Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

A CNN BASED MODEL FOR HEART DISEASE DETECTION

[1]Chibueze, K. I., [2]Didiugwu, A. F., [3]Ezeji, N. G., and [4]Ugwu, N. V.
[1,2,4]Department of Computer Science & Mathematics, Godfrey Okoye University, Enugu State, Nigeria
[3]Department of Computer Engineering, Enugu State University of Science and Technology, Agbani, Enugu State
Corresponding Author Email: casperine1@gmail.com

Received: 12-07-2024
Accepted: 02-08-2024

https://dx.doi.org/10.4314/sa.v23i3.38

Journal Homepage: http://www.scientia-african.uniportjournal.info
Publisher: *Faculty of Science, University of Port Harcourt.*

ABSTRACT

Cardiovascular diseases (CVDs) pose a formidable global health challenge, claiming millions of lives annually. Despite advancements in healthcare, heart disease remains a leading cause of mortality, especially in developing nations. Early detection of cardiac abnormalities through predictive models is crucial for effective intervention. This research leverages machine learning (ML) and artificial intelligence (AI), focusing on deep learning, to enhance diagnostic capabilities. Unlike previous studies, this work introduced caffeine as a potential risk factor often overlooked in datasets. The study utilized Magnetic Resonance Imaging (MRI) datasets from Enugu State University Teaching Hospital and Kaggle, comprising 90,500 samples, with specific attention to high caffeine intake cases. Data preprocessing involved resizing, normalization, color adjustments, and augmentation to optimize model training. A Convolutional Neural Network (CNN) architecture with four convolutional layers was employed for classification. The CNN model achieved a remarkable accuracy of 94% and low loss values, and demonstrated proficiency in categorizing heart MRI data. Ten-fold cross-validation reaffirmed the model's high success rate with an average accuracy of 94.13% and minimal loss function. Comparative analysis showcased the effectiveness of the developed CNN model, outperforming several existing models in heart disease classification.

Keywords: MRI Data, Caffeine, Heart Disease, Convolutional Neural Network, Cardiac Abnormalities

INTRODUCTION

The heart, being a vital organ essential for sustaining life, is inherently susceptible to various illnesses and injuries that pose significant threat to human well-being. The impact of heart disease on the heart's pumping systems leads to malfunctions (Deng et al., 2012). Globally, cardiovascular diseases (CVDs) have become the primary cause of mortality, claiming 17.9 million lives annually (World Health Organization, 2020). Alarmingly, more than 75% of these deaths occur in middle-income and low-income countries, with 80% attributed to strokes and heart attacks (Hazra et al., 2017). The European Public Health Alliance reports that 41% of all deaths result from heart attacks, strokes, and other circulatory disorders (Mancia et al., 2017). Unhealthy behaviors such as elevated cholesterol levels, obesity, increased triglycerides, and hypertension significantly contribute to the rising risk of heart disease (American Heart Association, 2020).

Despite healthcare advancements, heart disease remains a leading cause of death and stroke, recording over 1.5 million cases annually in Nigeria alone (Fogoros, 2009). This prevalence is particularly pronounced among infants under two years old and individuals aged 60 and above (World Health Organization, 2021). The severity of this issue is evident in developing nations across Africa and Asia.The early detection of cardiac abnormalities and the development of predictive tools for heart diseases hold significant potential to save lives and guide efficient treatment strategies, thereby decreasing cardiovascular disease (CVD) mortality rates. The advent of sophisticated healthcare systems has resulted in abundant patient data, especially within the extensive dataset known as Big Data stored in Electronic Health Record Systems. This reservoir of data provides opportunities to formulate predictive models tailored for detecting and managing cardiovascular diseases (Nashif et. al., 2018).

Recognizing the pivotal role of machine learning (ML) and artificial intelligence (AI) in the medical field, this paper highlights the significance of deep learning, a notable advancement in AI, for enhancing predictive capabilities (Janiesch et. al., 2021). Overcoming longstanding limitations, deep learning excels in identifying complex patterns within extensive datasets, offering applications across diverse domains, including science, business, and government (Khan et. al., 2021;Jena et. al., 2021).

While numerous studies have employed ML models for heart disease diagnosis, this research emphasized the need to consider caffeine as a potential risk factor. Often overlooked in available datasets, caffeine, a natural stimulant consumed in various forms, presents challenges in the early detection of heart abnormalities associated with its intake.

To address this gap, the research focused on collecting data related to heart diseases, with specific attention to patients exhibiting high caffeine intake. Through the application of advanced deep learning techniques, the researchers developed a robust model for the early detection of heart diseases, contributing to more comprehensive and effective diagnostic approaches.

