IDENTIFICATION OF CORONARY HEART DISEASE THROUGH IRIS USING DEEP LEARNING

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ABSTRACT

Now-a-days, coronary heart disease is one of the deadliest diseases in the world. An unfavorable lifestyle, lack of physical activity, and consuming tobacco are the causes of coronary heart disease aside from genetic inheritance. Guaranteeing early detection of heart disease provides a possibility of having non-surgical treatment as suggested by biomedical researchers and associated institutions. Sometimes the patient does not know whether he has abnormalities in heart function or not. Therefore, this study proposes a system that can detect heart abnormalities through the iris, known as the Iridology method. The system is designed automatically in the iris detection to the classification results. However, our observation discovered that, a clinical practicable solution which could be both sensible and specific for early detection is still lacking. Due to this, the rate of majority vulnerable to death is highly increasing. The delayed diagnostic procedures, inefficiency, and complications of available methods are the other reasons for this catastrophe. Therefore, this research proposes the novel IFB (Iris Features Based) method for diagnosis of premature, and early-stage heart disease. The method incorporates computer vision and iridology to obtain a robust, non-contact, nonradioactive, and cost-effective diagnostic tool. Deep neural network is comparatively newer machine learning methodology which is giving prominent results in classifying heart sound signals and cardiovascular images. The present study will help to automate diagnosis process of heart disease by providing guidelines and avenues to new researchers in domain of machine learning.

Keywords: *Iris, Iridology, Coronary Heart, Circle Hough Transform;*

I. INTRODUCTION

Computer vision has contributed largely in industrial and medical applications. It softens complex tasks such as faults detection, cognitive functions, and disease diagnosis. In this work, computer vision involves development of the interconnected techniques and algorithms from image processing and pattern recognition to obtain an automatic visual diagnostic tool. Iridology is an alternative branch of natural medicine practice that performs diagnosis in iris by examining variations in fibre patterns, textures, and color changes to determine patient healthy status. The changes differ from one point of iris to another, based on the location of a point, this is because, each location responds to distinct impulses from a particular organ.

Complications emerging during surgery that cause deep chest infection, stroke, and kidney failure, are the reasons for low survival rate. Besides, about of survivors aged are re-hospitalized in 30 days after discharge. Additionally, of all discharged patients die within 5 years, the main reason being neurohormonal imbalance that keeps the disease progressing.

Motivated by the weakness of the current methods, and in intent to have computer aided–early-stage heart disease diagnostic tool, this study introduces an IFB-method that integrates image and pattern recognition processes into iris features to determine benign or malignant abnormalities /broken tissues in iris that infer heart status as per iridology. The applied image processes, involve the following techniques, iris segmentation, h-region localization, enhancement, tensor-based gradient, and Gabor filters. In other hand, pattern recognition processes involve textural analysis methods, and SURF algorithm, for features extraction; K-SVM and MCO-SVM classifiers, for classification purpose.

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This work has beneficial impacts on securing medical expenses and reducing mortality rate. In addition, the method is computationally and practically non-contact, and robust to random errors. Moreover, the study intends to benefit iridology practitioners and other medical experts by providing fundamental diagnostic tool for revealing any sign of abnormality in heart, even for patients expressing no physical symptoms.

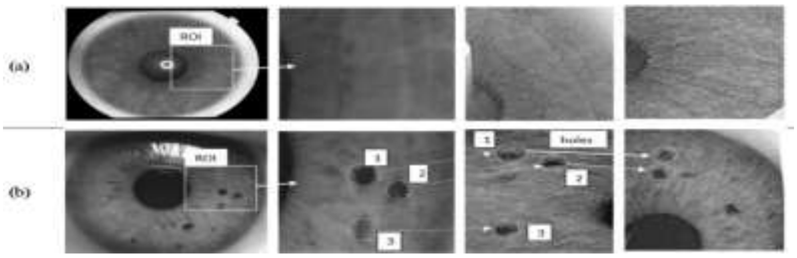

Fig1.1 (a) Normal iris and (b) Iris revealing abnormal tissues.

