number of feature representations. To attain maximal pooling, stride (S=1) was utilized. As the typical data for RegNet networks, 224x224 is the largest input size allowed by the framework.

$$D_2^m = ReLU(p_n(v_{12}^m * \mathcal{X}_1^m + f_{12}^m) \tag{4}$$

$$[E^m, H^m] = ReLU(p_n\left(conLSTM\left(Y_2^Q[E^{m-1}, H^{m-1}]\right)\right)) \tag{5}$$

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The prior output of $ConvLSTM\ E^m$ and the entry entity D_2^m in equation (5) indicate the input of ConLSTM inside the module. Based on the source of inputs, the $ConvLSTM$ determines whether the data inside the memo cell is sent to the E^m output hidden characteristic map.

3.3 Tyrannosaurus optimization Algorithm (T-Rex) for Feature Selection

This section presents the T-Rex optimization strategy for grabbing the best features by improving the feature in PCA pictures. The Tyrannosaurus rex, a predatory dinosaur notable for its acute senses and calculated strategy to snaring food, served as the model for the T-Rex optimization technique. This algorithm extends into a larger category of nature-inspired algorithms, which mimic natural processes to effectively tackle challenging optimization problems. The prey-predictor hunting process is the source of inspiration for the T-Rex approach. Together with this technique, the prey's and the T-Rex's locations are also randomly created. The hunting is done according to where the prey is nearest. The Tyrannosaurus Rex pursues its prey until it seizes them; in the interim, the victim makes an effort to escape the T-Rex. Figure 3 shows the overall working flow chart of the developed T-Rex model.

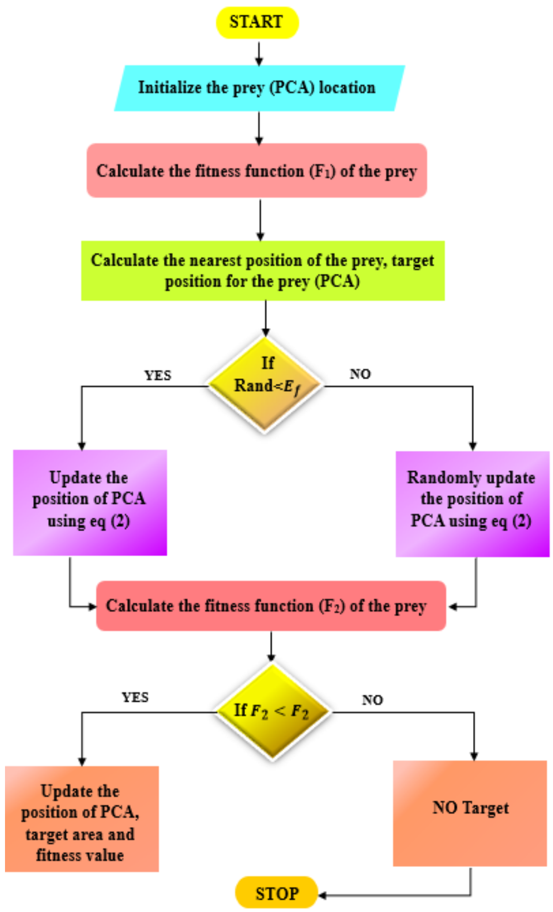

Figure 2: *Flow chart of T-Rex model*

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The representative initialization in the problem's search space at random points is the first step in the optimization process. Every agent assesses its position at each step of the process using a predetermined goal function. The technique prevents early convergence on inferior solutions by dynamically adjusting the influence of the best-found position and the interactions among agents during the iterations.

3.4 Classification using Deep Neural Network

An artificial neural network or DNN is composed of multiple layers of interconnected nodes, or neurons. Because they frequently feature a large number of hidden layers placed among the input and output layers, these networks are known as deep networks. They are able to understand complicated patterns and representations from data because of their complexity. In DL, a subfield of ML that utilizes multi-layered neural networks to resolve complicated issues, deep neural networks play a key role. A DNN typically consists of three different types of layers: the input layer, which takes in initial data in the form of text or images; hidden layers, which process the data and extract pertinent features; and the output layer, which uses the learned representations to provide the final prediction or classification.

$$m = \begin{cases} f < 0 & m(f) = 0 \\ f \geq 0 & m(f) = l \end{cases} \tag{6}$$

The ReLU is a nonlinear activation function that is frequently used in regression analysis. ReLU outputs become zero when the parameter value l is smaller than zero. Currently, HD stages like normal and abnormal are accurately classified using the DNN model. When compared to other cutting-edge networks, the model recommended achieves superior reliability.