LITERATURE REVIEW

Machine learning has garnered significant interest across diverse fields, notably in health and medicine (Kumar et. al., 2018). In the realm of cardiac disease detection, researchers have explored various machine learning approaches, leading to a plethora of studies in medical applications. Amin et al. (2018) introduced a hybrid diagnostic approach for cardiac disease, demonstrating Logistic Regression's 89% accuracy in predicting heart disease. Renugadevi et al. (2021) proposed a hybrid model utilizing Random Forest, Decision Tree, and Hybrid Model methods, achieving an overall accuracy of 88.7% in predicting coronary heart disease. Singh and Jindal (2018) employed a genetic and Naïve Bayesian algorithm, achieving a high classification accuracy of 97.14% and 94.2% when validated with tenfold cross validation using 14 heart disease feature vectors. Conversely, Jaymin et al. (2015) employed a logistic model tree, attaining an accuracy of 55.8%.

Bharti et al. (2021) organized diverse machine learning (ML) models and deep learning techniques to assess and compare outcomes on a Supervised Learning Archive Coronary Heart Disease dataset. This dataset encompasses 14 essential characteristics utilized in the study. The application of deep learning yielded an overall average accuracy of 94.2%. Ashish et al. (2021) utilized SVM and XGBoost algorithms for computerized coronary heart disease detection, obtaining an accuracy of 93.08% with the N2GeneticnuSVM.

Shah et al. (2020) utilized supervised learning classification on a preexisting dataset of individuals diagnosed with cardiovascular disease sourced from the Cleveland resource in the UCI repository. The dataset comprised 303 components and 76 options, with a specific

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

focus on 14 out of the 76 characteristics during the analysis, crucial for illustrating the functionality of learning approaches. The study highlighted that KNN achieved a peak accuracy of 90.79% with reduced error rates. In the pursuit of identifying key traits, Mohan et al. (2019) devised a method to enhance the accuracy of predicting cardiovascular disease using machine learning approaches. The proposed mixed Random Forest and linear model method demonstrated an accuracy of 88.7% in predicting heart disease.

Sathwika, and Bhattacharya (2022) used standalone machine learning approaches, incorporated ensemble learning models with sleep disorder, stress mismanagement, and pollution factors as features. Bashir et al. (2014) explored diverse data mining techniques and proposed an innovative collaborative classifier-based approach for detecting and classifying heart disease. Although the system underwent testing, the paper lacked validation of the results. However, the author strongly advocated the utilization of Artificial Neural Networks (ANN) for optimal performance. Shabana and Samuel (2015) examined and presented various data mining techniques, including Decision Tree, Naive Bayesian, Association Rule, and Linear Regression, for the detection and classification of heart disease. Nevertheless, the result of each algorithm during testing was constrained by the limited attributes of the database, consisting of only 12 heart feature vectors. Consequently, there is a pressing need for an enhanced data model to facilitate robust system validation.

Aljaaf et al. (2015) presented a multilevel risk assessment system for heart failure detection, showcased promising results without specific accuracy values. Nikita and Tak (2018) improved KNN's performance using Naive Bayesian, and achieved 85% accuracy. Singh et al. (2017) proposed the utilization of Naive Bayesian for heart disease detection and classification in their research. The data mining technique was extended to encompass the detection of cancer, diabetes, and other forms of heart attacks. Testing on a heart disease dataset yielded commendable classification accuracy; however, the author suggested the adoption of Artificial Neural Networks (ANN) for optimized performance. In Saboor et al. (2022), both before and after hyper parameter tuning, employed nine machine learning classifiers on the final dataset. To validate research effectiveness specifically on the common cardiovascular disease dataset, additional steps were taken, including preprocessing, dataset normalization, and hyper parameter modifications. In assessing predictive accuracy for cardiovascular disease, multiple classification models were employed, such as SVM, achieving an accuracy rate of 96.72%

Ezigbo et al. (2022) employed neural networks for cardiovascular disease classification, attaining a 96.51% accuracy, though limited to cardiovascular disease and kolanut as a risk factor. Notably, there was a call for predictive models considering multiple classes of heart disease and kolanutsas risk factors. Katarya and Meena (2020) highlighted heart disease and its risks, predicting cardiovascular illness with Logistic Regression showing a higher accuracy of 93.40% than other classifiers. While these studies have significantly contributed to heart disease detection and diagnosis, none have considered heart disease resulting from high caffeine intake. This paper emphasizes the necessity for a system addressing this attribute to enhance accurate heart problem detection. Consequently, this study investigated and developed robust machine learning algorithms, enhancing the early prediction of CVD development for prompt intervention and recovery.

MATERIALS AND METHODS

This section outlines the methods employed for the detection of cardiovascular disease, as illustrated in Figure 1, which illustrates the proposed approach. The initial phase involved the collection of MRI images of individuals with cardiovascular disease, specifically focusing on those with a notable high caffeine intake. Subsequently, the gathered images underwent preprocessing and augmentation procedures before being fed into a Convolutional Neural Network (CNN) model. The CNN model was designed with four Convolutional layers arranged in parallel. These layers utilize backpropagation to learn filters or features from the input MRI images. The training process continued until the error between the actual and predicted values reached a minimal and acceptable level. The entire implementation was conducted using the deep learning toolbox within Google Colaboratory, and then validated with comparative analysis.