Coronary heart disease is the number one cause of death worldwide. According to data from the World Health Organization (WHO), there are 17 million people in the world who die from coronary heart disease. In Indonesia, coronary heart disease is the highest cause of death after stroke, with a mortality rate of 12.9% in 2014. Every year there are 1.9 million people die of coronary heart disease due to consuming tobacco. An unhealthy lifestyle and lack of physical activity are the leading causes of coronary heart disease. The death rate is higher among the older age population. Consuming foods high in carbohydrates and obesity will cause constriction of blood vessels in the heart.

II. RELATED WORK

The heartbeat signals collected from ECG devices are decomposed into the wavelet coefficient using WPD (Wavelet Packet Decomposition) algorithm and features are extracted by applying a WPCA (wavelet-based kernel PCA). For instance, we may refer to the research work carried out by Sira's Ahmed et al. [20], who developed an intelligent medical decision support system based on data mining techniques. This work incorporates a total of five data mining algorithms.

E. E. Tuppo, M. P. Trivedi, J. B. Kostis, J. Daevmer, J. Cabrera, and W. J. Kostis, [3] "The role of public health versus invasive coronary interventions in the decline of coronary heart disease mortality," Now-a-days, coronary heart disease is one of the deadliest diseases in the world.. From the system simulation results, the use of the Gaussian kernel can be relied on in the classification of iris conditions with an accuracy rate of 91%, then the Polynomial kernel accuracy reaches 89%, and the linear kernel accuracy reaches 87%. This study has succeeded in detecting heart conditions through the iris by dividing the iris into normal iris and abnormal iris.

I. A. Qasmieh, H. Alquran, and A. M. Alqudah, "Occluded iris classification and segmentation using self-customized artificial intelligence models and iterative randomized Hough transform," proposed efficient biometric security techniques for iris recognition system with high performance and high confidence are described. The system is based on an empirical analysis of the iris image, and it is split in several steps using local image properties. The system was implemented and tested using a dataset of 240 samples of iris data with different contrast quality. The classification rate compared with the well-known methods is discussed.

C. J. C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," [21] The tutorial starts with an overview of the concepts of VC dimension and structural risk minimization. Results of some experiments which were inspired by these arguments are also presented. We give numerous examples and proofs of most of the key theorems.

III. PROPOSED METHODOLOGY

Deep Learning

The term 'deep learning' (DL) is also called hierarchical or deep-structured learning [11–13]. Unlike, task-based methods, DL is a type of ML technique that is based on learned-data representation

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and here the learning can either be supervised, unsupervised, or semi-supervised. The models of DL are vaguely encouraged from the working of biological nervous systems like how the information is processed and communicated in it. However, these DL techniques are structurally and functionally different from human brains. These differences make them incompatible with neuroscience evidence. The architectures of DL such as convolutional neural networks (CNN), DL networks, recurrent NN, and deep belief networks have been employed to various research areas including recognizing human speech, computer vision (CV), audio recognition, manipulation of natural language, machine translation, filtering social sites, drug design, bioinformatics, processing of the medical image, board game programs, and material examination. These advanced machine learning models have generated equal to and, in some scenarios better results than humans

