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AI-powered cardiovascular risk prediction using deep learning images in IoT-blockchain systems

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ABSTRACT

The increasing prevalence of cardiovascular diseases (CVDs) necessitates the development of intelligent, secure, and scalable diagnostic systems capable of accurate and early disease prediction. The importance of this research is to develop a robust and secure system for predicting CVD risk from echocardiogram imaging integrated within an internet of things (IoT) framework and enhanced by blockchain technology. Due to non-invasive feature identification problems and dimensionality, prediction accuracy is degraded due to higher false positives, which leads to lower precision and recall rates. To resolve this problem, implement AI-powered CVD risk prediction based on smart-featured deep learning in Echocardiogram images for an IoT-blockchain environment. The first phase contains data analysis echocardio-dataset vision transformation technique is functional to find the risk level of the disease. The adaptive gaussian filter is applied for normalization process and design a spread-spectral canny edge morphological segmentation and SURF-scaled invariant feature selection for dimensionality scaling. Then, visual geometry network (VGNet) convolutional neural network (CNN) is applied for disease classification. In second phase, the advanced blockchain technology will provide a decentralized and immutable record of patient data, thereby ensuring data integrity and security. The proposed system produces higher performance by analysing the sensitivity specificity as well by ensuring the disease detection level. The blockchain provides higher security to safe in repository for image data for carrying sensitive data with a platform for sharing and validating predictive insights among healthcare providers, researchers, and patients, thus fostering collaborative healthcare efforts.

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1. INTRODUCTION

Cardiovascular diseases (CVDs) remain the leading cause of death globally, accounting for an estimated 17.9 million lives each year, according to the World Health Organization (WHO). Early diagnosis and effective monitoring are critical in mitigating the mortality and morbidity associated with CVDs. Among the diagnostic tools available, echocardiography provides a non-invasive and real-time view into cardiac health [1]–[6]. However, despite its effectiveness, the interpretation of echocardiogram images is often challenged by subjectivity, variability among operators, and high-dimensional image features that complicate automatic analysis [7]–[12].

Recent advances in artificial intelligence (AI) and deep learning have opened new possibilities in medical imaging for automating disease detection with higher accuracy. Particularly, convolutional neural networks (CNNs) have demonstrated significant promise in image-based diagnostics [13]–[18]. However, in the context of echocardiogram analysis, challenges such as non-distinct feature localization, high-dimensional data, and the risk of false positives hinder performance and reliability [19]–[22]. Moreover, the growing concern over data privacy and security in healthcare systems calls for trustworthy data management frameworks [23]–[27].

To address these challenges, this research proposes an AI-powered system that integrates smart-featured deep learning with internet of things (IoT) devices and blockchain technology. Echocardiographic data collected from IoT-enabled medical imaging devices are processed using an advanced deep learning architecture, named visual geometry network convolutional neural network (VGNet-CNN), designed for high-precision classification. Prior to classification, a novel spread-spectral canny edge morphological segmentation and speeded-up robust features (SURF)-scaled invariant feature selection method is introduced to enhance feature extraction and reduce dimensionality, thus improving accuracy and computational efficiency, as shown in Figure 1.

In parallel, blockchain is integrated into the system to ensure data integrity, transparency, and security. By creating a decentralized ledger of patient echocardiogram records and diagnostic outcomes, blockchain not only protects patient confidentiality but also enables secure data sharing among stakeholders, including healthcare professionals and researchers. This promotes a collaborative healthcare ecosystem where predictive insights can be reliably validated and accessed.