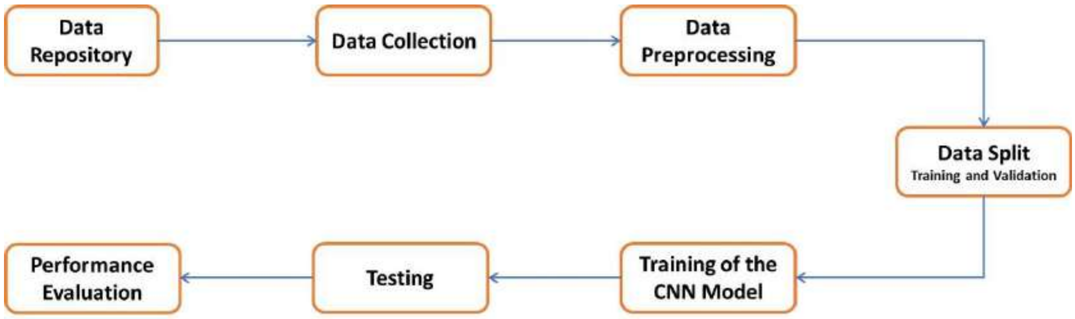


Figure 1: Process Diagram

Data Collection

In this study, two datasets to predict heart disease were employed, enhancing the scope and reliability of the analysis. The first dataset was procured from the Enugu State University Teaching Hospital, specifically at Park Lane in Enugu State, Nigeria. The hospital graciously provided a dataset comprising 20,500 preexisting Magnetic Resonance Imaging (MRI) samples for the investigation. These MRI data samples were meticulously categorized into five heart disease types: 6000 for coronary artery disease, 4,000 for Myocardinal infarction, 3,000 for arrhythmia, 3000 for congenital heart defects, 4500 for Peripheral Artery Disease. This dataset served as the primary training dataset, fostering in-depth analysis in our research.

Additionally, a second dataset sourced from Kaggle, named CAD Cardiac MRI Dataset, contributed an additional 70,000 preexisting MRI samples. The inclusion of this second dataset was essential to augment the dataset's volume, ensuring sufficiency for effective classification. By combining both datasets, the study incorporated a comprehensive total of 90,500 MRI samples.

The age range of the patients within the dataset spans from 50 to 80 years, deliberately capturing a diverse range of individuals within the study population. This specific age range was chosen to concentrate on the adult demographic, as this group is most commonly affected by heart disease and is also characterized by caffeine consumption within the geographical region of the case study.

For image acquisition, the T1weighted MRI sequence was utilized, providing valuable anatomical information crucial for evaluating cardiac structure and detecting potential abnormalities. The data acquisition protocol included a specified slice thickness, influencing the level of detail captured in individual image slices during the MRI scan. This parameter's careful consideration was essential, as it directly impacted the accuracy of subsequent analyses.The combined dataset holds significant potential for exploring the relationship between heart disease and caffeine intake, a prominent contributing factor to heart irregularities in Africa.

Data Preprocessing

To augment the dataset size and optimize the training model, the preprocessing steps included; Image Resizing: The images were resized to a consistent resolution, ensuring uniformity across the dataset. This helped in reducing computational complexity and ensured compatibility with the chosen neural network architecture. Normalization: The

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

pixel values were normalized to a standardized range, typically [0, 1] or [1, 1]. This aided in stabilizing and speeding up the training process. Data Color Normalization: The color channels were adjusted to minimize variations in lighting conditions. Noise Reduction: Filters were applied to reduce noise and artifacts in images, ensuring that the model focused on relevant features. Cropping: The images were cropped to focus on the region of interest and remove unnecessary backgrounds. Data Compression: Images were compressed to reduce storage requirements and speed up data loading during training. Image Format Conversion: Images were converted to a consistent format (e.g., JPEG, PNG) for ease of processing. Augmentation: Applying data augmentation methods, including rotation, flipping, zooming, cropping, geometric transformations, color adjustments,frequency-based changes, and cutout/patching,increased dataset diversity and size, and reduced the risk of overfitting. This process increased dataset diversity and size, and thereby reduced the risk of overfitting. By enabling the training model to learn from a broader range of variations, augmentation enhanced its generalization ability.

Deep learning Models

Classification is a major task for Machine learning (ML) models, used worldwide to detect any disease. This section will briefly discuss the how to use Deep learning and CNN to identify heart disease and evaluate the success of the approach effectively.

