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CONVOLUTIONAL NEURAL NETWORK MODEL FOR HEART DISEASE CLASSIFICATION

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ABSTRACT

Heart disease has dominated the cause of mortality rate in the world. In western African, high kolanut intake has been reported to be one of the main factors which have provoked the rising cases of the problem among the elderly within this global region. The aim of this research is to develop a classification model for heart disease considering kolanut as a risk factor. This was achieved using 23,200 Magnetic Resonance Image (MRI) data collection from the Enugu State University Teaching Hospital, Parklane, these data were augmented and then used to train a convolutional neural network algorithm to generate a classification model. The result of the model was evaluated considering accuracy and loss function which reported 99.01% and 0.011241 after tenfold validation. The model was compared with other state of the art algorithm and then result reported that the new system was more reliable when compared to the rest.

Keywords: Heart Disease; Convolutional Neural Network; MRI data, Kolanut

1. INTRODUCTION

Today heart disease has become a growing concern to all part of the world, posing a significant challenge especially in the under developed and developing countries due to limited access to adequate healthcare. While heart disease was previously considered predominantly affecting men, it is now recognized as the leading cause of death for both men and women (Richard, 2009). Cardiovascular diseases (CVDs) as it often referred to according to the World Health Organization (WHO, 2022), accounts for approximately 18 million people which lost died in 2019, i.e 32% of total deaths rate in the entire year. Diagnosing CVDs accurately and early is a challenge even for medical professionals, as 25% of individuals suffer to heart disease suddenly without prior symptoms. Thus, there is a crucial need to establish an early detection system for heart diseases (Shah et al., 2020).

Among the various types of heart disease, coronary, myocardinal infraction and arrhythmia are some of the most popular and occur due to several habits such as smoking, diabetes, excessive alcohol consumption, sedentary lifestyle (obesity), stress, excess intake of kolanut, and high blood pressure (Nwoodo et al., 2021; Adebapo et al., 2023). The diagnosis of heart disease requires significant time, effort, and resources. To enhance the accuracy of diagnosis, the integration of deep learning and image classification techniques can assist medical professionals in obtaining valuable insights about heart patients (Reddy et al., 2020).

Deep learning, a significant advancement in the field of artificial intelligence, has greatly enhanced AI capabilities (Janiesch et al., 2021). Introduced in 2006, deep learning is a branch of machine learning inspired by the structure of the human brain, specifically neural networks. It employs a multi-layered approach for data processing, utilizing weighted inputs, nonlinear transformations, and output propagation across layers (Cai et al., 2020; Ras et al., 2022). Deep learning overcomes longstanding limitations in artificial intelligence, excelling at identifying complex patterns in vast amounts of data, making it applicable across various domains such as science, business, and government (LeCun et al., 2015; Khan et al., 2021; Jena et al., 2021).

Over the years, deep learning has experienced significant growth in the field of computer vision, particularly in image recognition research (Lan et al., 2020). However, the progress in computer vision heavily relies on the availability of high-quality images and properly labelled datasets for training, testing, and validating algorithms. In the case of medical field, deep learning has been applied so solve complex medical problem using medical imaging technology and has achieved great success in addressing medical health related challenges (Jena et al., 2021). However, Ranganathan (2021) argued that the limited availability of certain problem datasets often poses a challenge and restricts successful performance of most deep learning algorithm. For instance in the case of heart disease prediction, most of the available dataset never considered Kolanut as a key cause of the problem. This is because this attributes of heart attack is localized to majorly the western African region of the globe, and hence most of the available dataset develop in European and Asian laboratory, never considered this factor, and hence is a limitation (Ezigbo, 2022). This as a result makes the early detection of heart abnormally caused by this kolanut risk factor very difficult. To solve this problem, this research collect data of heart diseases, considering patients with high kolanut intake and then train with a deep learning techniques which generates a model for the early detection of heart diseases.