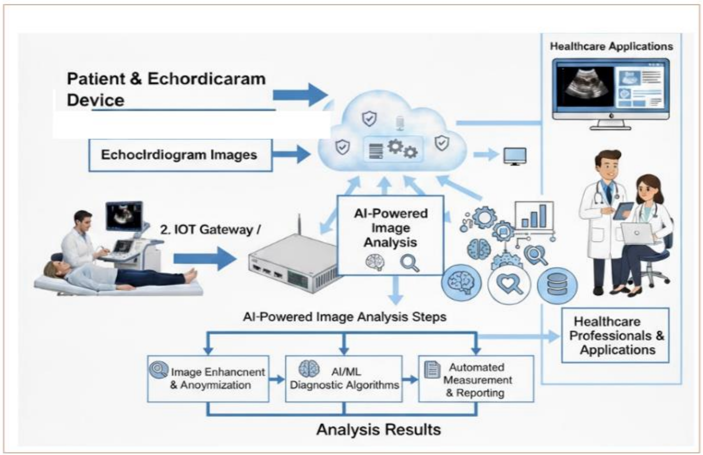

Figure 1. Progressive analysis of echocardiogram

2. RELATED WORK

CVD is considered the leading cause of death worldwide. A method based on machine learning (ML) for cardiovascular disease diagnosis (MaLCaDD) is proposed to effectively predict cardiovascular disease with high accuracy. Specifically, the framework first addresses missing values and data imbalance [1]. Then, feature selection is done using feature importance techniques. Finally, a combination of logistic regression and K-nearest classifiers is proposed to achieve even higher prediction accuracy. However, the integrity of the process is high and the storage range is wide. ML techniques are extremely useful in medicine, enabling faster and more accurate diagnosis of heart disease [2]. However, both generate robust and effective features from the data, which can then be used in predictive models. Both processes present numerous challenges when dealing with large and complex data sets.

In recent years, with the increasing prevalence of sub-health, high risk prediction of CVD has become more important and urgent in the medical field [3]. They propose a complete, fully-fledged model called Deep Risk based on the attentional mechanism and deep neural network (DNN). To integrates heterogeneous and temporally sorted clinical data to ultimately predict the patient's CVD risk. However, this model is computationally expensive and less reliable. As CVD remains one of the leading causes of death worldwide, sophisticated predictive models are needed for early detection and prevention [4]. This paper utilizes various ML algorithms to evaluate the accuracy and performance of these models. However, the sudden loss of heart activity, breathing, and consciousness can be fatal if not treated immediately.

Deep learning-based models in clinical informatics are utilized to predict and diagnose CVD. One such model is proposed using a DNN to provide early prediction of CVD with regression methods [5]. The disease can inhibit blood flow to the legs and arms, resulting in pain and other symptoms. Although numerous efforts have been made to mitigate CVD progression, it remains the leading cause of death in most nations worldwide. Although potential genetic biomarkers for predicting CVD effects has been established, high-throughput technologies for targeting genomic data [6]. The systems and technologies potentially discussed in this special issue may assist in patients with the management of CVD. Nevertheless, one challenge remains that may result in long-term physical disability in survivors of either a heart attack or stroke.

Heart disease remains one of the leading causes of death globally, and echocardiography is the most common modality in diagnosing heart disease. To particular challenges, this project has the goal of developing advanced deep learning models that can automatically classify heart disease from echocardiographic data [7]. Despite the challenges heart disease typically brings, chronic long-term care is frequently required that may require prolonged stays in a hospital system.

A three-dimensional cardiac modeling system based on neonatal echocardiographic images is proposed [8]. To propose a set of algorithms and interfaces for creating cardiovascular models of various congenital heart diseases, allowing editing of the topology and shape of the 3D models. However, treating CVDs often requires prolonged hospitalization and ongoing, expensive medical care.
Cardiovascular neural crest diseases are a consequence of improper migration and development of neural crest cells, a population of cells responsible for the development of both the nervous and human cardiovascular systems [9]. Explainable AI models are intended to provide publicly available datasets, concept to standardize reporting to improve reproducibility and develop standardized performance metrics. However, this puts the individual at an additional risk of stroke and heart failure.

Myocardial activity monitoring is an important clinical tool for the prevention and detection of CVD (CVD, the leading cause of death worldwide). To address these challenges, this paper proposes a neural cardiac motion field (NeuralCMF) [10]. Neural CMF uses implicit neural representations (INRs) to model the heart’s 3D structure and integrated 6D forward/backward motion. However, the incidence of anxiety and depression in coronary artery disease (CAD) patients is higher than in the general population.

Heart disease is one of the top causes of death, globally. Echocardiography is a common method that is used for heart disease diagnosis [26]–[29]. This deep learning model would be set up to classify heart disease cases, so that it is better suited for early disease detection and prognostication. Stress can activate the body’s “fight or flight” response that can contribute to heart damage and worsen heart disease.

The potential of ML techniques for improving heart disease predictions would provide up and coming avenues for health researchers and practitioners [30]–[32]. The discovery of the best ML techniques will help to improve accuracy of diagnosis, and patient care for CVDs. Once diagnosed with a CVD, people may experience more concerning cardiovascular health if they are non-adherent to their medical. One of the deadliest diseases is heart disease, condition affects a large portion of the world’s population CNNs are used to create early prediction and medical diagnostic systems [33]–[35]. The CNN receives 13 clinical features as input and is trained using a modified backpropagation training method. However, heart disease occurs when blood supply to the heart muscle is blocked.