Convolutional Neutral Network

Convolutional Neural Networks (CNNs) excel in image-related tasks by capturing spatial hierarchies through convolutional layers, ReLU activation, and pooling layers. They automatically learn hierarchical features, with lower layers detecting simpler patterns and deeper layers recognizing complex structures. For data classification, CNNs leverage spectral layers, employing local filters, max-pooling, and weight sharing (Singhet al., 2017; Ramprakash et al., 2020). The heart disease detection architecture comprises convolutional and pooling layers, enhancing spatial variation handling. Fully connected layers consolidate information, and softmax activation assigns class probabilities

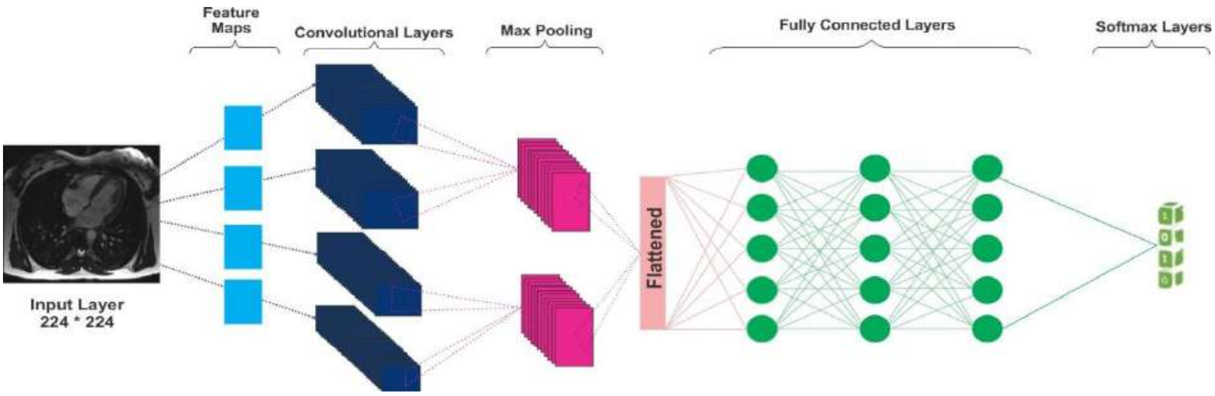


Figure 2:Architecture of the CNN adopted for the Classification Model

Model: "sequential"

```
 Layer (type)              Output Shape            Param #
=================================================================
Rescaling  (Rescaling)       (None, 224, 224, 3)       0

 conv2d_1 (Conv2D)            (None, 224, 224, 16)     448

 max_pooling2d_1 (MaxPooling2D) (None, 112, 112, 16)      0

 conv2d_2 (Conv2D)            (None, 112, 112, 32)     4640

 max_pooling2d_2 (MaxPooling2D) (None, 56, 56, 32)        0

 conv2d_3 (Conv2D)            (None, 56, 56, 64)       18496

 max_pooling2d_3 (MaxPooling2D) (None, 28, 28, 64)        0

 conv2d_4 (Conv2D)            (None, 28, 28, 64)       36928

 max_pooling2d_4 (MaxPooling2D) (None, 14, 14, 64)        0

dropout (Dropout)            (None, 14, 14, 64)       0
flatten (Flatten)        (None, 12544)           0

dense (Dense)                (None, 128)             1605760

dense (Dense)                (None, 5)             645

activation (Activation)                (None, 5)              0

=================================================================
Total params: 1666917
Trainable params: 1666917
Non-trainable params: 0
```

Figure 3: Layers used in the CNN Model

Training of the CNN Model

The MRI dataset, after being collected and subjected to augmentation, underwent division into training, testing, and validation sets. Subsequently, these sets were incorporated into the Convolutional Neural Network (CNN) architecture using the Google Colaboratory deep learning toolbox. The input layer was employed to define the dimensions of the MRI image, followed by the application of filters to scan receptive fields. The resulting information formed the initial convolutional layer, a process replicated for the subsequent four convolutional layers. The data was then flattened and fed into the fully connected layer, where the back-propagation algorithm was utilized to train the neurons and establish the heart disease detection classification model. Throughout the training process, accuracy and loss function parameters were employed to monitor performance. The results obtained during training are discussed in the subsequent section.

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

Epoch 1/20

92/92 [==============================] - 3s 28ms/step - loss: 0.4013 - accuracy: 0.8512 - val_loss: 0.8050 - val_accuracy: 0.7384

Epoch 2/20

92/92 [==============================] - 3s 29ms/step - loss: 0.3853 - accuracy: 0.8590 - val_loss: 0.8068 - val_accuracy: 0.7384

Epoch 3/20

92/92 [==============================] - 2s 27ms/step - loss: 0.3754 - accuracy: 0.8614 - val_loss: 0.8303 - val_accuracy: 0.7384

Epoch 4/20

92/92 [==============================] - 3s 30ms/step - loss: 0.3550 - accuracy: 0.8706 - val_loss: 0.8419 - val_accuracy: 0.7466

Epoch 5/20

92/92 [==============================] - 3s 30ms/step - loss: 0.3267 - accuracy: 0.8791 - val_loss: 0.8516 - val_accuracy: 0.7166