2. LITERATURE REVIEW

Nikita et al. (2018) used Naive Bayesian to improve the performance of KNN for the detection of heart disease and achieved accuracy of 85%, however the result can be improved further. Singh et al., (2017) in the research proposed the use of Naive Bayesian for the detection and classification of heart disease. The data mining technique was further extended for detection of cancer, diabetes and other types of heart attack. It was tested using heart disease dataset and the result produced good classification accuracy, however the author recommended the use of ANN for optimized performance. Navdeep et al (2018) predicted heart disease using genetic and Naïve Bayesian algorithm. The study achieved a classification accuracy of 97.14% using 14 heart disease feature vectors as input variables and when validated with tenfold reported 94.2%. Jaymin et al. (2015) detected and predicted heart disease using logistic model tree and achieved an accuracy of 55.8%. The result however still needs to be improved with a better accuracy. Persi et al. (2016) presented a paper on delicate calculating approaches as a data mining technique for competent analysis of coronary heart disease. The data used for the mining process has 76 attributes and was trained with fuzzy logic. The system was tested but the accuracy was not recorded and hence the result cannot be validated. Kim et al., (2019) presented a fuzzy based adaptive heart disease classification system model using data mining method. They system was implemented as an expert system used for diagnoses of heart disease. The system despite the performance can be improved using ANN predictive model.

Seera et al., (2020) in this paper a hybrid intelligent system that comprises of the Fuzzy Min-Max neural network, Random Forest model, Regression Tree was developed. They system was tested but the hybrid model was complex to understand as a standalone system and hence needs to be simplified. Bashir et al., (2014) investigated the various data mining techniques and proposed a novel classifier based collaborative approach for detection and classification of heart disease. The system was tested and the result not validated in the paper. However from all indication the author recommended the use of ANN for optimized performance. Shabana et al., (2015) studies and presented various data mining techniques such as Decision Tree, Naive Bayesian, Association Rule and Linear Regression for the detection and classification of heart disease. However the result for each algorithm when tested was limited by the database attributes which is only 12 heart feature vectors, hence there is need for an improved data model to be used for the system validation. Aljaaf et al., (2015) presented a multi level risk assessment system for the detection of heart failure. They system employed five level of risks in heart failure C4.5 decision tree classifier. The system was tested using various data collected from a case study hospital and the result showed promising without any specific accuracy value presented.

These studies all achieved great contribution for heart disease detection and diagnosis; however solution has not been obtained which considered heart disease that occurs due to high kolanut intake. This type of heart disease is peculiar with people from the Western part of Africa as most of the elderly within the region consume kolanut all the time and as a result suffers heart issues. There is need for the system which can consider this attribute and then detect heart problem correctly. Ezigbo et al. (2022) used neural network for cardiovascular disease classification considering kolanut and other 12 attributes and then recorded 96.51% accuracy, however only cardiovascular disease was considered. There is need for a predictive model which will consider multiple classes of heart disease and kolanuts as the risk actor. This will be achieved in this paper using deep learning technique.

3. METHODOLOGY

The methodology begins with data collection of heart disease MRI images from patients characterized with high Kolanut intake, which is major cause of heart irregularity in West Africa. The data was augmented to improve the volume before loading into a Convolutional Neural Network (CNN) model which resized the data with the input layer into 180 * 120 and then scanned with filter and formulate 4 convolutional layers which are arranges in parallel and then train the features in the convolutional layer using back-propagation algorithm and evaluate with accuracy and loss unction until a tolerable error between actual prediction and predicted values was minimal. This was implemented with deep leaning tool box using Matlab and then validated with comparative analysis.

3.1 Data collection

The data collection for heart disease was conducted at the Enugu State University Teaching Hospital, specifically at Park Lane in Enugu State, Nigeria. The hospital generously provided a dataset consisting of 23,200 pre-existing Magnetic Resonance Imaging (MRI) samples for the purpose of this study. The MRI data was collected using a closed-bore MRI machine with a field scan rating of 1.5 Tesla. This traditional type of MRI machine features a narrow opening where patients lie down and undergo heart scans. The 23,200 MRI data samples were classified into 4 heart disease types which are 5000 data health patient MRI data, 5200 data of coronary artery disease, 7000 data of Myocardinal infraction, 6000 data of arrhythmia, and were carefully stored and utilized as the training dataset for further analysis in this research.