4 Results and Discussion

4.1 Cleveland Heart Disease (CHD) Dataset

Research on heart disease prediction makes extensive use of the CHD Dataset that may be obtained from the UCI machine learning Repository. It has 76 attributes and 303 patient records; however, only 14 of them are usually used in predictive modelling. The purpose of this dataset is to provide a standard for creating and assessing machine learning models that diagnose cardiac disease. The effectiveness of the developed approach is implemented with Matlab-2019b in the ensuing section.

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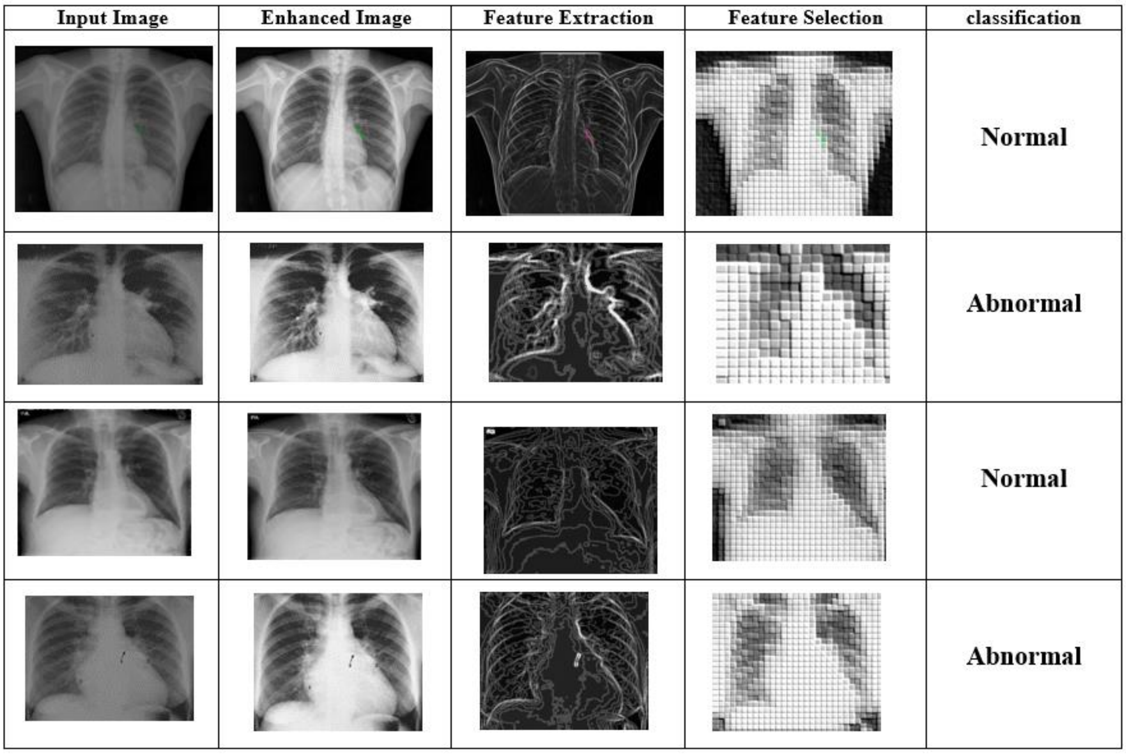

Figure 3: *Experimental outcomes of the proposed model*

Figure 3 displays the virtualization result of the developed method. The input CXR images are in column 1 and the enhanced images are displayed in the 2 column. Then after extracting the features the extracted images are shown in the 3 column. Finally the feature selected images and the classification result are displayed in column 4 and 5.

4.2 Performance analysis

The proposed model's capabilities were evaluated with specific metrics like precision, recall, and accuracy.

$$Accuracy = \frac{T_{pos}+T_{neg}}{Total\ no.of\ samples} \tag{7}$$

$$Precision = \frac{T_{pos}}{T_{pos}+F_{pos}} \tag{8}$$

$$Recall = \frac{T_{pos}}{T_{pos}+F_{neg}} \tag{9}$$

Where T_{pos} and T_{neg} indicates the positive and negative CXR images. F_{pos} And F_{neg} shows the false positive and negative CXR images.