3. PROPOSED WORK

The proposed system is a multi-layered architecture designed to perform accurate, secure, and real-time CVD risk prediction from echocardiogram images within a decentralized healthcare environment. It comprises three major components: IoT-based data acquisition, AI-driven image analysis, and blockchain-enabled data management (BC). The architecture of the proposed CNN-BC-advanced encryption standard-galois/counter mode (AESGCM) framework, which is AI-powered and designed for CVD prediction and secure healthcare data management in an IoT-blockchain environment. There are two primary stages in which the architecture functions. Additionally, sophisticated image modification techniques are used for the preparation and analysis of echocardiography data.

The Gaussian Filter is also capable of reducing spurious intensity variations to create a cleaner, smoother image, which greatly enhances the output of the next step segmentation, as vessel structures and cardiac tissues can be properly outlined to do more analysis and classification, as shown in (1).

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where x and y are the horizontal and vertical distances to the center of the kernel and the spatial influence of each neighboring pixel on the center pixel is ascertained. The extent of the Gaussian spreading, which directly corresponds to the standard deviation σ, controls the extent of the smoothing, and therefore removes random noise in the CVD images, but can blur smaller vessel details, where a smaller σ keeps the boundaries sharp like arterial walls or myocardial edges. The kernel value $G(x, y)$ places a weight on each of the neighboring pixels, but weight of the pixel that is nearer to the center is more significant, such that structural information in the areas of interest such as vessels and heart chambers is preserved without unrelated variations, as shown in (2).

$$I_s(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x+i, y+j) \,.\, G(i,j) \tag{2}$$

In this case, $I(x, y)$ denotes the original CVD image with noise and variations in intensity, and $I_s(x, y)$ denotes the resultant processed image.

Canny edge segmentation will offer an accurate and noise-insensitive edge map that can be used to analyze the structural abnormalities and help clinicians to diagnose CVD and make image-based evaluations, as shown in (3).

$$I_s(x,y) = I(x,y) * G(x,y) \tag{3}$$

The convolution process of $I(x, y)$ and the filter would result in a smoothed image $I_s(x, y)$ which preserves the important details of the heart, but prepares the image to extract accurate edges, as shown in (4).

$$G_x = \frac{\partial I_s}{\partial_x},\ G_y = \frac{\partial I_s}{\partial_y} \tag{4}$$

The calculation of this is done to determine regions where pixel brightness changes rapidly pointing to potential boundaries of arteries, veins, or heart chambers on CVD images, as shown in (5).

$$M(x,y) = \sqrt{G_x^2 + G_y^2} \tag{5}$$

This is the strength of these edges, the higher the values the stronger the edges like vessel walls or boundaries of heart tissues, as shown in (6).

$$\theta(x,y) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{6}$$

It defines the direction of such structures, which aid the segmentation algorithm to know the directional flow of vessels and cardiac contours form. In combination, the variables demonstrate the pivotal structural changes that characterize CVD-affected areas, as shown in (7).

$$E_{nms}(x,y) = \begin{cases} M(x,y), & if\ M(x,y) \text{ is local maximum along } \theta(x,y) \\ 0, & otherwise \end{cases} \tag{7}$$

The process is to make sure that only the most notable and correct vessel boundaries are maintained. Weaker or redundant pixels are suppressed by comparing the gradient magnitude $M\ (x, y\ )$ of each pixel with those of its neighbors along the gradient direction $\theta(x, y)$. The resulting edge map $E_{nms}(x, y)$ has thin and sharp silhouettes of the cardiac structures and further enables better visualization of arteries, veins and other vascular routes in the CVD images, as shown in (8).

$$E_T(x,y) = \begin{cases} \text{strong edge}, & \text{if } M(x,y) \geq T_H \\ \text{weak edge}, & \text{if } T_L \leq M(x,y) < T_H \\ 0, & otherwise \end{cases} \tag{8}$$

In the (6), two intensity levels are used: T_H in strong edges and T_L in weak edges. Strong edges (CVD imaging) are sharp edges of vessels or walls of the heart, whereas weak ones can be small differences in tissue or less pronounced vessels. This categorization will maintain vital medical characteristics and reduce the interference of the background to a minimum. The variation in T_H and T_L gives the flexibility in the detection of large and fine structures of the cardiovascular, as shown in (9).

