# HEART SAVIOUR: A Dense Network Four Way Transformer Network for Remote Heart Disease Monitoring using Medical Sensors for Blockchain Cloud Assisted Healthcare

**S. Geetha[1,*], M. Vigenesh[1], R. Santhosh[1]**

[1]Department of Computer Science and Engineering, Faculty of Engineering, Karpagam Academy of Higher Education
Coimbatore, Tamil Nadu, India
Emails: sgeethame@gmail.com; mvigenesh@gmail.com; santhoshrd@gmail.com

**Abstract**

Internet of Things (IoT) with Cloud Computing (CC) offers seamless connectivity in the healthcare environment which provide remote monitoring and diagnosis to the patients based on their health status. However, remote healthcare environment faced with security, privacy, bandwidth, and latency constraints which can be addressed by adopting blockchain, CC, and Edge Computing (EC) with medical IoT applications. In this research, HEART SAVIOUR model is developed which ensures real time remote heart disease analysis using Deep Learning (DL) and Transformer based method. The propounded research was tested and trained on the Hungarian and Cleveland dataset from the UCI repository. Initially, the patient data are passed to the edge gateway which are pre-processed in three folds which includes missing value replacement, noise reduction, and data normalization respectively. Within the edge gateway, the pre-processed data are subjected to encryption for guaranteeing secure communication using Binary Search Encryption Algorithm (BSEA). The encrypted sensitive data is then passed to the cloud server for automated remote heart disease analysis using Dense Nested Four Way Transformer Network (DNFW-Net). The analyzed results are securely stored in the block chain and based on the request raised by the healthcare specialists the automated and reliable reports are generated and securely provided to the remote patients. We have validated the proposed research on five performance metrics with 10% to 100% data distribution in which the proposed work achieves achievable performance than the existing works. The inclusion of edge computing, encryption, and block chain technologies with advanced AI algorithms, we ensure superior remote heart disease detection performance than the prior works.

**Keywords:** Internet of Things (IoT); Remote Heart Monitoring; Cloud Computing (CC); Edge Computing; Block chain; Security

## 1. Introduction

In recent decade, the development of IoT and sensor technology associated with wearable medical devices has been improved the patient's healthcare quality excellence via smart remote health monitoring devices [1]. In modern time the cloud-based IoT systems has been used widely in medical monitoring devices and smart remote health [2]. The combination of Internet of Thinks and Cloud Computing has many benefits especially in resource management [3]. In addition, these benefits include powerful processing, resource distribution, preventing data from being scattered across various databases and allowing users to monitor system [4]. Current remote healthcare monitoring system in cloud-based IoT environment transmits and stores patient's biological data in order to analysis data from anywhere at any time. Therefore, transferring patient's medical data via the IoT networks and storing it in the cloud, ensuring data security and privacy has become a key concern in the system [5]. Thus, applying implementing data security techniques like lightweight block encryption is important for safely securing health data management on restricted IoT platforms in essential systems [6]. These IoT platforms is essential for wide-range access and the internet is one of the greatest inventions



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

ever. The Internet of Thinks are very smart in healthcare systems and the Internet of Medical Thinks is most helpful for healthcare experts to remotely diagnose patients and convenient access to medical services for patients [7]. Fog and cloud computing are most crucial technologies in healthcare which is capable of providing e-healthcare services across several applications. Hearth disease have become most common cause of death in today's world. Conditions like Arrhythmias, coronary artery disease and cardiac valve dysfunction a rice in modality [8]. Risk factors include obesity, depression, aging, sugar intake, inactivity, high blood pressure and smoking which should be managed to prevent severe outcomes such as heart attacks, blindness, stoke and heath failure [9]. Techniques including Machine Learning (ML), Deep Learning (DL) and Ensemble learning (EL) enhance accuracy and performance of predictive healthcare analytics [10].

Health application have advanced rapidly with IT application that allow for remote patient status monitoring and control. IoT has completely changes the healthcare system by gathering physiological data about patients through wearable technology and sensor networks [11]. Cloud-IoT manages massive amounts of sensor data and medical record data for healthcare analytics by utilizing Clouds enormous processing and storage capacity [12]. Analytics consequent the qualitative analysis of sensitive data and systematic quantitative for efficient decision making. Furthermore, predictive analytics develops advanced analytics which uses the data at hand to determine the probability of future events [13]. In healthcare analytics is used for predictive risk assessment, remote health monitoring and medical decision support. By integrating large of data through sources like medical imaging, screening results, electronic health records and administrative data to support swift decision making has become effectively addressed by medical analytics [14]. These predictive analytics helps clinicians to make informed decisions, identify problem early, reduce complications, manage chronic illnesses, and prevent hospital readmissions, lower costs and support medical research [15]. Furthermore, predictive analytics in healthcare system employs various techniques from traditional techniques to advanced AI and ML algorithms. DL a subfield of ML can automatically manage and learn with large number of complex healthcare data and providing valuable insights and solutions to complex issues. It outperforms traditional models in many medical applications including Recurrent Neural Network (RNN) a subfield of DL is especially good at managing data over time and are widely used for analysing events.

Internet of Medical Things (IoMT) joins medical devices and people using wireless connections to share healthcare data. At this time, with a growing population and new technologies these healthcare costs have been increased drastically [16]. Therefore, IoMT offers effective accurate diagnoses, fewer complications and reduces treatment costs. Technology like smartphone application allows patients to send health records to doctors in order to enhance the detection and monitoring of various disease [17]. IoMT provides accurate data processing, efficient workflows and error reduction which allows real-time patient tracking and reducing the need for frequent doctor visits. Cloud servers collects patient's data and process patient data for quantitative assessments. Furthermore, IoMT data transfer faces medical security challenges particularly data protection due to device integration and data exchange [18]. Regardless, there are still some legal and compliance issues also increase the inadequate data protection standards and accessibility. Block chain ensure secure data management for data acquisition and cloud connectivity. Blockchain store the patient data as encrypted string in blocks. Intelligent contracts can be useful for securing data integrity and verifiability [19]. In addition, it is used to enhance block chain security and stability. These blockchain tracks sensor data to prevent malicious replicate and indicates unmodified file identifiers throughout the network. Moreover, IoMT systems utilizes a distributed ledger for secure data definition, transfer and authentication [20]. As the knowledge and intentions of healthcare medical professional's patient safety and quality of care and trust is essential in the healthcare.

To address these issues, in this paper we developed a HEART SAVIOUR remote cardiac monitoring framework which ensures security, reliability, scalability and communication efficacy to the healthcare environment. The proposed framework includes remote patients with sensor embedded IoT devices, edge gateway and blockchain enabled distributed cloud servers. The collected medical information such as heart rate, blood pressure, cholesterol is carried out to secure connection to the edge gateway and initially put through pre-processing which includes replacing missing values, reducing data noise and data normalization. The pre-processed data are then encrypted by utilizing a Binary Search Encryption Algorithm (BSEA) which addresses the problems of traditional encryption such as higher energy consumption, multiple rounds and linear attacks for enabling safe storage and analysis. Furthermore, we utilize a Deep Learning (DL) and Transformer solution Called Dense Nested Four Way Transformer Network (DNFW-Net) for reliable and accurate data analysis. It can process the encrypted features in nested and dense fashion to achieve higher accurate diagnosis results. Moreover, the obtained results and patient information are safely stored as blocks in the blockchain network. Lastly, a result can be generated by validating the automated analysis and doctor's action that produce an excellent and reliable analysis. The major contributions of the research are provided as below,

- **Integrating Binary Search Encryption Algorithm for Secure Data Transmission:** This research uniquely adopts BSEA for guaranteeing secure sensitive patient data transmission to the cloud server. The adoption of BSEA algorithm guarantees data security by the encrypting the sensitive data in the remote healthcare. To be clearer, the BSEA amplifies security by ensuring patient data from potential cyber security breaches.