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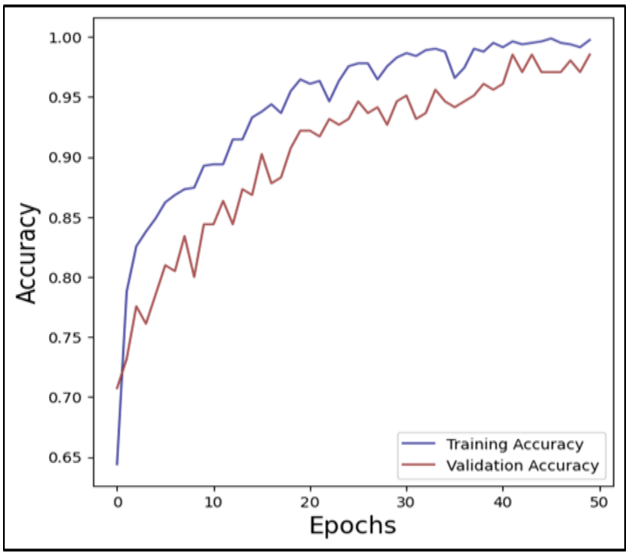

Figure 4: *Accuracy graph of the developed method*

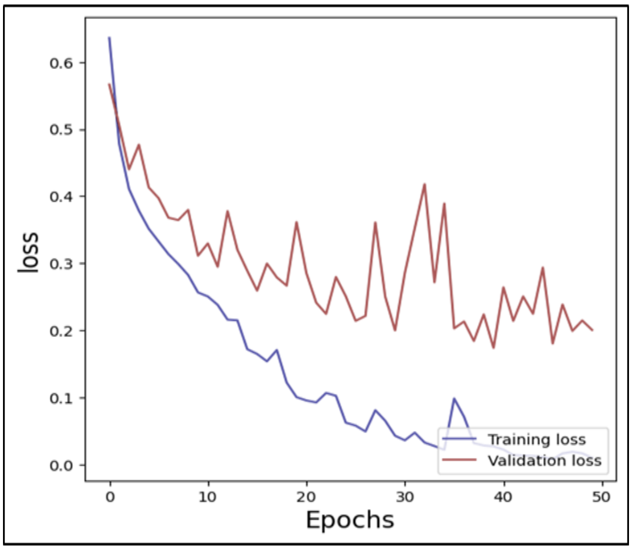

Figure 5: *Loss graph of the developed method*

A range of accuracy and 100 epochs were used to create the accuracy graph in Figure 4. The accuracy of the developed approach grows with the total number of epochs. The loss range and epochs are shown in Figure 5, which indicates that the loss of the recommended model decreases with increasing epochs. The proposed method uses CXR images to identify heart disease at different stages with high accuracy. The proposed HD-RegNet achieves an accuracy rate of 99.53% in the normal class and 99.37% in the abnormal class

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4.3 Comparative Analysis

Table 1: *Comparison of accuracy between existing and proposed method*

Author	Technique	Accuracy
Chunyan Guo et al	RFRF-ILM [12]	99.08%
Shams Nafisa Al et al	LU-Net [17]	98.93%
Shrivastava, P.K. et al	CNN & Bi-LSTM [18]	98.70%
Proposed Method	RegNet	99.45%

Table 1. Highlights the accuracy comparison of the developed and existing method. The developed HD-RegNet achieves an accuracy rate of 99.53% in the normal class and 99.37% in the abnormal class. It achieves an overall accuracy rate 0.37%, 0.52% and 0.75% compared to the existing methods such as RFRF-ILM [12], LU-Net [17] and CNN & Bi-LSTM [18] respectively.

5 Conclusion

In this paper a novel HD-RegNet have been proposed for heart disease prediction using CXR images. Initial the input CXR images are pre-processed using Adaptive Gaussian Star Filtering. Then the pre-processed images are subjected into RegNet for extracting the features. The best features are selected using Tyrannosaurus optimization Algorithm. Finally the normal and abnormal classes of heart diseases classified using the DNN. The CHD dataset are used to assess the performance of the proposed of specific metrics such accuracy, precision and recall. The proposed HD-RegNet attains an accuracy rate of 99.53% in the normal class and 99.37% in the abnormal class. It achieves an overall accuracy rate 0.37%, 0.52% and 0.75% compared to the existing methods such as RFRF-ILM [12], LU-Net [17] and CNN & Bi-LSTM [18].

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