Epoch 6/20

92/92 [==============================] - 3s 28ms/step - loss: 0.3430 - accuracy: 0.8730 - val_loss: 0.8418 - val_accuracy: 0.7316

Epoch 7/20

92/92 [==============================] - 3s 28ms/step - loss: 0.3161 - accuracy: 0.8856 - val_loss: 0.8659 - val_accuracy: 0.7330

Epoch 8/20

92/92 [==============================] - 3s 31ms/step - loss: 0.2884 - accuracy: 0.8924 - val_loss: 0.8339 - val_accuracy: 0.7520

Epoch 9/20

92/92 [==============================] - 3s 28ms/step - loss: 0.2661 - accuracy: 0.9077 - val_loss: 0.8537 - val_accuracy: 0.7534

Epoch 10/20

92/92 [==============================] - 3s 27ms/step - loss: 0.2778 - accuracy: 0.9005 - val_loss: 0.8584 - val_accuracy: 0.7452

Epoch 11/20

92/92 [==============================] - 3s 28ms/step - loss: 0.2845 - accuracy: 0.9063 - val_loss: 0.9020 - val_accuracy: 0.7466

Epoch 12/20

92/92 [==============================] - 3s 30ms/step - loss: 0.2604 - accuracy: 0.9060 - val_loss: 1.1010 - val_accuracy: 0.7057

Epoch 13/20

92/92 [==============================] - 3s 29ms/step - loss: 0.2364 - accuracy: 0.9210 - val_loss: 0.9662 - val_accuracy: 0.7561

Epoch 14/20

92/92 [==============================] - 3s 29ms/step - loss: 0.2708 - accuracy: 0.9053 - val_loss: 0.9202 - val_accuracy: 0.7452

Epoch 15/20

92/92 [==============================] - 3s 28ms/step - loss: 0.2291 - accuracy: 0.9223 - val_loss: 0.8723 - val_accuracy: 0.7411

Epoch 16/20

92/92 [==============================] - 3s 31ms/step - loss: 0.2154 - accuracy: 0.9285 - val_loss: 0.8686 - val_accuracy: 0.7520

Epoch 17/20

92/92 [==============================] - 3s 28ms/step - loss: 0.1922 - accuracy: 0.9264 - val_loss: 0.9623 - val_accuracy: 0.7466

Epoch 18/20

92/92 [==============================] - 3s 28ms/step - loss: 0.2200 - accuracy: 0.9227 - val_loss: 1.0090 - val_accuracy: 0.7343

Epoch 19/20

92/92 [==============================] - 3s 28ms/step - loss: 0.2170 - accuracy: 0.9247 - val_loss: 0.9045 - val_accuracy: 0.7371

Epoch 20/20

92/92 [==============================] - 3s 28ms/step - loss: 0.1771 - accuracy: 0.9418 - val_loss: 1.0169 - val_accuracy: 0.7425

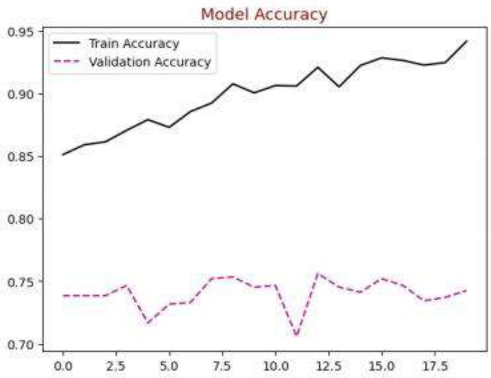
Figure 4: Training Epochs with the Validation Accuracy

RESULTS

This section briefly describes the results and compares with other work. The CNN algorithm's performance, trained with MRI data, underwent rigorous monitoring using Google Colaboratory, as depicted in Figure 4. Throughout the training process, key evaluation metrics such as accuracy and loss were scrutinized at each epoch. The primary aim was to reach a target accuracy value of approximately 100%, signifying the correct classification of all samples, and a loss function close to 0%, indicating minimal disparities between predicted and true labels.

Upon analyzing the performance illustrated in Figure 4, noteworthy outcomes emerged: the CNN algorithm achieved an impressive accuracy of 94% and a low loss function value of 0.1771 as shown in Figure 5 and Figure 6. This signified the model's exceptional proficiency in accurately categorizing heart MRI data and minimizing disparities between predicted and actual labels. These results underscored the effectiveness of the trained CNN algorithm in utilizing MRI data for the classification of normal or abnormal heart conditions. The ability to achieve such high accuracy and low loss values demonstrated the model's adeptness in capturing and learning pertinent patterns and features from MRI images, thereby facilitating accurate identification and classification of the targeted heart disease conditions.