During the data collection process, comprehensive patient information was gathered to enable the identification of individuals with pre-existing heart conditions and a history of high Kolanut intake, which is a prominent factor contributing to heart irregularities in the Western region of Africa. The age range of the patients included in the dataset spans from 45 to 85 years, capturing a wide range of individuals in the study population. This age range was chosen to focus on the adult population most commonly affected by heart disease and also most characterized with the consumption of Kolanut within the case study region. The specific MRI sequence utilized to acquire the images was the T1-weighted sequence. This sequence provides valuable anatomical information about the heart, allowing for the assessment of cardiac structure and potential abnormalities. In terms of the data acquisition protocol, a specific slice thickness was employed. Slice thickness refers to the thickness of the individual image slices obtained during the MRI scan. This parameter influences the level of detail captured in the images and can impact the accuracy of subsequent analysis. The dataset collected from the Enugu State University Teaching Hospital holds significant potential for investigating the relationship between heart disease and Kolanut intake. It provides a robust resource for further analysis, this research to explore the impact of Kolanut consumption on cardiac health and potentially identify patterns or associations between Kolanut intake and heart disease risk.

3.2 Data preparation

To enhance the dataset size and optimize the training model, data augmentation techniques were employed. The following augmentation approaches were utilized in the process: Flipping Process: This technique randomly flips the orientation of image pixels along a common axis (Shorten and Khoshgoftaar, 2019). Data Translation: Through affine transformation, a collection of 10 pixels in the image was randomly shifted vertically or horizontally after capturing from different parts (Shorten and Khoshgoftaar, 2019). Rotation Approach: The images were rotated by 30 degrees using affine transformation to generate additional data (Connor and Taghi, 2019).

Cropping: Random resizing of the image resolution was applied as a cropping technique (Connor and Taghi, 2019). Brightness and Contrast Enhancement: The multiplication of image pixels with a scale factor of +/- 20% was used to reproduce images under varying lighting conditions (Alomar et al., 2023). These data augmentation methods were implemented to increase the diversity and size of the dataset, enabling the training model to learn from a wider range of variations and improve its generalization ability. The four data argumentation approach adopted and used to improve the size of data by replicating one extra from each technique. The total sample size of the data is 92,800.

3.3 The Convolutional Neural Network (CNN)

CNN is advanced deep neural network models that utilize spectral layers to learn features at both lower and higher levels (Singhal et al., 2018; Ramprakash et al., 2020). They have proven to be highly effective for tasks such as data classification. CNNs leverage three key concepts, namely local filters, max-pooling, and weight sharing, which distinguish them from regular deep neural networks. Figure 1 illustrates the architecture of a CNN used for detecting the heart disease. The CNN comprises four pairs of convolutional layers designed for feature extraction, followed by pooling layers. Each pooling layer is positioned immediately after a convolutional layer. The purpose of the max-pooling layer is to select the maximum activation within a specified window from different positions, thereby creating a lower-resolution representation of the convolutional features. This process enhances the model's capability to accommodate slight variations in the spatial positions of object parts and contributes to faster convergence. Subsequently, fully connected layers consolidate inputs from all positions and generate a 1-D feature vector. Finally, a softmax activation function layer is employed to classify the overall inputs, enabling the model to assign probabilities to different classes of heart disease. By employing the described architecture and mechanisms, CNNs demonstrate remarkable performance in extracting relevant features from input data and making accurate predictions in the domain of heart disease classification.