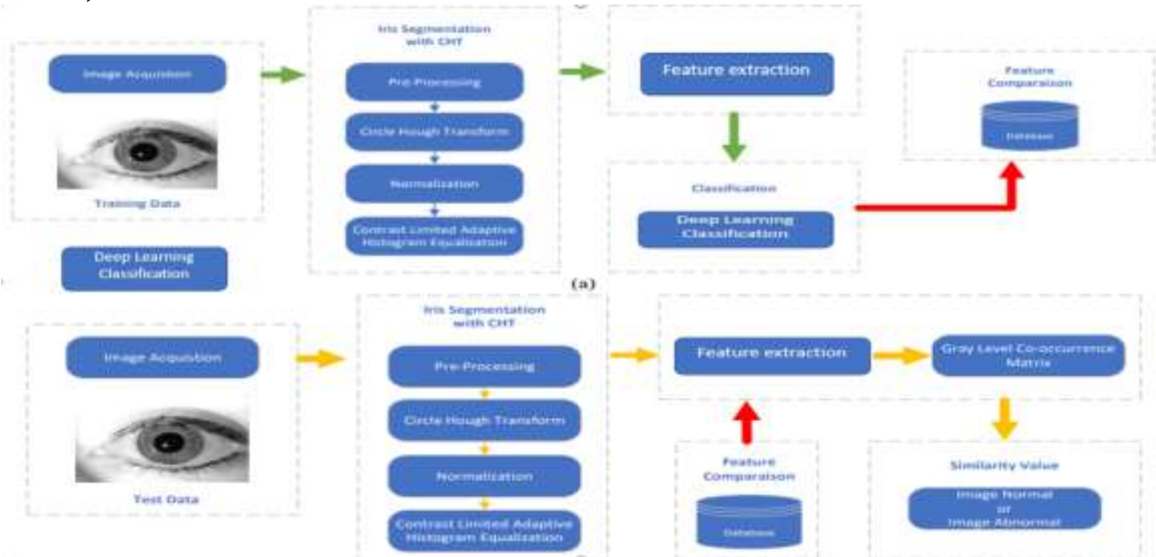

Fig 2. Proposed method

Applications Of Deep Learning

Recently, DL techniques have regenerated the NN models. Researchers have represented the stacked restricted Boltzmann machines and autoencoders, which are exhibiting the remarkable performance in the field of digital image processing. These methods are showing improved performance in numerous areas like in the field of recognizing handwriting, translating, and modelling languages, and acoustic speech modelling. 1.5 Applications in Healthcare Because of the promising results of DL approaches in various fields, now researchers are employing these methods in the field of medicine as well. Skip-gram works by identifying the low-dimensional HER data representation like process, diagnostic, medication codes, etc. We employed this concept in our proposed technique to obtain the same data representation. Our work is concerned with temporal data modelling by utilizing CNN for HF prediction at its earliest stage.

The main contributions of the proposed method are as follows:

• The proposed method (named as Cardio Help) predicts the probability of the presence of cardiovascular disease in a patient by incorporating a state-of-the-art deep learning algorithm called convolutional neural network.

• To our best knowledge, this is the first-time deep learning model applied in the medical field for predicting a coronary heart disease (CHD) which works with just 14 attributes.

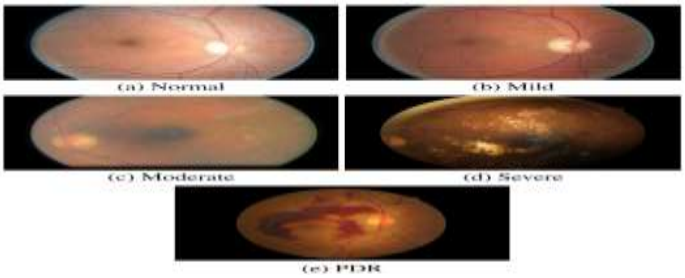

Fig 3. Retinal image analysis

Convolutional Neural Networks (CNN)

As depicted in the figure below, the architecture of the proposed convolutional neural network (CNN) is a feedforward network which works on a sequential single–input–single–output fashion. For binary classification experimentation, we assume that patients with the presence of CHD will be classified as ‘1’, and others (with CHD absent) will be classified as ‘0’. An experiment multi-class classification is also performed will be discussed later. As mentioned earlier, the number of active CHD attributes (phenotypes) obtained from the majority voting algorithm is 14. Let us proceed with an assumption that the number of training examples is N, so the input layer indicated in Fig. 1 has RN×14 dimension. This layer effectively normalizes various variable types before the nonlinear transformation, which is done by Proposed CNN architecture.