$$E_f(x,y) = E_T(x,y) + \text{connected}\left(E_{weak,}E_{strong}\right) \tag{9}$$

The proposed method employs a VGNet-CNN to achieve high accuracy and stability in cardiovascular disease (CVD) diagnosis. VGNet-CNN identifies complex changes in image intensity, pictorial structure, and morphology, thereby assisting clinicians in automated and reliable CVD identification and classification.

$$F_{i,j}^{(l)} = \sum_m \sum_n I_{(i+m),(j+n)}^{(l-1)} . K_{m,n}^{(l)} + b^{(l)} \quad (10)$$

The input CVD image, $I^{(l-1)}$, is processed through the convolution operation using small learnable filters, $K^{(l)}$, to identify spatial patterns such as blood vessel edges, tissue boundaries, and lesion areas, as described in (10). Each filter extracts different medical features; for example, one filter may detect fine vascular structures, whereas another identifies plaque buildup. The convolution output, $F_{i,j}^{(l)}$, represents the activation strength of the matched feature, while the bias term $b^{(l)}$improves the flexibility of feature learning. VGNet-CNN progressively learns hierarchical image representations through multiple convolutional layers, starting from low-level texture features and advancing to more complex disease-related patterns, as represented in (11).

$$A_{i,j}^{(l)} = \max\left(0, F_{i,j}^{(l)}\right) \quad (11)$$

The activation function offers non-linearity to the VGNet-CNN, which enables it to acquire complex and nonlinear associations in CVD images. The rectified linear unit (ReLU) is used to transform all negative values in the features to zero, retaining the positive ones, so that only the most important cardiac features are enabled. This assists in highlighting effective structural indicators including bright vessel edges or calcified and lowers superfluous or clamorous background areas. Consequently, the $A_{i,j}^{(l)}$ becomes an optimized map of meaningful features that identify CVD, as shown in (12).

$$P_{i,j}^{(l)} = \max_{(m,n)\in R_{i,j}} A_{m,n}^{(l-1)} \quad (12)$$

The network in the pooling layer eliminates features of a spatial scale without discarding the most important features. The largest activation (or the most dominant feature in that local area) in each pooling region $R_{i,j}$ is selected. The operation guarantees translation invariance - that is, when the heart or vessels are slightly moved or rotated, this does not produce any effect on accuracy of recognition. Pooling in the imaging of CVD aids in keeping specific focus on the most significant pathological locations such as thickened arteries, lesions, or blockage hence retaining key diagnostic information with minimal computing complexity, as shown in (13).

$$f = \text{flatten}\left(P^{(L)}\right) \quad (13)$$

The flatten process reduces the final pooled feature maps $P^{(L)}$ into a one-dimensional feature f, which is a consolidation of all extracted spatial and textural features of the CVD image. The feature vector is a unified signature of the cardiovascular structure, which is comprised of vessel geometry, wall thickness, and tissue density patterns. VGNet-CNN transforms multi-dimensional image data to a linear form, which can subsequently be classified in the succeeding dense (fully connected) layers, as shown in (14).

$$z_k = \sum_{i=1}^{N} w_{ki} . f_i + b_k \quad (14)$$

Each feature f_i in the fully connected layer is then given a learnable weight w_{ki} with that feature influencing a particular output class. The bias b_k makes the model flexible by adjusting the threshold of the model. This layer is a decision-making phase, and the learnt cardiovascular characteristics are integrated to identify the signs of disease, including vessel blockages, abnormal vessel thickness or irregular heart tissue structure. As shown in (15), calculate the raw score or activation strength of a potential CVD class is denoted as the output z_k.

$$P(C_k \mid f) = \frac{e^{z_k}}{\sum_{j=1}^{K} e_{z_j}} \quad (15)$$

The last classification is reached with the help of the softmax function that transforms the scores of outputs z_k into the probability of each disease class C_k. This makes sure that the total likelihood of all the classes add up to one so that VGNet-CNN can classify the most likely cardiovascular condition (e.g., normal, mild, or severe). The decision that is made by the model is the one with the greatest-value probability. This is an important step in CVD image analysis to give a clear interpretable prediction that can be used by the medical professional to diagnose the severity of the disease and make informed decisions about treatment based on the data.