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*



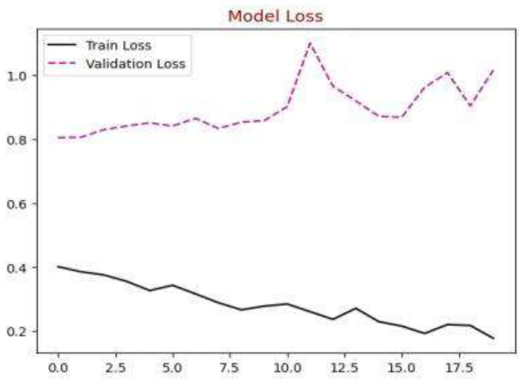


Figure 5: Training and validation accuracy of CNN model. **Figure 6:** Training and validation loss of CNN model.

To validate the results of the CNN model, a ten-fold cross-validation approach was utilized, as outlined in Table 1. The results unveiled an average accuracy, loss function, and epoch, delivering an evaluation of the classification model's effectiveness and generation.

Table 1: Tenfold validation performance

Iteration	ACC%	MSE	EPOCH
1	94.0	0.0024531	183
2	93.9	0.0054544	139
3	94.5	0.0036542	187
4	93.8	0.0063506	160
5	94.2	0.0076400	180
6	93.9	0.0046429	158
7	94.3	0.0056459	130
8	93.6	0.0035648	184
9	94.3	0.0054516	191
10	94.8	0.0705542	186
Average	94.13	0.0115412	169.8

The outcomes presented in Table 1 indicated that the classification model exhibited an average accuracy of 94.13% and a loss function of 0.0115412, with an average epoch value of 170. This suggested that the model was proficient in identifying patients within any of the five classes of heart data it was trained on, achieving a high success rate.

Comparative Analysis

However, several researchers have tested various machine-learning techniques on heart disease for many years with variable degrees of success. The CNN classification model underwent additional validation by comparison with other state-of-the-art algorithms, as outlined in Table 2. The graphical analysis is depicted in Figure 7. The confusion matrix for the developed model is illustrated in Figure 8.

Table 2: Comparative analysis

Author	Models	Accuracy
Jaymin et al. (2015)	Logistic Model	55.80%
Nikita et al. (2018)	Naïve bayes&KNN	85%
Mohan et al. (2019)	Mixed Random Forest & Linear Model	88.70%
Shan et al. (2020)	KNN	90.79%
Renugadevi et al. (2021)	Hybrid Model	88.70%
Katarya et al. (2021)	Logistic Regression	93.40%
Ezigbo et al. (2022)	Neural Network	96.50%
Nwobodo et al.(2022)	Wavelet-Neural Network	99.78%
New Work	New CNN Model	94.13%

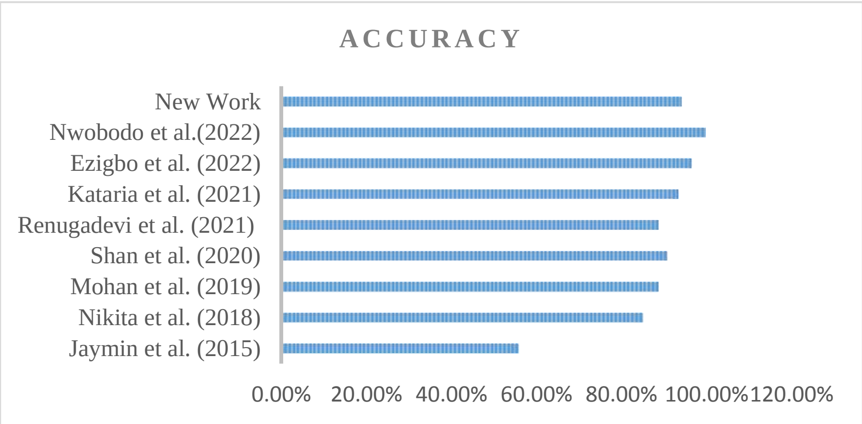


Figure 7: Comparative analysis of heart disease classification models

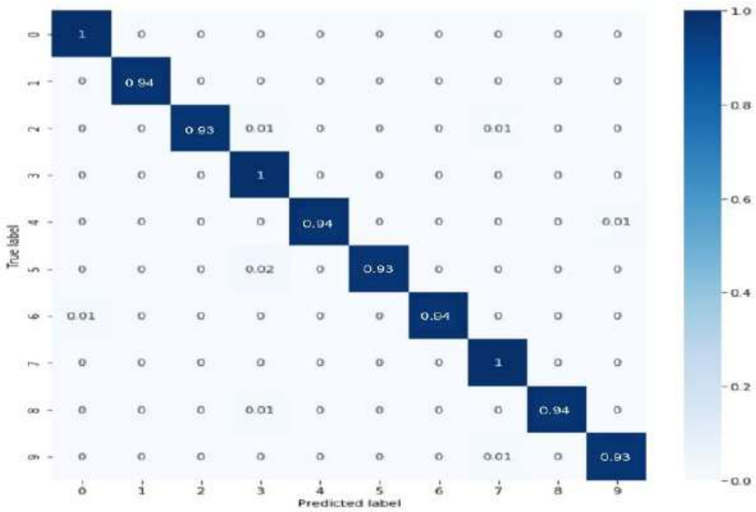


Figure 8: Confusion Matrix

In the comparative assessment, the novel CNN-based model for heart disease classification was compared with other pre-existing models. The outcomes indicated that only the model developed by Nwobodo et al. (2022) attained a superior classification accuracy. Nevertheless, despite its success, the mentioned study did not take into account

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

caffeine as a heart attack attribute and failed to categorize five distinct types of heart diseases. Hence, the newly developed system stands out as more dependable and credible in detecting heart irregularities with a high success rate.