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

- **Designing Dense Nested Four Way Transformer Network (DNFW-Net) for Remote Heart Disease Analysis:** The proposed HEART SAVIOUR model designed a novel model for precise remote heart disease analysis named Dense Nested Four Way Transformer Network (DNFW-Net). The reliability of the remote heart disease model gets enhanced by adopting DL and transformer-based methods. More specifically, the DNFW-Net performs comprehensive analysis on the medical data leads to precise outcomes which is highly advanced than the conventional remote heart disease models.

The remaining of the paper is organized as follows; section II explains the related works with its corresponding research gap. Section III exposes the detailed system model with corresponding mathematical and theoretical explains along with diagrams. Section IV emphases the implementation details with validation results among proposed and existing works with respect to performance metrics. Finally, section V concludes the proposed research.

## 2. Related works

Authors in this paper [21] proposed a remote health monitoring framework by utilizing a lightweight block encryption method for secure health data in a cloud-based IoT environment. This framework predicts patient's health through data mining of biological data from smart medical IoT devices in order to ensure data protection with resource efficient encryption. In this paper authors [22] develops a healthcare monitoring system for heart disease prediction using deep learning. The deep learning has been great at analyzing huge amount of data accurately which is helpful for early diseases prediction. This framework also uses data in IoT devices and electronic health records for heart disease prediction. Authors in [23] proposed an IoT-Fog-Cloud framework to analysis heart patients utilizing Ensemble Deep learning. Furthermore, it was trained on merged data of Long-Beach, Cleveland and Hungarian heart disease datasets. This method was tested on eight ML method and applied ensemble method24s to achieve higher improved results. In this paper authors [24] presents a heart disease diagnostic system for manual prediction of user's health by utilizing machine learning techniques. This machine learning is capable of predicting the presence and absence of heart diseases in our body. In this work many ML algorithms has been employed in order to predict and detect hearth disease. Authors in this paper [24] proposed a novel Health Cloud method for monitoring health status by using Machine learning and cloud computing. This method uses various machine learning algorithms and evaluates those algorithms for accuracy, sensitivity, specificity, AUC scores, executive time, latency and memory usage by using 5-fold cross-validation. Authors in [26] develops a framework for identifying hearth disease by using feature extraction and signal processing through Artificial Neural Networks. It uses data from ten metal oxide semiconductor sensors to identify scent patterns. Sensor data is then converted from analog to digital and process by ANN. In this paper [27] authors present a real-time heart disease monitoring system for early disease prediction using IoT. In addition, it uses a hybrid fuzzy-based decision tree algorithm for early perdition and compared them with various classifiers including Naïve Bayes, J48, KNN with NB, GA with FCM to achieve higher accuracy results. Authors in [28] paper develops a novel IoT-based tuned adaptive neuro-fuzzy inference system classifier for accurate heart disease prediction. Furthermore, the tuning parameters are optimized by using Laplace Gaussian mutation-based moth flame optimization and grasshopper optimization framework to achieve higher heart disease prediction accuracy. In this paper [29] authors designed a model to detect heart disease by utilizing Machine learning algorithms. This model data processes with categorical variables including database collection, logistic regression and dataset attribute assessment. Additionally, a random forest classifier algorithm has been utilized to detect heart diseases. Authors in [30] proposed a novel method called CardioHelp to predict heart disease using Convolutional Neural networks. Moreover, it associated with temporal data modelling using CNN for early heart disease prediction.

In this paper authors [31] develops a prediction system for heart disease using Machine Learning algorithms. It has various ML algorithms including KNN, logistic regression has been utilized to classify patients. This method has showed development in prediction accuracy compared to other previous works. Authors in this paper [32] proposed a heart disease detection method which is based on Machine learning technique. This method aim is to achieve early heart disease identification to improve treatment and minimize major complications. Furthermore, it analyses four machine learning methods which is based on precision, F1-measure, recall and accuracy showcasing the usage of XGBoost to improve diagnosis accuracy. Authors in [33] present an effective Block chain-based system for predicting diabetes and cardiovascular illnesses in fog computing. This method gathers patient's data from fog nodes, stored on a block chain and grouping them using a rule-driven algorithm. In addition, it uses a feature selection-based adaptive neuro-fuzzy inference system for predicting diseases. This paper authors [34] introduce a blockchain-enabled federated edge-cloud system for heart disease prediction. Moreover, blockchain ensures data sharing and model aggregation, edge devices manage data preprocessing and feature extraction. Furthermore, cloud servers manage model training and validation. Authors in [35] propose a three-tire block chain based system to secure medical data management and disease prediction. Furthermore, medical sensors within the user sensor layer continuously check patient's status. Smart contracts manage authorization and access control, while a ML algorithm based on transfer learning predicts disease varieties. In this paper author [36] develops a novel block chain-enabled heart disease prediction framework by utilizing ML algorithms. This paper uses a Sine Cosine Weighted K-Nearest Neighbour algorithm for heart disease prediction using a tamper-resistant block chain data. This ensure storage environment for



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

patient data. Authors in this paper [37] introduce a block chain-assisted secure data management framework (BSDMF) for Internet of Medical Things. This method enhances patient data exchange, scalability and accessibility. The BSDMF maintain secure data management among personal servers, cloud servers and implantable medical devices. This paper authors [38] presents novel PMHE framework for health care using block chain and privacy computing. This framework uses the collected health data form wearables and were stored on a block chain. Moreover, it uses encryption for disease prediction through smart contracts which handle prediction via encrypted data and preventing data. Authors in paper [39] proposes a block chain-assisted IoMT authenticated key exchange (BIoMTAKE) for healthcare system using hyper ledger Fabric. This BIoMTAKE generates secure session for authenticated devices to avoid unauthorized access. Experimentation shows that the BIoMTAKE achieve higher performance rate. Authors in this paper [40] develops a HealthFaaS, an AI-Based Smart Healthcare System for health patients by utilizing a serverless computing. This method collects data through IoT devices and managed by AI models on Google Cloud Platform (GCP) for scalability, cost-effectiveness and simplicity. Moreover, the light gradient boosting machine achieve higher accuracy compared to other non-server less platforms.

## 3. Methodology

In order to overcome the large volume of generated data from the IoT enabled wearable sensors we have combine the Deep Learning (DL) algorithm and transformer for handle such complex data named HEART SAVIOUR. By combining IoT wearable sensors with DL, the healthcare environment achieves with better accuracy. Figure 1 shows the overall pipeline of the proposed model. The proposed HEART SAVIOUR model composed of processes such as (i) Data acquisition and collection, (ii) Data pre-processing and encryption, and (iii) remote heart disease detection. The module involved in the proposed HEART SAVIOUR is presented below,

- ***IoT Devices & Sensors:*** This module composed of medical IoT devices embedded with sensors for collecting patient physiological information. Furthermore, we also collect Electronic Health Records (EHR) to obtain patient medical history. As the medical IoT devices are at high risk for cyber-attacks, so that we include a security resistant hardware in the medical IoT devices which resolves compromisation attacks.
- ***Edge Gateway (EGD):*** The EDG is responsible for pre-processing, encryption, and data transmission respectively. This module enables secure communication for the sensitive medical data to the cloud storage.