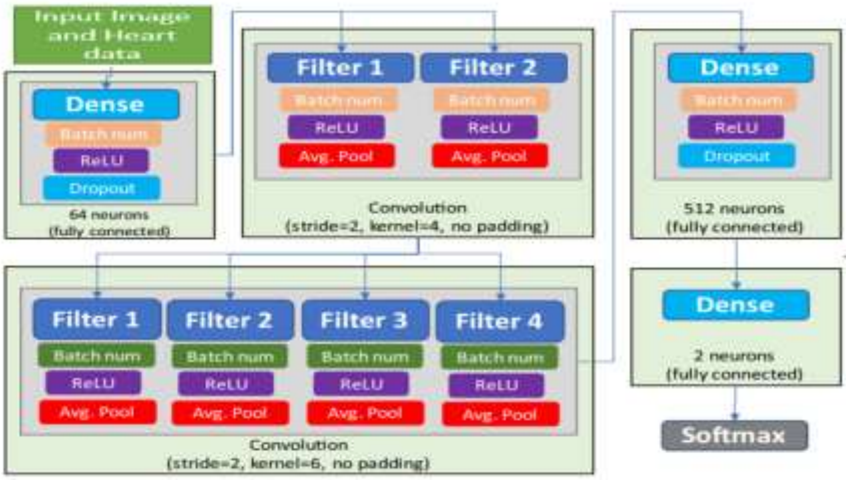

Fig 4. Architecture of CNN

Training Schedule

Although the dropout layers are used in the proposed CNN models, this training schedule is also used to improve the classification accuracy and further reduce overfitting. The concept of penalty helps the algorithm know its deficiency resultantly improve its working. Here, the class weight ratio is adjusted as a penalty because of imbalance in a class. We define it as a ratio to CHD and a Non-CHD dataset. For instance, a class weight ratio of 5:1 shows that we penalize a wrong classification of a CHD training sample 5 times more than a wrong classification on a non-CHD sample during the calculation of error after each epoch before the backpropagation stage. This is done for initial training of the model with 1: N to a large number of epochs and then gradually increasing the weight ratio with a sudden decline in epochs357

Algorithm 1. Fitting the proposed CNN model, D, with varying number of epochs (e) and weight ratio (φ)

1. Initialize $\varphi = N$, $e = N$, D=1, end = 1, i=1
2. While $\varphi \le p_0$

    D.fit(inputData, e, φ)

    $\varphi \leftarrow$ floor $(\frac{\varphi}{2})$

    e $\leftarrow$ floor $(\frac{e}{2})$
3. While ($i \le end$ and Train_loss(i) $\le$ Train_loss($i-1$)

    D.fit(inputData, i, φ_0)

Dataset

In this section, we briefly describe the dataset incorporated in the experimental work of this study. As mentioned in previous sections, we make use of a state-of-the-art dataset especially available at [41] for this purpose. This set of attributes is a subset of a dataset compiled by medical practitioners in African countries. We incorporate only 14 attributes from this dataset to predict the presence of a CHD in a subject. Table 1 depicts a list of attributes used in the algorithm with their short description and the possible range of values wherever applicable.

HARDWARE REQUIREMENTS

To carry out this research work and analyse the results, we establish an experimental environment on a personal computer. We equipped the experimental workstation with an Intel Quad-Core i7 4th generation processor, working at a clock rate of 2.3 GHz with an L1 cache of 32 KB, L2 of 256 KB and L3 cache memory with 4 MB of size. Sixteen gigabytes of DDR3 RAM are installed in the workstation and a total of a SATA hard disk having 1 TB capacity, rotating at 7 K RPM is installed. Software Requirements This work incorporates Microsoft Windows 10 Pro as the base operating system. MATLAB version 2019a.

IV. RESULT ANALYSIS

In this study, system training was carried out using 40 normal iris data and 40 abnormal iris data. Normal iris data is the iris of people who have no history of heart disease; on the contrary for abnormal iris data is the iris of people who have heart disease. Fig. 11 shows the training data using linear, polynomial, and gaussian kernel variations. Iris data in training can be separated according to normal (red) and abnormal (blue) classes. The results of linear kernel training separate the data into each class with an even distribution of data. The difference in the polynomial kernel training where the data has been separated and more centralized. The results of the training using the Gaussian Kernel resulted in a tighter grouping than using the two previous kernels. The results of the training can separate between classes according to existing characteristics, which can help in the classification of test data and affect the level of recognition accuracy. The further apart the hyperplane in the SVM that separates the classes, the higher the accuracy. Taking five types of texture characteristics on iris data is needed to obtain more detailed information in training and testing. Normal and abnormal iris data have different characteristic values.