The integrity hash h_C is calculated using the cryptographic hash function $H(\cdot)$. This hash is stored as a blockchain ledger record of an immutable verification receipt of the associated CVD image data. During retrieval or decryption of an image, the calculated hash may be reassessed with the one stored in the blockchain to ascertain the authenticity of the data. This is to ensure that there have been no alterations made in the ciphertext of the image since encryption. In the CVD dataset management system, h C is the fixed digital signature that identifies each ciphertext medical record to its valid blockchain transaction.

The hyperparameter tuning process as in Table 1 focused on critical model parameters such as learning rate, batch size, number of epochs, optimizer type, dropout rate, and convolutional filter configurations. Each parameter was evaluated across a predefined range of values, and the best combination was selected based on validation accuracy and loss minimization.

The results indicate that the Adam optimizer with a learning rate of 0.001 provides stable convergence and faster training. A batch size of 32 ensures a balance between computational efficiency and gradient stability, while 50 epochs were sufficient to achieve optimal performance without overfitting.

Table 1. Hyperparameter settings for VGNet-CNN

Hyperparameter	Tested values	Optimal value
Learning rate	0.1, 0.01, 0.001, 0.0001	0.001
Batch size	16, 32, 64, 128	32
Number of epochs	20, 50, 100	50
Optimizer	Adam, SGD, RMSprop	Adam
Dropout rate	0.2, 0.3, 0.5	0.3
Number of convolutional layers	3, 4, 5	4
Filter size	3×3, 5×5	3×3
Activation function	ReLU, Leaky ReLU	ReLU
Pooling type	Max Pooling, Average Pooling	Max Pooling
Fully connected neurons	64, 128, 256	128

4. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the experimental results obtained through a series of data as the section shows, the given workflow is effective in terms of protecting and controlling sensitive health information in addition to achieving high performance in a distributed healthcare setting. In general, the workflow minimises the risks of sensitive data leakage while also providing auditability, privacy, authenticity, and integrity and is scalable, secure, and suitable for large distributed healthcare datasets. Furthermore, the proposed VGNet-CNN method enables the validation of predictive insights across patients using performance metrics such as sensitivity, specificity, precision, recall, F1-score, time complexity, accuracy, and the receiver operating characteristic (ROC) curve to compare with previous XGBoost, DNN, and region-based convolutional neural network (RCNN) techniques.

Table 2 demonstrates the performance, integrity and scalability of the workflow was tested by the choice of simulation parameters. As shown in Table 3, the precision analysis can accurately identify the pattern of CVDs based on medical imaging data. Furthermore, the analysis precision of the proposed VGNet-CNN algorithm on both the test and training data, measured by the number of images, is shown to be 89.26%. Similarly, the analysis precision of the proposed algorithm is shown to be 79.24%, 83.04%, and 85.19% compared to the previous XGBoost RCNN and DNN algorithms.

As demonstrated in Table 4, the recall analysis effectively identifies CVD patterns from medical imaging data. The results also indicate that the proposed VGNet-CNN algorithm achieves a recall of 92.13% on both test and training datasets, based on the number of images. Additionally, the analysis recall of the proposed algorithm is 81.12%, 84.22%, and 87.24%, outperforming the previous XGBoost RCNN and DNN algorithms.

As shown in Table 5, F1-score analysis can effectively identify patterns of CVD in medical imaging data. The results also show that the proposed VGNet-CNN algorithm achieves an F1-score of 93.18% on both the test and training datasets, depending on the number of images. Furthermore, the analytical F1-scores of the proposed algorithm are 83.16%, 85.23%, and 88.17%, respectively, which exceed the previous XGBoost RCNN and DNN algorithms.

As shown in Table 6, accuracy analysis effectively identifies patterns of CVD in medical imaging data. The results also demonstrate that the proposed VGNet-CNN algorithm achieves an accuracy of 96.29% on both the test and training datasets, depending on the number of images. Furthermore, the analytical accuracy of the proposed algorithm is 85.18%, 89.27%, and 92.13%, respectively, which surpasses that of the previous XGBoost RCNN and DNN algorithms.

Time complexity analysis effectively identifies patterns of CVD in medical imaging data, as shown in Table 7. The findings also show that, depending on the number of images, the suggested VGNet-CNN method achieves a temporal complexity of 8.02 ms on both the test and training datasets. Additionally, the proposed algorithm's analytical time complexity is 20.09 ms, 17.05 ms, and 13.08 ms, respectively, which is faster than that of the earlier XGBoost RCNN and DNN methods.