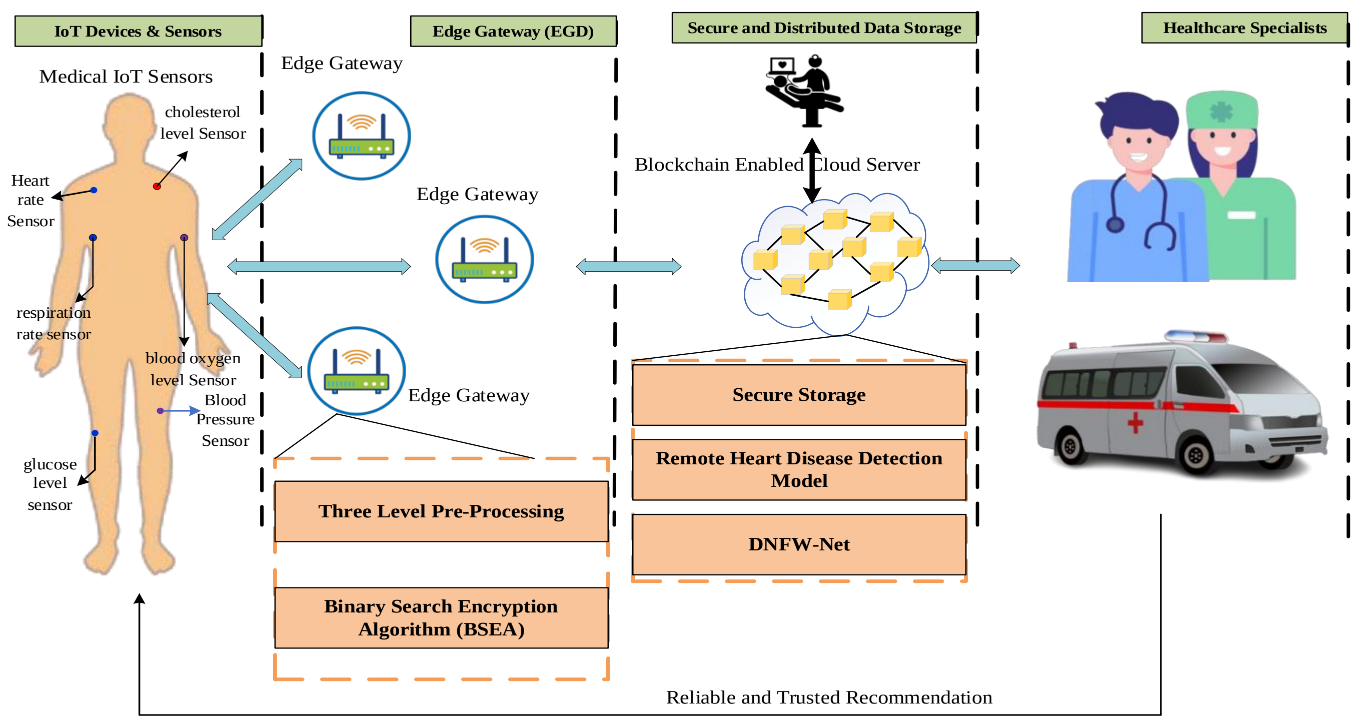


**Figure 1.** Overall Pipeline of the Proposed HEART SAVIOUR Model



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

- ***Secure and Distributed Data Storage:*** The encrypted data from the EGD is provided to then block chain enabled distributed server which performs automated heart disease diagnosis using AI algorithm framework, and secure storage.
- ***Healthcare Specialists:*** This module composed of healthcare staffs, doctors, and emergency service providers (i.e. ambulance). Based on the automated diagnosis results, the doctors intervened them and provide optimal recommendation to remote patients.

### A. Data Acquisition & Collection

The designed healthcare system attains data from the daily health status monitoring and Electronic Health Report (EHR) respectively. From the daily health status monitoring, we attain physiological data such as Electroencephalogram (EEG), Electromyogram (EMG), Electrocardiogram (ECG), cholesterol level, blood oxygen level, respiration rate, glucose level, and Blood Pressure (BP), and heart rate. From the HER, we obtain patients laboratory reports, observation reports, and their medical history which are stored in private cloud database. Furthermore, this research adopts Hungarian and Cleveland dataset from the UCI repository for detecting heart disease from the acquired patient data. The attributes of the adopted dataset are mentioned in table 1 below:

**Table 1:** Attributes of Adopted Dataset

| SI. No | Attribute | Description |
|---|---|---|
| 1 | Target | Status of Heart Disease (1=No, and 0=Yes) |
| 2 | Thal | 8=Reversable Fault; 7=Fixed Fault; 4=Normal |
| 3 | Ca | Vessel numbers (1-4) by fluoroscopy |
| 4 | Slope | T segment slope in peak exercise (0=unsloping,1=down sloping, and 2=flat) |
| 5 | Oldpeak | ST depression induced by exercise |
| 6 | Exang | Angia induced exercise (0=yes;1=no) |
| 7 | Thalach | Recorded heart sound in maximum rate |
| 8 | Restecg | ECG value during rest (0=definite ventricular;1=normal, and 2=abnormal) |
| 9 | Fbs | Blood sugar value during fasting >120mg/dl (1=false, and 0=true) |
| 10 | Chol | Value of cholesterol |
| 11 | Trestbps | Blood pressure during resting |
| 12 | Cp | Chest pain type (4=angina, 3= atypical angina, 2=non-angina, 1=no angina symptoms) |
| 13 | Sex | 1=male;0=female |
| 14 | Age | Patient age in years |

### B. Data Pre-Processing & Encryption

Initially, the sensor data acquired from the remote patients using their respective IoT devices are denoted as $\mathrm{PD} = \{\mathrm{PD}_1, \mathrm{PD}_2, \dots, \mathrm{PD}_n\}$. Those sensor data are subsequently provided to the edge gateway (EDG) for performing pre-processing and encryption respectively. The pre-processing steps involved of missing value replacement, noise reduction, and data normalization respectively. The pre-processed patient data $\mathrm{Pr}_{\mathrm{PD}}$ are then encrypted using Binary Search Encryption Algorithm (BSEA) for ensuring privacy and secure communication for the sensitive medical data.

#### (i) Medical Data Pre-Processing

As we mentioned above, the pre-processing processes involved are missing value replacement, noise reduction, and data normalization respectively. The detailed steps in the pre-processing are provided as follows,



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

- **Missing Value Replacement**: At first the missing values in the PD are determined. From the determined missing PD, we apply predictive modelling approach to fill the missing PD values. We utilize K- Nearest Neighbors (KNN) as a predictive modelling approach to fill the missing values. Initially, we calculate the distance among the missing value and data points using Euclidean distance as,

$$\mathrm{dis}(Y_j, Y_i) = \sqrt{\sum_{n=1}^{N}(Y_{jn} - Y_{in})^2} \quad (1)$$

From the above equation, $N$ denotes the number of features. $Y_{jn}$ and $Y_{in}$ denotes the n-th feature value, and $Y_j$ & $Y_i$ are the data points. After that, we categorize the 'k' data points which is minimum distance among the missing data value. With the k nearest value, we impute the missing values and can be formulated as,

$$Y_{new,j} = \frac{1}{k}\sum_{i\in M(j)} Y_i \quad (2)$$

From the above equation, $Y_{new,j}$ denotes the j-th data point imputed value, $M(j)$ denotes the KNN set indices, and $Y_i$ denotes the j-th neighbor feature value.

- **Noise Reduction:** For noise reduction, we utilize Savitzky-Golay Filter (SGF) that firmly smoothens the data point sets. To be mor clear, it computes polynomial regression on the data point to get smoothed value. The co-efficient of SGF are obtained from the least square polynomial fitting method. Given the size of window $2r + 1$ with order of polynomial p, the formulation is provided as below,

$$\widehat{U}_j = \sum_{i=-r}^{R} co_i U_{j+i} \quad (3)$$

From the above equation, the j-th position smoothed values is denoted by $\widehat{U}_j$, the window actual data points are denoted by $U_{j+i}$, and $co_i$ denotes the coefficient of filter obtained from polynomial fitting.

- **Data Normalization**: Data normalization allows the various features to contribute equally to the detection model to resolve the issues in model training. For data normalization, we utilize robust scaler method which outperforms the other method in terms of outlier resistance. The formulation of robust scaler is provide as below,

$$PD' = \frac{PD - Med(PD)}{IQR(PD)} \quad (4)$$

From the above equation, $PD'$ is the normalized patient data, PD is the actual data, $Med(PD)$ is the median feature data, and $IQR(PD)$ is the interquartile feature range of the feature data.