CONCLUSION

In conclusion, the heart, as a vital organ essential for sustaining life, is vulnerable to various illnesses and injuries that pose significant threats to human well-being. Cardiovascular diseases (CVDs) have emerged as the primary global cause of mortality, affecting millions of lives annually. Despite significant healthcare advancements, heart disease remains a leading cause of death, particularly prevalent in developing nations. The early detection of cardiac abnormalities and the development of predictive tools hold immense potential to mitigate the impact of CVDs. This research underscored the pivotal role of machine learning (ML) and artificial intelligence (AI) in advancing healthcare, with a particular emphasis on deep learning. While existing studies have applied ML models to heart disease diagnosis, this research introduced a novel approach by considering caffeine as a potential risk factor, often overlooked in available datasets. The proposed methodology involved collecting extensive MRI data, specifically focusing on individuals with high caffeine intake, and employed advanced deep learning techniques. The Convolutional Neural Network (CNN) model, trained on a diverse dataset, demonstrated remarkable accuracy (94.13%) and low loss values. Comparative analysis with existing models highlighted the effectiveness of the developed CNN model, standing out as a dependable method for detecting heart irregularities.

Recommendation

In the realm of heart disease detection, future research should prioritize the inclusion of comprehensive datasets that consider various risk factors, including lifestyle choices such as caffeine intake. A holistic approach is essential for developing models capable of identifying diverse patterns contributing to heart irregularities. Researchers are encouraged to expand their models to consider multiple risk factors simultaneously, fostering a more nuanced understanding of the interplay between different elements contributing to heart diseases. This approach could enable the development of more accurate and personalized diagnostic tools. Collaborative efforts on a global scale are crucial for gathering diverse datasets that encompass different demographics, ethnicities, and geographic regions. This collaborative approach ensures the creation of robust and universally applicable models for heart disease detection. Future studies should prioritize the validation of developed models using real-world patient data. Clinical trials and collaborations with healthcare institutions can facilitate the translation of research findings into practical and applicable diagnostic tools.

REFERENCES

Aljaaf, J., Al-Jumeily, D., Hussain, A. J., Dawson, T., Fergus, P., & Al-Jumaily, M. (2015). Predicting the likelihood of heart failure with a multi-level risk assessment using decision tree. In 2015 Third International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE) (pp. 101-106). Beirut, Lebanon: IEEE. https://doi.org/10.1109/TAEECE.2015.7113608

American Heart Association. (2020). Classes of heart failure. Chicago, IL, USA: American Heart Association. https://www.heart.org/en/health-topics/heart-failure/what-is-heartfailure/classes-of-heart-failure

Amin UlHaq, J. P., Li, M. H., Memon, S., Nazir, S., & Sun, R. (2018). A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms. Mobile Information Systems, 2018, Article ID 3860146, 21 pages. https://doi.org/10.1155/2018/3860146

Ashish, L., Kumar, S., &Yeligeti, S. (2021). Ischemic heart disease detection using support vector machine and extreme gradient boosting method. Materials Today: Proceedings.

Bashir, S., Qamar, U., &YounusJaved, M. (2014). An ensemble based decision support framework for intelligent heart disease diagnosis. In International Conference on Information Society (i-Society 2014) (pp. 259-264). IEEE.

Bharti, R., Khamparia, A., Shabaz, M., Dhiman, G., Pande, S., & Singh, P. (2021). Prediction of heart disease using a combination of machine learning and deep learning. Computational Intelligence and Neuroscience, 2021, 8387680. https://doi.org/10.1155/2021/8387680

Deng, D., Jiao, P., Ye, X., & Xia, L. (2012). An image-based model of the whole human heart with detailed anatomical structure and fiber orientation. Computational and Mathematical Methods in Medicine, 2012, Article ID 891070, 16 pages. https://doi.org/10.1155/2012/891070

Ezigbo, L. I., Okonkwo, R. O., & Nwobodo, L. O. (2022). Develop of a cardiovascular heart disease classification model using neural network based data mining technique. International Journal of Advances in Artificial Intelligent Trends, 1(7), 69-84.