As described in Table 8, the security performance analysis demonstrates the effectiveness of the IoT-blockchain-based framework in securing CVD healthcare data. The proposed chaos-aware key distribution (CAKD)-AESGCM technique achieved a security performance of 96.21%, outperforming the existing unified elliptic curve cryptography (UECC), role-based access control (RBAC), and blockchain lightweight healthcare security (BLWHS) techniques, which attained 83.11%, 87.14%, and 91.15%, respectively.

Table 2. Simulation parameter

Parameters	Values
Dataset name	CVD- ech-card dataset
No of data records	25000 images
Block chain type	Ethereum
Authentication	Hash master- node
Crypto-algorithm	Sha-256 with aes folding
No of nodes	50-100
Access trust threshold (ts)	0.7 – 0.9
Testing – training validation	7:3 ratio

Table 3. Performance of precision

Number of images	XGBoost	RCNN	DNN	VGNet-CNN
6,250	70.12	73.25	75.17	77.23
12500	74.21	77.14	79.28	81.11
18750	77.15	80.26	82.31	85.17
25000	79.24	83.04	85.19	89.26

Table 4. Performance of recall

Number of images	XGBoost	RCNN	DNN	VGNet-CNN
6,250	72.31	75.14	78.17	80.14
12,500	76.31	77.23	80.35	83.22
18,750	79.27	81.19	84.26	87.15
25,000	81.12	84.22	87.24	92.13

Table 5. Performance of F1-score

Number of images	XGBoost	RCNN	DNN	VGNet-CNN
6,250	72.4	75.14	77.17	80.18
12,500	76.3	79.22	81.26	85.25
18,750	79.12	82.31	84.15	89.10
25,000	83.16	85.23	88.17	93.18

Table 6. Performance of accuracy

Number of images	XGBoost	RCNN	DNN	VGNet-CNN
6,250	74.12	77.28	82.15	86.23
12500	78.11	81.14	85.29	89.09
18750	81.19	85.17	89.18	92.06
25000	85.18	89.27	92.13	96.29

Table 7. Performance of time complexity

Number of images	XGBoost	RCNN	DNN	VGNet-CNN
6,250	31.02	28.11	23.05	19.06
12500	27.05	25.16	20.16	15.04
18750	23.07	21.10	17.14	11.03
25000	20.09	17.05	13.08	8.02

Table 8. Performance of security

Number of nodes	UECC	RBAC	BLWHS	CAKD-AESGCM
25	70.12	73.17	76.31	81.17
50	74.16	77.28	80.28	85.26
75	79.14	82.15	85.22	90.12
100	83.11	87.14	91.15	96.21

5. CONCLUSION

In conclusion, an IoT-Blockchain environment was used to deploy a smart-featured deep learning system for CVD risk prediction utilising echocardiography images. The suggested framework showed a strong two-phase methodology. The initial phase involved normalising, segmenting, and reducing the dimensionality of echocardiography data using sophisticated image processing techniques, including adaptive Gaussian filtering, spread-spectral Canny edge morphological segmentation, and SURF-scaled invariant feature selection. A VGNet-CNN model was then used to classify the disease risk precisely. The system's strong performance, as measured by standard metrics such as sensitivity and specificity, demonstrated reliable disease identification. Blockchain technology ensured that patient data was stored securely and in a decentralised manner during the second phase. Data integrity, confidentiality, and immutability-all crucial elements in medical applications-were preserved by the framework using CAKD-AESGCM. Furthermore, the VGNet-CNN validates patient predictions using metrics such as sensitivity, specificity, precision, recall, F1-score, accuracy, and ROC, comparing them to XGBoost, DNN, and RCNN. Tests utilised simulated patient records, vital signs, and laboratory results. CAKD-AESGCM can be compared to UECC, RBAC, and BLWHS in terms of security, energy efficiency, data volumes, trust, and transaction loads for blockchain-based health data protection. The results also demonstrate that the proposed VGNet-CNN algorithm achieves an accuracy of 96.29%. Additionally, the security performance analysis can be used to secure CVD healthcare data based on the application of IoT blockchain technology. Furthermore, the security analysis performance of the proposed CAKD-AESGCM technique is shown to be 96.21% compared to the previous method.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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