(ii) Binary Search Tree Encryption:

The $Pr_{PD}$ is then encrypted using novel BSTE algorithm for enabling secure data transmission for the sensitive medical data. The major reason for adopting BSTE is that lesser overhead with enormous security level due to its property of varied cryptographic key encryption. The steps involved in the proposed BSTE are provided as follows,

**Step 1:** The patient $Pr_{PD}$ are initially stored in the list of plaintexts (i.e. array of characters). Every $Pr_{PD}$ characters are converted into ASCII values and stockpiled in the actual ASCII character value $Va^{OR}$.

**Step 2:** After that, the offset variable $OFF^{Va}$ is generated from Q with tree properties of root node (RN), adjusted Q Value ($Q^k$), and $Q^k$ reflected value ($Q^e$). The formulation of $OFF^{Va}$ is provided below,

$$OFF^{Va} = \begin{cases} Q \times Q^k \mathrm{mod} Q^e & \text{if } Q^k < \text{Root} \\ Q \times Q^e \mathrm{mod} Q^k & \text{if } Q^k > \text{Root} \end{cases} \quad (5)$$

$$Q^k = Q \bmod maxi^{len} \quad (6)$$

$$Q^e = (maxi^{len} - Q^k) + 1 \quad (7)$$

From the above equation, $maxi^{len}$ denotes the maximal range of ASCII characters (i.e. 127).

**Step 3:** The reflected initial value ($Va^{Fref}$) for every character in the list are computed in equation as follows,

$$Va^{Fref} = (maxi^{len} - Va^{OR}) + 1 \quad (8)$$



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

**Step 4:** Once the $Va^{Fref}$ is computed, utilizing variance of pseudo random generator a dynamic offset is generated based on the second first key value with its position of characters as,

$$D_{off} = (PS)modVar \qquad (9)$$

Where, Var denotes the variance, and PS denotes the pseudorandom number based on the position of character.

**Step 5:** After that we generate the variable C by summating the $OFF^{Va}$ and offset constant $OFF^{Co}$can be formulated in equation below,

$$Ref_{Va} = \begin{cases} (C \% maxi^{len}) + OFF^{Co}, C > maxi^{len} \\ C, \; C \leq maxi^{len} \end{cases} \qquad (10)$$

From the above equation, $Ref_{Va}$ denotes the reflected variable, and variable $C = Va^{Fref} + OFF^{Co} + OFF^{Va}$.

**Step 6:** After that, the final reflection value $Ref_{Va}$ is computed by summating the C with $D_{off}$ as,

$$Ref_{Va} = Ref_{Va} + D_{off} \qquad (11)$$

**Step 7:** The encrypted data is generated by converting the $Ref_{Va}$ into ASCII character. The encrypted list is appended to form the encrypted text file ($Enc_{Pr_{PD}}$).

### C. Remote Heart Disease Detection

The constituents of a conventional U-Shape formation are an encoder and easy skip connections as indicated in Figure 2. The accessible field is extended and high-level data is removed by implementing the encoder. The decoder assists in the size improvement of feature maps awaiting them eventually match the dimensions of the input images to achieve progressive multi scale feature fusion. The ordinary skip connections supply as a bridge to relocate this high level and low-level features from the encoder to decoder sub networks.

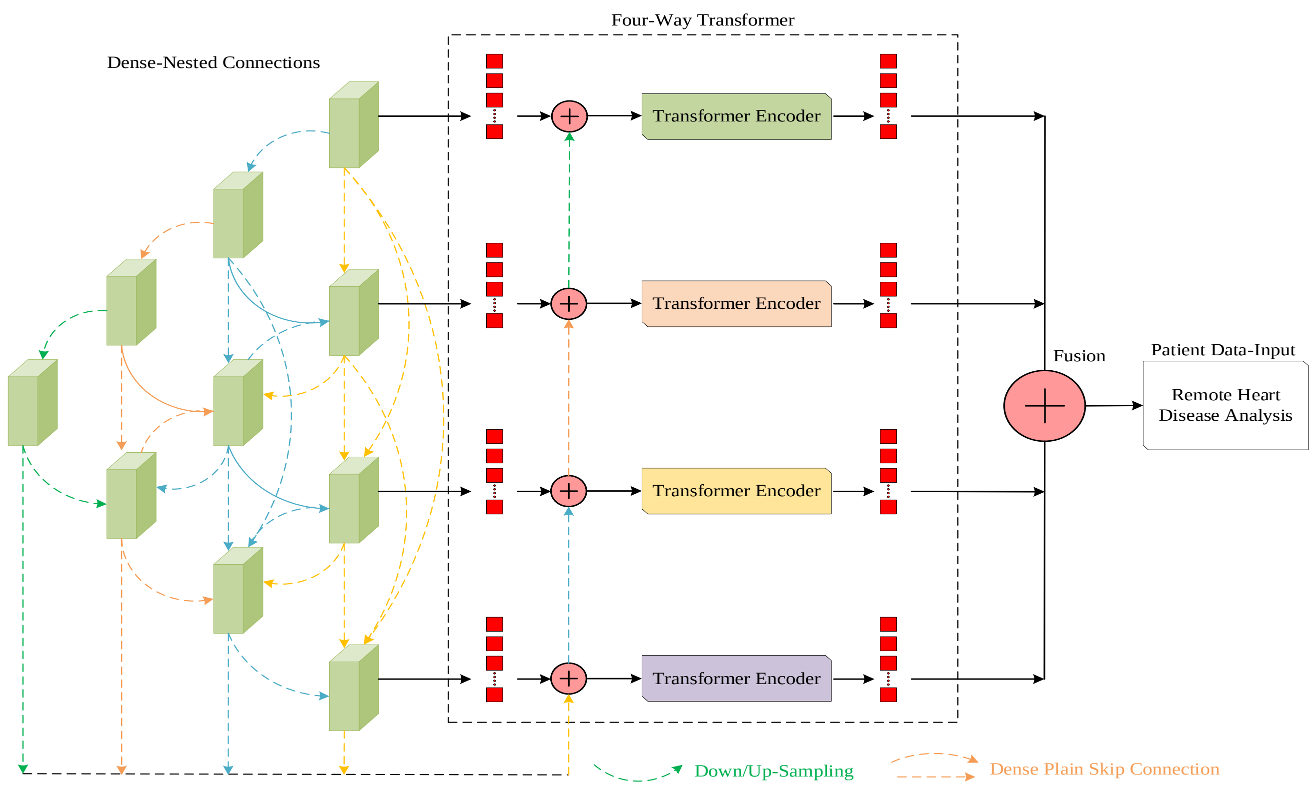


**Figure 2.** Representation of DNFW-Net



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

**(d) Dense Interaction Module**

We created a broad nested arrangement by stacking a number of U-Shaped sub networks together as indicated in Fig. These U shape sub networks with different depths are logically model for targets with unusual sizes as the optimal accessible field modifies greatly for targets of different sizes. We enforce many nodes in the pathway among the encoder and decoder sub networks related on this theory. A network with nested shapes is shaped by the dense connections among all of these transitional nodes. Respective multi-layer fusion outcomes from every node capacity to recognize the features from both its personal and the neighbouring layers as indicated in Figure. Better results are probable as a outcome of maintaining the demonstrations of tiny objectives in the deep layers.