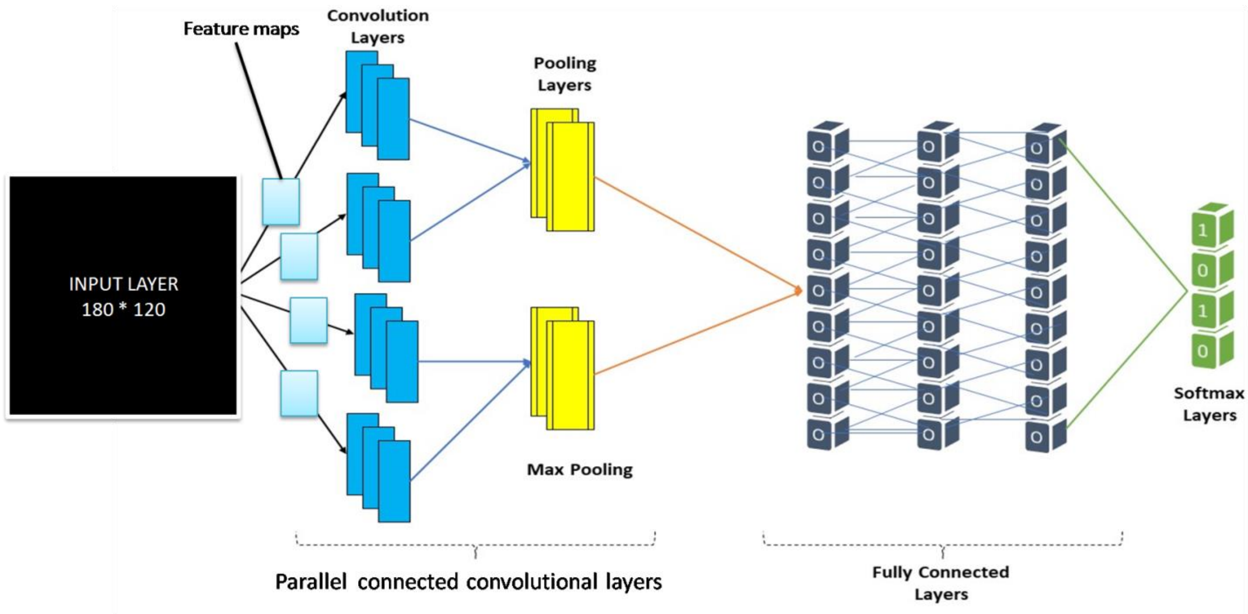

Figure 1: Architecture of the CNN adopted for the Classification Model

In broad terms, a neural network is comprised of interconnected input/output units, where each connection is assigned a weight. The network undergoes a learning phase in which it adapts the weights to accurately predict the class labels of input tuples. Back-propagation serves as a neural network learning algorithm, employing a rapid matrix-based approach to calculate the network's output. When training a CNN-based classification model, a modified back-propagation training method is utilized (Singhal et al., 2018).

4. The CNN Configuration

Since the input image size of 180x120, 4 parallel convolutional layers, with a filter size ranging from 3x3 to 3x5 and using a stride of 1, the output dimensions of each convolutional layer can be calculated as follows:

1. The input image size is 180x120
2. Convolutional layer 1: The output size can be calculated using the formula:

$$\text{Output size } = \frac{(\text{Input size} - \text{Filter size} + 2 * \text{Padding})}{\text{Stride} + 1} \tag{1}$$

Since no padding was used in this modeling, the output is presented as;

$$\text{Output size } = \frac{(\text{Input size} - \text{Filter size })}{\text{Stride} + 1} \tag{2}$$

Applying this formula to considering the image, filter and strides size gives output size $= \frac{(180-3)}{1+1} =$ 178; Calculating the height dimension of the output: Output height = (Input height - Filter height) / Stride + 1 = (120 - 3) / 1 + 1 = 117 / 1 + 1 = 117 + 1 = 118. Therefore the output of the convolutional layer 1 is 178x118x16. The equation 2 was used to calculate other convolutional layer output.

3. Convolutional Layer 2: Number of filters used for convolutional 2 is 32, size is 3x3, stride is 1, and then output is 176x116x32.
4. Convolutional Layer 3: Number of filters is 64 filters, Filter size is 3x5, stride is 1 and No padding is used. Then the output is 174x112x64
5. Convolutional Layer 4: Number of filters is128, Filter size is 3x5, stride is 1, and the output volume is 172x108x128.
6. Max Pooling: Pool size is 2x2, Stride is 2 is used, the output volume is 86x54x128
7. Flatten Layer: The output volume from the last convolutional layer is flattened into a vector of size 86 * 54 * 128 = 592,128.
8. Fully Connected Layer 1: Number of neurons is 512 neurons, Output size is 512.
9. Fully Connected Layer 2: Number of neurons is 256 neurons, Output size is 256.
10. Fully Connected Layer 3 (Output Layer): The output size is the 4 classes which are data health patient, coronary artery disease, myocardinal infraction, arrhythmia considered during the data collection.
11. Softmax Activation: The softmax activation function is applied to the output layer to obtain class probabilities.

4.1 TRAINING OF THE CNN

The MRI data collected and augmented were splitted into training, test and validation sets before loading into the CNN architecture using deep learning toolbox. The input layer was used to dimension the size of the MRI image, then the used filter to scan the receptive fields and then formulate the first convolutional layer which the output is defined with equation 2. Similarly is the output o the other three convolutional layers and then flattened and feed to the fully connected layer which used back-propagation algorithm to train the neurons and generate the classification model for heart disease detection. During the training, accuracy and loss function parameters were used to monitor the training performance and then reported results was discussed in the next section.