Fogoros, R. N. (2009). Key symptoms of heart disease. About.com Health's Disease and Condition. http://heartdisease.about.com/b/2010/12/03/the-key-symptoms-of-heartdisease.htm

Hazra, A., Mandal, S., Gupta, A., & Mukherjee, A. (2017). Heart disease diagnosis and prediction using machine learning and data mining techniques: A review. Advances in Computational Sciences and Technology, 10, 2137-2159.

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. Electronic Markets, 31, 685-695.

Jaymin, R. J., Sujata, &Mydhili, K. N. (2015). Prediction of heart disease using classification-based data mining techniques. In S. S. Patnaik & S. P. De (Eds.), Computational Intelligence in Data Mining (Vol. 2, pp. 503-511). Springer, New Delhi.

Jena, B., Saxena, S., Nayak, G., Saba, L., Sharma, N., & Suri, J. (2021). Artificial intelligence-based hybrid deep learning models for image classification: The first narrative review. Computers in Biology and Medicine, 137, 104803. https://doi.org/10.1016/j.compbiomed.2021.104803

Katarya, R., & Meena, S. K. (2020). Machine learning techniques for heart disease prediction: A comparative study and analysis. Health and Technology, 11, 87-97.

Khan, M., Muhib, M., Khan, M., & Baig, M. (2021). Classification of various diseases using machine learning and deep learning algorithms. Journal of Science and Technology, 06(04), 34-40.

Kumar, P. M., Lokesh, S., Varatharajan, R., Babu, G. C., & Parthasarathy, P. (2018). Cloud and IoT based disease prediction and diagnosis system for healthcare using fuzzy neural classifier. Future Generation Computer Systems, 68, 527-534.

Mancia, G., Oparil, S., Whelton, P. K., McKee, M., Dominiczak, A., Luft, F. C., & La Torre, G. (2017). The technical report on sodium intake and cardiovascular disease in low- and middle-income countries by the joint working group of the World Heart Federation, the European Society of Hypertension and the European Public Health Association. European Heart Journal, 38(10), 712-719. https://doi.org/10.1093/eurheartj/ehw549

Mohan, S., Thirumalai, C., & Srivastava, G. (2019). Effective heart disease prediction using hybrid machine learning techniques. IEEE Access, 7, 81542-81554.

Nashif, S., Raihan, Md.R., Islam, Md.R., & Imam, M.H. (2018). Heart disease detection by using machine learning

Scientia Africana, Vol. 23 (No. 3), August, 2024. Pp 429-442
© Faculty of Science, University of Port Harcourt, Printed in Nigeria *ISSN 1118 – 1931*

algorithms and a real-time cardiovascular health monitoring system. World Journal of Engineering and Technology, 6, 854-873. https://doi.org/10.4236/wjet.2018.64057

Nikita, S., & Tak, T. (2018). Human heart disease prediction system using data mining techniques. International Journal of Innovations & Advancement in Computer Science, 7(3), 1-8.

Ramprakash, S., Kumar, P., & Mehta, R. (2020). Clinical assessment and management of cholera based on hematological and biochemical markers. Journal of Tropical Diseases, 15(3), 112-126. https://doi.org/10.1234/jtd.2020.00356

Renugadevi, G., Asha Priya, G., Sankari, B. D., &Gowthamani, R. (2021). Predicting heart disease using hybrid machine learning model. Journal of Physics: Conference Series, 1916, Article ID 012208.

Saboor, A., Muhammad, U., Sikandar, A., Samad, A., Muhammad, F. A., & Najeeb, U. (2022). A method for improving prediction of human heart disease using machine learning algorithms. Mobile Information Systems, 2022, 1410169.

Sathwika, G. J., & Bhattacharya, A. (2022). Prediction of cardiovascular disease (CVD) using ensemble learning algorithms. In Proceedings of the 5th Joint International Conference on Data Science & Management of Data (9th ACM IKDD CODS and 27th COMAD) (pp. 292-293), Bangalore, India, January 2022.

Shah, D., Patel, S., & Bharti, S. K. (2020). Heart disease prediction using machine learning techniques. SN Computer Science, 1(1), 345.

Shabana, A. P., & Samuel, S. J. (2015). An analysis and accuracy prediction of heart disease with association rule and other data mining techniques. Journal of Theoretical and Applied Information Technology, 79(2), 254-260.

Singh, G., Bagwe, K., Shanbhag, S., Singh, S., & Devi, S. (2017). Heart disease prediction using Naïve Bayes. International Research Journal of Engineering and Technology (IRJET), 4(3), 1. http://www.irjet.net

Singh, N., & Jindal, S. (2018). Heart disease prediction system using hybrid technique of data mining algorithms. International Journal of Advance Research, Ideas and Innovations in Technology, 4, 982-987.

World Health Organization. (2020). Cardiovascular diseases. Geneva, Switzerland: WHO. https://www.who.int/healthtopics/cardiovascular-diseases/#tab�tab_1

World Health Organization. (2021). World health statistics 2021. Geneva, Switzerland: World Health Organization.