In this paper, we load up $\mathcal{A}$ layers of DIM to appearance feature extraction element. We obtain the $a^{th}$ $(a = 0,1,2,\ldots.1)$ DIM layer as an illustration to suggest this construction as indicated in Fig. Assume $\mathbb{G}^{a,b}$ signifies the output of node $\mathbb{g}^{a,b}$ here $a$ is the $a^{th}$ down sampling layer beside the encoder $b$ is the $b^{th}$ convolutional layer of dense block beside the plain skip pathway. While$b = 0$, every node only obtains features from dense plain skip connection. The stack features maps signified by $\mathbb{G}^{a,b}$ are calculated as

$$\mathbb{G}^{a,b} = \mathbb{T}_{max}(\mathfrak{Q}(\mathbb{G}^{a-1,b})) \quad (12)$$

Here $\mathbb{T}_{.}$ signifies multiple cascaded convolution layers of the same convolution block. $\mathbb{T}_{max}$ Signifies max-pooling with a tramp of 2. While$b > 0$, every node accepts outputs from three directions containing dense plain skip connection and nested bi-direction interactive skip connection, the feature maps stack signifies by $\mathbb{G}^{a,b}$ is created as

$$\mathbb{G}^{a,b} = [\mathbb{T}[\mathbb{G}^{a,c}]_{c=0}^{b-1}, \mathbb{T}_{max}(\mathbb{T}(\mathbb{G}^{a+1,b-1})), \mathbb{W}(\mathbb{T}(\mathbb{G}^{a+1,b}))$$

(13)

Here $\mathbb{W}$ signifies the up-sampling layer and concatenation layer.

**3.1. Channel and Spatial Attention Module**

As indicated in Fig, CSAM is implemented for adaptive feature improvement behind every multi-layer feature fusion of DNIM. The CSAM contains two cascaded attention units. The feature maps $\mathbb{G}^{a,b}$ from node $\mathbb{g}^{a,b}$ $(a \nexists \{0,1,2,\ldots..a\}, b \nexists \{0,1,2,\ldots..b\}$ are chronologically practiced by a 1D channel attention map $\mathbb{H}_d \nexists \mathbb{Z}^{\mathcal{K}_a x1x1}$ and 2D spatial attention map$\mathbb{H}_e \nexists \mathbb{Z}^{1x\wp_a x\sigma_a}$. The channel attention procedure will be abridged as pursues.

$$\mathbb{H}_d(\mathbb{G}) = \infty[\mathrm{MLP}(\mathbb{T}_{max}(\mathbb{G})) + (\mathrm{MLP}\left(\mathbb{T}_{avg}(\mathbb{G})\right)] \quad (14)$$

$$\mathbb{G} = \mathbb{H}_d(\mathbb{G}) \approx \mathbb{G} \quad (15)$$

Here $\approx$ signifies the element wise multiplication, $\infty$ signifies sigmoid function, $\mathcal{K}_a, \wp_a, \sigma_a$ signifies the amount of channels height and width on$\mathbb{G}^{a,b}$. $\mathbb{T}_{avg}$ signifies the average pooling with the stride of 2. The collective network is calculated of a multi layer perceptron (MLP) with on hidden layer.
Previous to multiplication, the attention maps $\mathbb{H}_d(\mathbb{G})$ are extended to the size on $\mathbb{H}_d(\mathbb{G}) \nexists \mathbb{Z}^{\mathcal{K}_a x\wp_a x\sigma_a}$.
Similar to channel attention procedure, the spatial attention procedure able to be abridged as pursues

$$\mathbb{H}_e(\mathbb{G}') = \infty[\mu^{7x7}(\mathbb{T}_{max}(\mathbb{G}')), \mathbb{T}_{avg}(\mathbb{G}')] \quad (16)$$

$$\mathbb{G}'' = \mathbb{H}_e(\mathbb{G}') \approx \mathbb{G}' \quad (17)$$

Here $\mu^{7x7}$ signifies a convolutional operation with the filter size of 7x7. The attention maps $\mathbb{H}_e(\mathbb{G})$are also extended to the size of $\mathbb{H}_d(\mathbb{G})\nexists\mathbb{Z}^{\mathcal{K}_a x\wp_a x\sigma_a}$ previous to multiplication.

(ii) Four Way Transformer Module

The features are initially malformed into feature embedding sequences to portray the long-range relationship between numerous levels and then fed into three typical transformer encoders with widespread weights after that in conclusion resized to the features' original dimensions.

Especially, every input feature $\mathbb{R}_u(u = 3 \ldots 5$ are initially compressed into 1D sequence $\{\mathbb{R}_u^{\partial} | \mathbb{m} = 1 \ldots. \mathbb{z}\}$ here $\mathbb{z}$ is the amount of patches. Every patch $\mathbb{R}_u^{\partial}$ is then marked into a latent D-dimensional embedding space by a trainable linear projection layer. Moreover, we study exact position embedding that are added to the patch embedding to maintain positional data. The procedure able to be explained as



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

$$\mathbb{E}_u^0 = [\mathbb{R}_u^1 + \mathrm{PSE}^1; \mathbb{R}_u^2 + \mathrm{PSE}^2 \dots \dots .. \mathbb{R}_u^n + \mathrm{PSE}^n] \quad (18)$$

Here $PSE = \{PSE^{\mathbb{m}} | \mathbb{m} = 1 \dots \dots . n\}$ is a 1D learnable positional embedding.

The residual framework layers the $TL$ transformer layer and is considerably the same as the common transformer encoder. It able to be observed in fig. The MLP sub layer and multi layer self Attention (MSA) sub layer are suggest in every transformer layer. Earlier to these two sub layers, Layer normalization (LN) is presented and allowing these two sub layers is the outstanding connection. The procedure is described as

$$\{\mathbb{E}_u^{TL'} = \mathrm{MSA}\left(\mathrm{LN}(\mathbb{E}_u^{TL-1})\right) + \mathbb{E}_u^{TL-1}\} \quad (19)$$

$$\{\mathbb{E}_u^{TL} = \mathrm{MSA}\left(\mathrm{LN}(\mathbb{E}_u^{TL'})\right) + \mathbb{E}_u^{T'}\} \quad (20)$$

Here TL signifies the amount of transformer layers in the standard transformer encoder.

## 4. Numerical results and discussion

This work main aim is to analyze various deep learning method for heart disease prediction using heart disease dataset. The deep learning method involves Transformer with Dense Nested Four Way Transformer Network named HEART SAVIOR. This approach uses the information on the Cleveland and Hungarian Heart disease through the University of California, Irvine (UCI) online resource of both Machine learning and Data mining. These datasets comprise 303 and 294 records with 14 features and these datasets were expanded to 100,000 records utilizing a tool named Mockaroo. These datasets records were split into 70% for training the models and 30% for testing them. Furthermore, the proposed HEART SAVIOR method involves various entities including remote patients with sensor embedded IoT devices, edge gateway and blockchain enabled distributed cloud servers. Thus, the model had a decay rate of 0.96 and the learning rate is 0.16. After that, the batch size was set to 128 and the momentum value is 0.82, the number of training epochs was also varied. A cloud server received data through wireless body sensor network for pre-processing and classification. The experiments were conducted on the i2k2 Cloud platform using TensorFlow along with Apache Spark for processing and Cassandran for server and storage.

### A. Evaluation Indices

The model performance was evaluated utilizing the effective metrics of accuracy, precision, specificity, F1 score and recall. The accuracy measures the model's prediction ability of the presented deep learning method actual outcomes. The model heart disease predict ability is measured by true positive (TP) and true negative (TN). The false prediction made by the models is identified by the false positive (FP) and false negative (FN). The precision shows the percentage of actual positive prediction out of all positive prediction. Recall measures the proportion of entire positive instances and the F1 score determines the average of recall and precision.

### B. Comparative Analysis

The research evaluating the accuracy results of the suggested approach with the other approaches is indicated in Table II, in order of increasing accuracy. Figure 3 displays the assessment of the performance results of the suggested method with the existing works. The suggested approach is appraised in provisions of prediction accuracy by implementing modern methods which employ heart disease datasets.