5 RESULTS AND DISCUSSION

The performance of the CNN algorithm trained with MRI data was closely monitored using a deep learning tool, as shown in Figure 2. Throughout the training process, evaluation parameters such as accuracy and loss were examined at each epoch. The objective was to achieve a target value of approximately 100% for accuracy, indicating that the algorithm correctly classified all samples, and approximately 0% for the loss function, indicating a minimal discrepancy between predicted and true labels. Upon analyzing the performance depicted in Figure 1, it was observed that the CNN algorithm achieved an impressive accuracy of 99% and a low loss function value of 0.03413 at epoch 186. This indicates that the model performed exceptionally well in accurately classifying the heart MRI data and minimizing the difference between predicted and actual labels. These results highlight the effectiveness of the trained CNN algorithm in leveraging MRI data for classification of normal or abnormal heart problems. Achieving such high accuracy and low loss values demonstrates the model's ability to capture and learn relevant patterns and features from the MRI images, enabling accurate identification and classification of the targeted heart disease conditions.

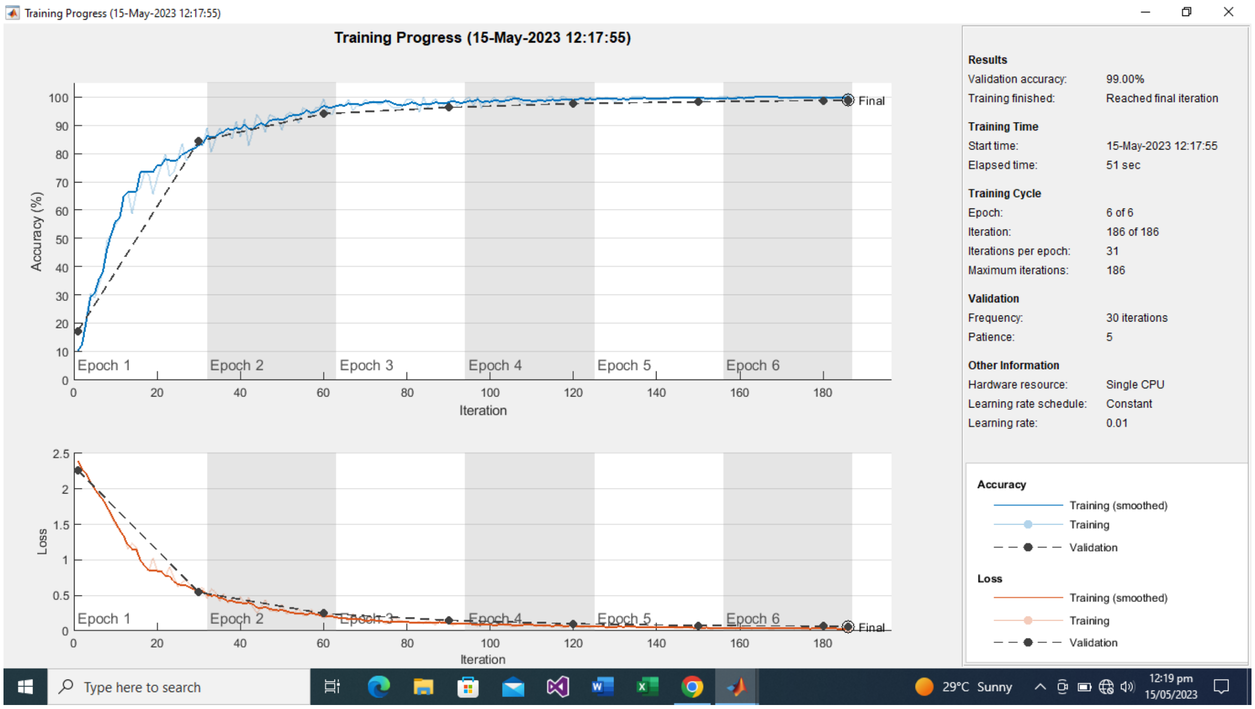

Figure 2: Result of CNN training

To validate the result, CNN model, first the ten-fold cross validation approach was used as reported in the table 1 and the result showed an average accuracy, loss function and epoch of which the classification model was evaluated and generated.