Layers of Training

Initial Stage of Layers Training

It can split each label and it can use the convolution neural networks layers.

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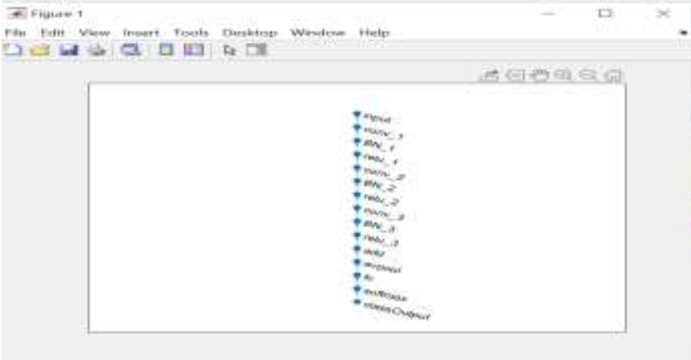
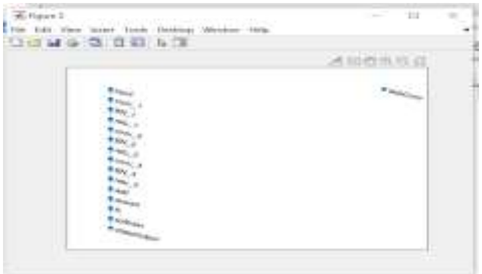


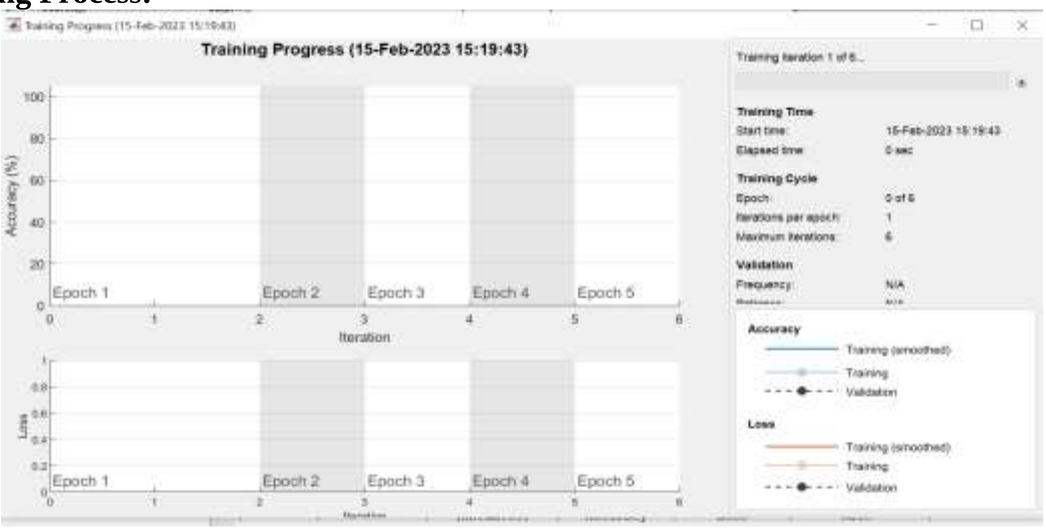
Secondary level of training:

In this figure it can identify the person will be normal or abnormal. when the person will be normal layers can't be split and person will be abnormal when the layers will be separated.



Iris input image:

Training Process:



Data Trained Successfully

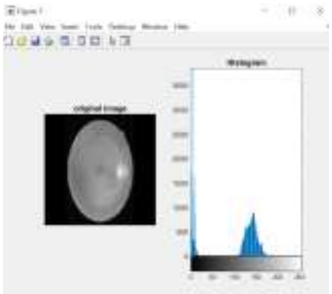
Initialisation of Data Set

Pre-processing of Iris Image:

We can add the noise and then enhance the noise with the help of median filter. When median filter is used to noise removal from an image. We can use the black and pepper noise in pre-processing steps.