**Table 2:** Comparative Analysis among Proposed Vs Existing

| Existing Works | Author/Year | Approach/Method | Accuracy |
|---|---|---|---|
| RHM-Net [21] | Akhbarifar, S 2023 | lightweight block encryption method | 85.65 |
| HMS-Net [22] | Nancy, A. A 2022 | deep learning model | 87.69 |
| IFCF [23] | Pati, A 2023 | Ensemble Deep learning model | 88.65 |
| HDDS [24] | Divya, K 2021 | Machine Learning approaches | 89.42 |
| HealthCloud [25] | Desai, F 2022 | Machine Learning and cloud computing | 90.62 |
| FE-ANN [26] | Naeem, A. B 2024 | feature extraction and signal processing through ANN | 92.78 |
| RMS [27] | Basheer, S 2021 | Internet of Things | 93.84 |
| HEART SAVIOUR | - | Dense Nested Four Way Transformer Network | 97.82 |



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

The suggested approach is better than the existing works along with the assessment with the related modern cardiac disease prediction methods. Large scale IoT driven healthcare-based works for actual time smart systems involve rapid processing as they engage context and delay sensitive applications. The creation of IoT devices and the development of information offered by these devices have led to immense the data traffic that has caused widespread bandwidth consumption and services problems. The cloud computing framework emerges not capable to manage the constraints faced by the cloud IoT approaches that contains latency, bandwidth use and connectivity because of its centralized nature. Decentralized edge computing (EC) approaches were made likely and permitting computation and storage to be managed at edge nodes which are earlier to the data source because of these disadvantages. These additional current computer technologies facilitate AI works at the edge nodes, extending and complementing the cloud. This hierarchal edge cloud approach efficiently manages the huge number of data collected by IoT devices when minimizing latency that notably lowers the delay limitations. The presented cloud related prediction system able to then be employed at the edge layers in the future to manage the exploit in IoT data when overcoming the inherent limitations of the cloud including higher latency and bandwidth consumption.

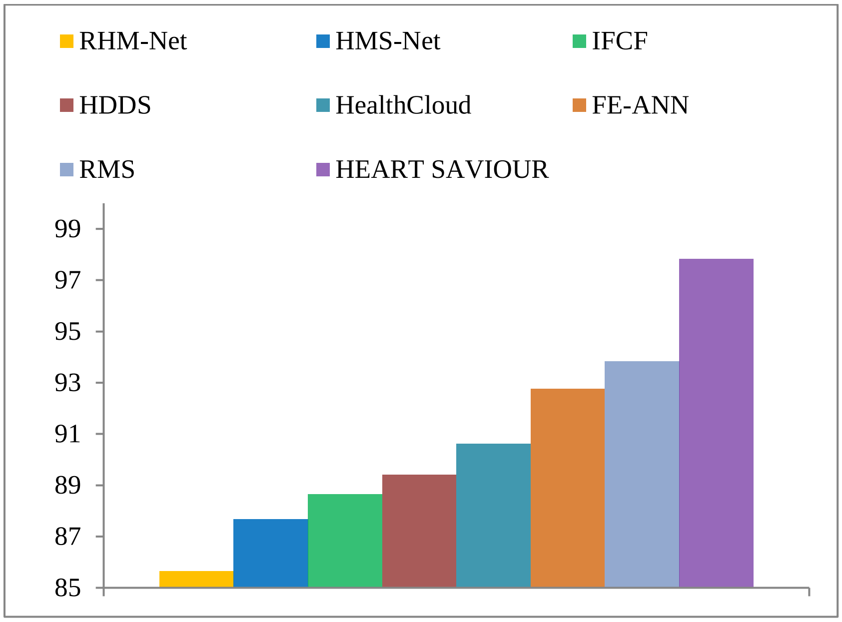


**Figure 3.** Illustration of Comparative Analysis

### B. Experimental Results & Discussion

Conducted experiments with different amounts of illustrations from 10% to 100% are mannered on the generic DL, generic Transformer and proposed method approach to evaluate the proposed system. The presentation of the generic DL, generic Transformer and proposed method models is exposed in Table III and IV with reverence to the appraisal indicator of accuracy, precision, recall, specificity and F1-Score.

**Table 3:** Data Distribution Analysis

| Data (%) | Accuracy | | | Precision | | | Re-call | | |
|---|---|---|---|---|---|---|---|---|---|
| | DL | Transformer | proposed | DL | Transformer | proposed | DL | Transformer | proposed |
| 10 | 85.47 | 83.77 | 86.74 | 84.69 | 82.66 | 89.66 | 85.66 | 84.65 | 90.32 |
| 20 | 86.45 | 84.66 | 88.79 | 85.61 | 83.55 | 89.99 | 85.99 | 84.99 | 91.65 |
| 30 | 87.48 | 85.36 | 89.66 | 86.77 | 84.99 | 90.32 | 86.35 | 86.32 | 92.67 |
| 40 | 88.64 | 87.69 | 90.66 | 88.80 | 85.42 | 91.65 | 87.02 | 87.15 | 92.90 |
| 50 | 88.91 | 88.69 | 90.99 | 89.61 | 86.47 | 92.89 | 87.96 | 88.14 | 93.45 |
| 60 | 89.75 | 89.45 | 91.25 | 90.65 | 88.92 | 93.66 | 88.65 | 89.63 | 94.75 |
| 70 | 90.41 | 90.25 | 93.66 | 90.99 | 89.64 | 94.87 | 88.99 | 90.36 | 95.62 |
| 80 | 91.45 | 91.67 | 95.42 | 91.65 | 90.36 | 95.78 | 89.62 | 90.99 | 96.75 |
| 90 | 92.65 | 92.78 | 97.69 | 91.96 | 91.55 | 96.84 | 90.65 | 91.65 | 97.38 |
| 100 | 93.36 | 93.75 | 98.45 | 92.25 | 93.66 | 97.90 | 91.66 | 92.69 | 99.64 |



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

**Table 4:** Data Distribution Analysis

| Data (%) | Specificity | | | F1-Score | | |
|---|---|---|---|---|---|---|
| | DL | Transformer | proposed | DL | Transformer | Proposed |
| 10 | 84.69 | 85.66 | 90.65 | 84.65 | 84.66 | 91.65 |
| 20 | 85.61 | 85.99 | 91.35 | 84.99 | 85.36 | 92.66 |
| 30 | 86.77 | 86.35 | 92.65 | 86.32 | 87.69 | 92.99 |
| 40 | 87.66 | 87.02 | 93.87 | 87.15 | 88.69 | 93.12 |
| 50 | 88.25 | 89.66 | 95.66 | 88.14 | 89.45 | 94.85 |
| 60 | 89.35 | 90.25 | 95.99 | 89.55 | 90.66 | 95.35 |
| 70 | 89.99 | 90.99 | 97.32 | 90.65 | 91.65 | 96.87 |
| 80 | 90.65 | 91.25 | 97.89 | 91.72 | 92.44 | 97.65 |
| 90 | 91.36 | 91.89 | 99.65 | 92.33 | 92.99 | 98.63 |
| 100 | 92.65 | 93.65 | 99.99 | 93.65 | 94.65 | 99.58 |