Table 1: Tenfold validation performance

Iteration	ACC%	MSE	Epoch
1	99.0	0.0034534	186
2	98.9	0.0064543	137
3	99.1	0.0026540	189
4	98.8	0.0053505	163
5	99.3	0.0056400	180
6	98.9	0.0056420	155
7	99.7	0.0046459	129
8	98.9	0.0045647	178
9	98.6	0.0034515	190

10	98.9	0.0705542	189
Average	99.01	0.011241	169.6

From the result in the table 1, it was observed that the classification model reported an average accuracy of 99.01% and a loss function of 0.011241 at an average each value of 170. The implication of the result showed that the classification model will successfully detect patients with any of the four classes of heart data used to train the CNN with high success rate. Having achieved the success rate from the ten-fold validation process, the classification model was further validated comparing with other state of the art algorithms as reported in the table 2, while the graphical analysis was presented in the figure 3;

Table 2: Comparative analysis

Author	**Models**	**Accuracy**
Nikita et al. (2018)	Naive bayes and KNN	85.00
Navdeep et al. (2018)	Naive Bayes	94.20
Jaymin et al. (2015)	Logistic model tree	55.80
Nwobodo et al. (2022)	Wavelet- Neural network	99.78
New work	CNN	99.01

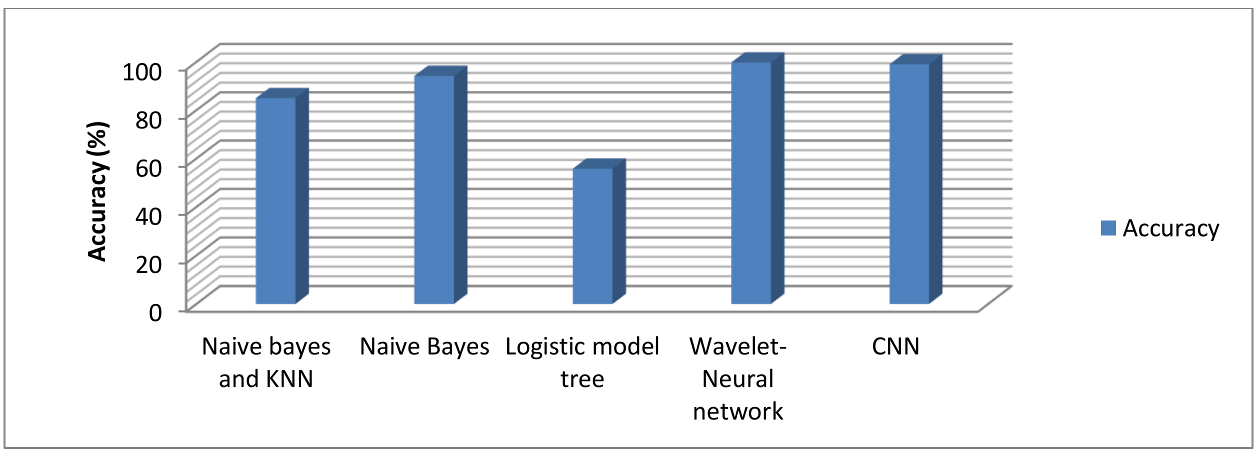

Figure 3: Comparative analysis of Heart disease classification models

From the comparative analysis, the new CNN based model for heart disease classification was compared with other existing model. The result showed that only Nwobodo et al. (2022) achieved better accuracy of classification, however despite the success, the study did not consider Kolanut as an attribute of heart attack, hence the new system is more reliable and trust worthy to detect heart irregularities with high success rate.

6 CONCLUSION AND RECOMMENDATION

Heart diseases pose a significant challenge in the medical field, and accurate classification is crucial. Achieving correct classification and classification results has been a key objective for researchers, doctors, and experts. It is important to ensure that patients with symptoms are not misclassified as negative or vice versa. However, achieving this goal requires real-time updates on the training dataset for the artificial intelligent agent to learn. The conventional system faces challenges as many data attributes used in the data model are not up to date, like heart disease problem causes by excess intake of cholesterol. This research developed a classification model for heart disease using convolutional neural network. The study collected data of four classes which are health patients, coronary artery disease, myocardinal infraction and arrhythmia. Then processed using resizing and data augmentation approaches to improve the volume of the dataset and then trained with CNN to generate the classification model for heart disease detection. The result when evaluated considering accuracy and loss function reported high success rate and tolerable error between the actual features and predicted features; which then implied that the classification model is reliable.

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