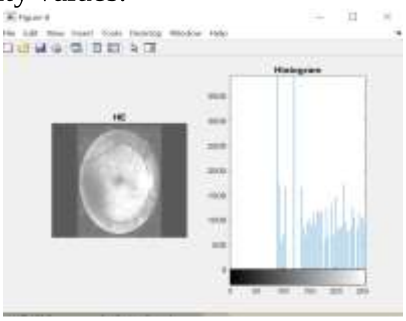
Histogram

Histogram indicated the pixel intensity values and it can show the number of pixels in an image at each different intensity values found in an image.



Histogram Equalisation

It is a computer image processing technique used to improve contrast in image. It can used to contrast adjustment using images histogram and it can use the enhance the contrast of an image by adjusting its intensity values.



Root Mean Square Error

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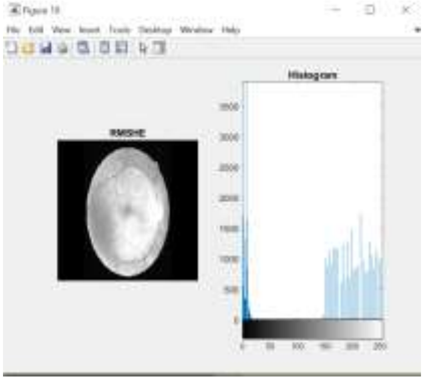
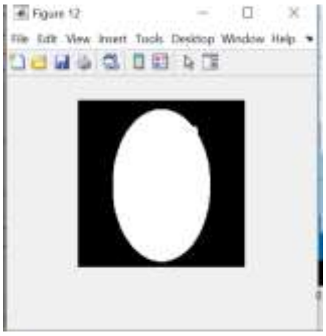
It can calculate the mean value in original image and it is the one of the most commonly used in measure that evaluating the quality predictions.

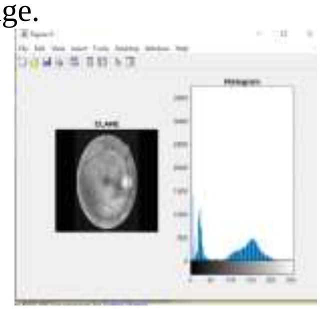


Circle Hough Transform



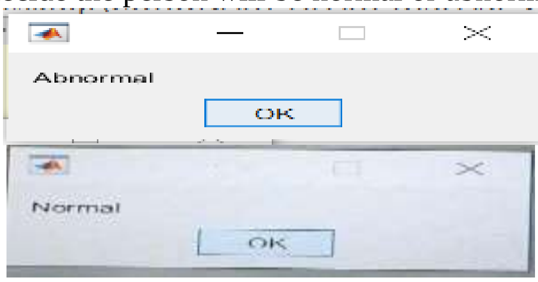
CLAHE Method

It is an adaptive histogram equalization which takes care of over amplication of contrast .it can operate the small regions in an image.



Result

Based on the input it can decide the person will be normal or abnormal



V. CONCLUSION & FUTURE SCOPE

The identification of coronary heart disease through the iris using deep learning has shown promising results. The use of deep learning algorithms for medical diagnosis has been widely studied in recent years, and the iris has been shown to contain valuable information that can be used to identify different diseases. The accuracy of the developed model has been found to be satisfactory, and the method can be further improved with the inclusion of more data and the use of more advanced deep learning techniques. The identification of coronary heart disease through the iris using deep learning can be further improved by expanding the dataset and using more advanced deep learning models. In addition, the incorporation of other physiological features along with iris data can provide more accurate results.

Further research can be conducted to identify the potential of using the iris to diagnose other diseases, as the iris contains valuable information related to different health conditions. The use of deep learning algorithms can also be explored for the early detection and prediction of coronary heart disease, which can improve patient outcomes and reduce healthcare costs. Additionally, efforts can be made to develop a user-friendly interface that can be used by healthcare professionals to diagnose patients efficiently and effectively.

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