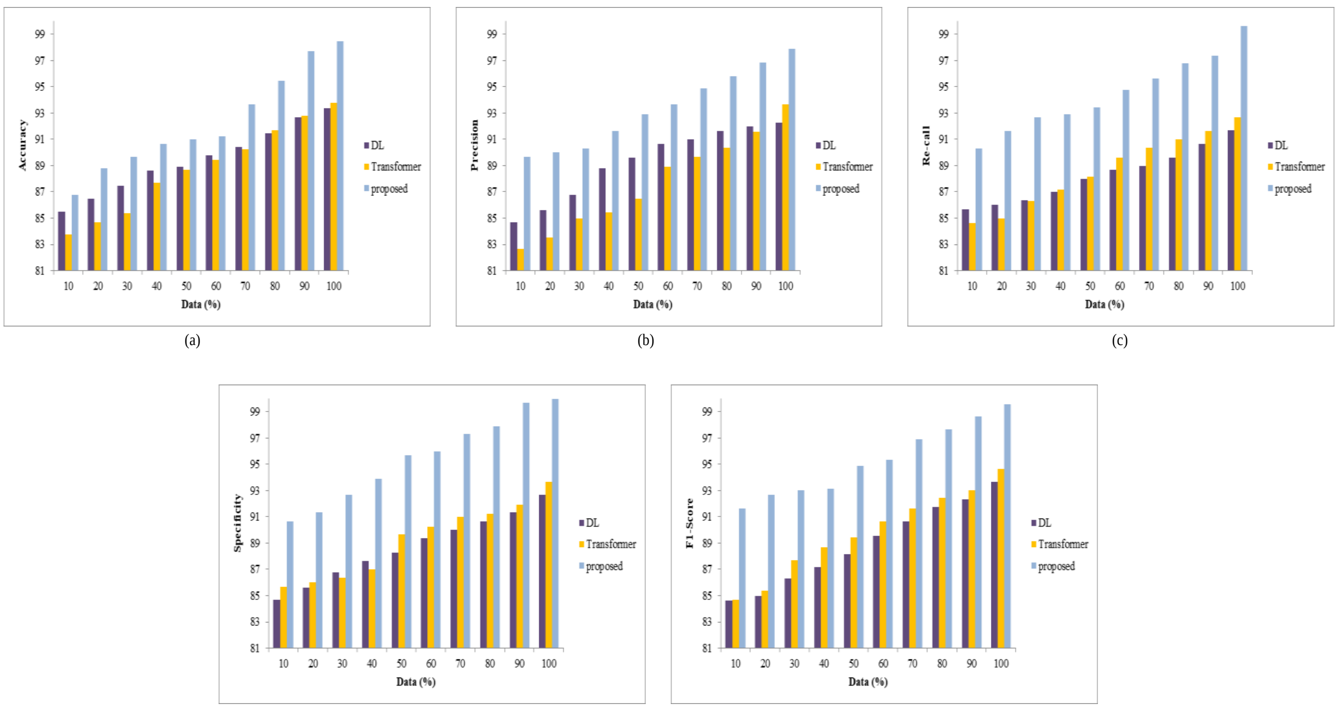


**Figure 4.** (a) Data Distribution Accuracy Comparison, 4(b) Data Distribution Precision Comparison, 4(c) Data Distribution Recall Comparison, 4(d) Data Distribution Specificity Comparison, 4(e) Data Distribution F1-Score Comparison

The assessment of the F1 Score, recall, specificity, accuracy and precision exposed by DL, Transformer and the suggested models as indicated on Fig and table V. Reports for the research of the three models below reflection are elevated from 10% to 100%.

**Table 5:** Overall Performance Comparison

| Performance metrics | DL | Transformer | Proposed |
|---|---|---|---|
| Accuracy (%) | 89.46 | 88.81 | 92.33 |
| Precision (%) | 89.30 | 87.73 | 93.36 |
| Recall (%) | 88.26 | 88.66 | 94.51 |
| Specificity (%) | 88.70 | 89.28 | 95.50 |
| F1-score (%) | 88.92 | 89.82 | 95.36 |



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

An improved neural network framework known as the Dense Nested Four Way Transformer Network (DNFW-NET) was formed to advance the performance of DL models, particularly while dealing with sequential or structured input. Parallel to DenseNet, the network creates the use of dense connections, which enhance gradient flow and maximize the use of feature maps from earlier layers. This assists to tackle the vanishing gradient concern and encourages more efficient training. Multiple degrees of information abstraction are also made possible by the nested structure that guarantees which the model more successfully arrests both high-level and low-level aspects. Dense connections, nested structures, and transformer mechanisms are merged to create the DNFW-NET that presents a strong, adaptable, and effective architecture for a diversity of deep learning applications. The comfortable feature representations produced by this architecture's ability to analyze data in a number of dimensions or viewpoints at once improve the model's capacity to reflect intricate patterns and relationships. As a result, the accuracy of the DNFW-NET is noticeably higher than that of regular transformers and general DL models. Because of this, the DNFW-NET is particularly valuable for applications which need to handle sequential data robustly, like time-series analysis, natural language processing, and structured data tasks like segmenting and classifying complex data.

## 5. Conclusion

Enormous data complexity, latency, and poor security are the major issues in remote healthcare environment. To resolve these issues, we propose a novel remote healthcare model which adopts CC, blockchain, and IoT technologies named HEART SAVIOUR. The entities involved in the proposed work are IoT device embedded with sensor, edge gateway, and blockchain embedded cloud server. The designed model is trained using a Cleveland and Hungarian dataset from UCI repository. Initially, the sensed data from the patients are provided to edge gateway where the collected data are subjected to three level pre-processing, and encryption respectively. We utilize a novel encryption algorithm named Binary Search Tree Encryption (BSTE) algorithm. By encrypting the sensitive data, the problem of various security attacks especially Man in the Middle (MITM) attacks can be resolved easily. The encrypted data is then provided as an input to the blockchain enabled cloud server for secure storage and automated analysis using novel Dense Nested Four Way Transformer (DNFW-Net) network. At last, reliable and trusted medical reports are generated by validating the automated results with healthcare specialist reports. The implementation of the proposed HEART SAVIOUR model is carried out using the i2k2 Cloud platform using TensorFlow along with Apache Spark framework. The propounded model is validated with five metrics (accuracy, precision, recall, sensitivity, and F1-score) in terms of data distribution (10% to 100%) and existing works. The experimental results show that the proposed research outperforms then the state-of-the-art works.

## References

**[1]** El-Rashidy, N., El-Sappagh, S., Islam, S. R., M. El-Bakry, H., & Abdelrazek, S. (2021). Mobile health in remote patient monitoring for chronic diseases: Principles, trends, and challenges. Diagnostics, 11(4), 607.

**[2]** Mahendran, R. K., & Velusamy, P. (2020). A secure fuzzy extractor based biometric key authentication scheme for Body Sensor Network in internet of medical things. Computer Communications, 153, 545–552. https://doi.org/10.1016/j.comcom.2020.01.077

**[3]** Philip, N. Y., Rodrigues, J. J., Wang, H., Fong, S. J., & Chen, J. (2021). Internet of Things for in-home health monitoring systems: Current advances, challenges and future directions. IEEE Journal on Selected Areas in Communications, 39(2), 300-310.

**[4]** Hilty, D. M., Armstrong, C. M., Luxton, D. D., Gentry, M. T., & Krupinski, E. A. (2021). A scoping review of sensors, wearables, and remote monitoring for behavioral health: uses, outcomes, clinical competencies, and research directions. Journal of Technology in Behavioral Science, 6, 278-313.

**[5]** Jiang, W., Majumder, S., Kumar, S., Subramaniam, S., Li, X., Khedri, R., ... & Deen, M. J. (2021). A wearable tele-health system towards monitoring COVID-19 and chronic diseases. IEEE Reviews in Biomedical Engineering, 15, 61-84.

**[6]** Sherubha, "Graph Based Event Measurement for Analyzing Distributed Anomalies in Sensor Networks", Sådhanå(Springer), 45:212, https://doi.org/10.1007/s12046-020-01451-w

**[7]** Piyush K. Pareek, Pixel Level Image Fusion in Moving objection Detection and Tracking with Machine Learning ",Fusion: Practice and Applications, Volume 2 , Issue 1 , PP: 42-60, 2020

**[8]** Shivam Grover, Kshitij Sidana, Vanita Jain, "Egocentric Performance Capture: A Review", Fusion: Practice and Applications, Volume 2, Issue 2 , PP: 64-73, 2020.

**[9]** Abdel Nasser H. Zaied, Mahmoud Ismail and Salwa El- Sayed, A Survey on Meta-heuristic Algorithms for Global Optimization Problems, Journal of Intelligent Systems and Internet of Things,Volume 1 , Issue 1 , PP: 48-60, 2020

**[10]** Mahmoud H.Alnamoly, Ahmed M. Alzohairy, Ibrahim M. El-Henawy, "A survey on gel images analysis software tools, Journal of Intelligent Systems and Internet of Things,Volume 1 , Issue 1 , PP: 40-47, 2021.



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

**[11]** Kumar, V.D.A., Sharmila, S., Kumar, A. et al. (2023). A novel solution for finding postpartum haemorrhage using fuzzy neural techniques. Neural Comput & Applic. 35(33), 23683–23696

**[12]** Anikwe, C. V., Nweke, H. F., Ikegwu, A. C., Egwuonwu, C. A., Onu, F. U., Alo, U. R., & Teh, Y. W. (2022). Mobile and wearable sensors for data-driven health monitoring system: State-of-the-art and future prospect. Expert Systems with Applications, 202, 117362.

**[13]** Yang, Y., Wang, H., Jiang, R., Guo, X., Cheng, J., & Chen, Y. (2022). A review of IoT-enabled mobile healthcare: technologies, challenges, and future trends. IEEE Internet of Things Journal, 9(12), 9478-9502.

**[14]** Sivani, T., & Mishra, S. (2022). Wearable devices: evolution and usage in remote patient monitoring system. In Connected e-Health: Integrated IoT and Cloud Computing (pp. 311-332). Cham: Springer International Publishing.

**[15]** Bhuiyan, M. N., Rahman, M. M., Billah, M. M., & Saha, D. (2021). Internet of things (IoT): A review of its enabling technologies in healthcare applications, standards protocols, security, and market opportunities. IEEE Internet of Things Journal, 8(13), 10474-10498.

**[16]** Hemamalini, Selvamani, and Visvam Devadoss Ambeth Kumar. (2022). Outlier Based Skimpy Regularization Fuzzy Clustering Algorithm for Diabetic Retinopathy Image Segmentation. Symmetry, 14(12), 2512.

**[17]** Aghdam, Z. N., Rahmani, A. M., & Hosseinzadeh, M. (2021). The role of the Internet of Things in healthcare: Future trends and challenges. Computer methods and programs in biomedicine, 199, 105903.

**[18]** Adeniyi, E. A., Ogundokun, R. O., & Awotunde, J. B. (2021). IoMT-based wearable body sensors network healthcare monitoring system. IoT in healthcare and ambient assisted living, 103-121.

**[19]** Rahman, A., Wadud, M. A. H., Islam, M. J., Kundu, D., Bhuiyan, T. A. U. H., Muhammad, G., & Ali, Z. (2024). Internet of medical things and blockchain-enabled patient-centric agent through sdn for remote patient monitoring in 5g network. Scientific Reports, 14(1), 5297.

**[20]** Mahendran, R. K., V., Prabhu., Parthasarathy.V., Usharani. T., Mary Judith. A., & Jagadeesan. S., (2021). An energy-efficient centralized dynamic time scheduling for internet of healthcare things. Measurement, 186, 110230. https://doi.org/10.1016/j.measurement.2021.110230.

**[21]** Akhbarifar, S., Javadi, H. H. S., Rahmani, A. M., & Hosseinzadeh, M. (2023). A secure remote health monitoring model for early disease diagnosis in cloud-based IoT environment. Personal and Ubiquitous Computing, 27(3), 697-713.

**[22]** Nancy, A. A., Ravindran, D., Raj Vincent, P. D., Srinivasan, K., & Gutierrez Reina, D. (2022). Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, 11(15), 2292.

**[23]** Balakrishnan, Chitra, and V. D. Ambeth Kumar. (2023). IoT-Enabled Classification of Echocardiogram Images for Cardiovascular Disease Risk Prediction with Pre-Trained Recurrent Convolutional Neural Networks. Diagnostics 13(4), 775

**[24]** Divya, K., Sirohi, A., Pande, S., & Malik, R. (2021). An IoMT assisted heart disease diagnostic system using machine learning techniques. Cognitive internet of medical things for smart healthcare: services and applications, 145-161.

**[25]** Desai, F., Chowdhury, D., Kaur, R., Peeters, M., Arya, R. C., Wander, G. S., ... & Buyya, R. (2022). HealthCloud: A system for monitoring health status of heart patients using machine learning and cloud computing. Internet of Things, 17, 100485.

**[26]** Sathya Preiya, V., and V. D. Ambeth Kumar. (2023). Deep Learning-Based Classification and Feature Extraction for Predicting Pathogenesis of Foot Ulcers in Patients with Diabetes. Diagnostics 13(12), 1983.

**[27]** Basheer, S., Alluhaidan, A. S., & Bivi, M. A. (2021). Real-time monitoring system for early prediction of heart disease using Internet of Things. Soft Computing, 25(18), 12145-12158.

**[28]** Sekar, J., Aruchamy, P., Sulaima Lebbe Abdul, H., Mohammed, A. S., & Khamuruddeen, S. (2022). An efficient clinical support system for heart disease prediction using TANFIS classifier. Computational Intelligence, 38(2), 610-640.

**[29]** Chang, V., Bhavani, V. R., Xu, A. Q., & Hossain, M. A. (2022). An artificial intelligence model for heart disease detection using machine learning algorithms. Healthcare Analytics, 2, 100016.

**[30]** Mehmood, A., Iqbal, M., Mehmood, Z., Irtaza, A., Nawaz, M., Nazir, T., & Masood, M. (2021). Prediction of heart disease using deep convolutional neural networks. Arabian Journal for Science and Engineering, 46(4), 3409-3422.

**[31]** Jindal, H., Agrawal, S., Khera, R., Jain, R., & Nagrath, P. (2021). Heart disease prediction using machine learning algorithms. In IOP conference series: materials science and engineering (Vol. 1022, No. 1, p. 012072). IOP Publishing.

**[32]** Nagavelli, U., Samanta, D., & Chakraborty, P. (2022). Machine Learning Technology-Based Heart Disease Detection Models. Journal of Healthcare Engineering, 2022(1), 7351061.

**[33]** Shynu, P. G., Menon, V. G., Kumar, R. L., Kadry, S., & Nam, Y. (2021). Blockchain-based secure healthcare application for diabetic-cardio disease prediction in fog computing. IEEE Access, 9, 45706-45720.

**[34]** Ghosh, U., Das, D., Chatterjee, P., & Shillingford, N. (2023, October). Federated Edge-Cloud Framework for Heart Disease Risk Prediction Using Blockchain. In IFIP International Internet of Things Conference (pp. 309-329). Cham: Springer Nature Switzerland.



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024

**[35]** Wang, M., Zhang, H., Wu, H., Li, G., & Gai, K. (2022, May). Blockchain-based secure medical data management and disease prediction. In Proceedings of the Fourth ACM International Symposium on Blockchain and Secure Critical Infrastructure (pp. 71-82).

**[36]** Hasanova, H., Tufail, M., Baek, U. J., Park, J. T., & Kim, M. S. (2022). A novel blockchain-enabled heart disease prediction mechanism using machine learning. Computers and Electrical Engineering, 101, 108086.

**[37]** Abbas, A., Alroobaea, R., Krichen, M., Rubaiee, S., Vimal, S., & Almansour, F. M. (2024). Blockchain-assisted secured data management framework for health information analysis based on Internet of Medical Things. Personal and ubiquitous computing, 28(1), 59-72.

**[38]** Zhao, J., Wang, W., Wang, D., Wang, X., & Mu, C. (2022). PMHE: a wearable medical sensor assisted framework for health care based on blockchain and privacy computing. Journal of Cloud Computing, 11(1), 96.

**[39]** Tomar, A., Gupta, N., Rani, D., & Tripathi, S. (2023). Blockchain-assisted authenticated key agreement scheme for IoT-based healthcare system. Internet of Things, 23, 100849.

**[40]** Golec, M., Gill, S. S., Parlikad, A. K., & Uhlig, S. (2023). HealthFaaS: AI based smart healthcare system for heart patients using serverless computing. IEEE Internet of Things Journal.



DOI: https://doi.org/10.54216/JCIM.150109
Received: February 01, 2024 Revised: April 23, 2024 Accepted: July 25, 2024