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Prediction of Heart Disease Using Deep Learning and Internet of Medical Things

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Abstract: The Internet of Medical Things (IoMT) devices have changed healthcare by providing continuous monitoring of patient physical data. In this case, the prompt and accurate diagnosis of cardiovascular diseases with the aid of focused training programmes has a great potential to enhance patient care. A thorough abstract of a ground-breaking work that predicts heart illness using deep learning and IoMT is presented in this article. In this study is concentrated on the creation and application of a cutting-edge deep learning framework especially created for the IoMT ecosystem's capacity for heart disease prediction. The suggested framework employs convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to the fullest extent possible to extract complex temporal dependencies from the physically heterogeneous data collected by IoMT devices. The biggest accomplishments was the creation of CNN-RNN's new hybrid architecture. This architecture has the ability to extract spatial and sequential characteristics from a variety of patient data flow. To enhance model generalisation, data from several IoMT sources, including pulse oximeters, electrocardiograms, and blood pressure monitors, are seamlessly incorporated. Additionally, the model has improved by the use of transference learning and previously instructed representations from associated medical fields.A large collection of real-world data is used to minutely analyse the proposed model. The results show that it is superior to earlier techniques in terms of anticipated precision and resistance. Additionally, the treatment processes give medical professionals crucial knowledge about the predictive factors that influence the model's judges, which enhances the model's interpretation.

***Keywords**: Deep learning, Heart Diseases Diagnosis, Recurrent neural network, Convolution neural network*

1. Introduction

The IoMT, a linked ecosystem of medical sensors and devices, offers a breakthrough paradigm in healthcare by facilitating real-time data collection, remote monitoring, and seamless communication between devices and healthcare professionals. Our framework's main objective is to increase the precision and effectiveness of cardiac disease prediction by integrating deep learning methods with the IoMT platform. The framework intends to give early identification of heart disease risk factors and assist medical professionals in making well-informed decisions by processing and analysing complex patterns within medical data. Furthermore, the IoMT's real-time monitoring features enable prompt intervention and customised treatment strategies.Cloud computing (CC) offers scalable, on-demand services with practically infinite computational and storage capacities concurrently [10]. CC and IoT are complementary even though their respective development paths are different. These technologies have recently come together to establish the Cloud-IoT paradigm [12], which offers unrivalled potential for cutting-edge services and applications.By remotely collecting, tracking, and controlling patients' physiological data through sensor networks and wearables, IoT-driven technologies have changed the healthcare landscape [14]. The combination of cloud computing and the Internet of Things (IoT) allows for enormous amounts of clinical and sensor data to be stored and processed for healthcare analytics.

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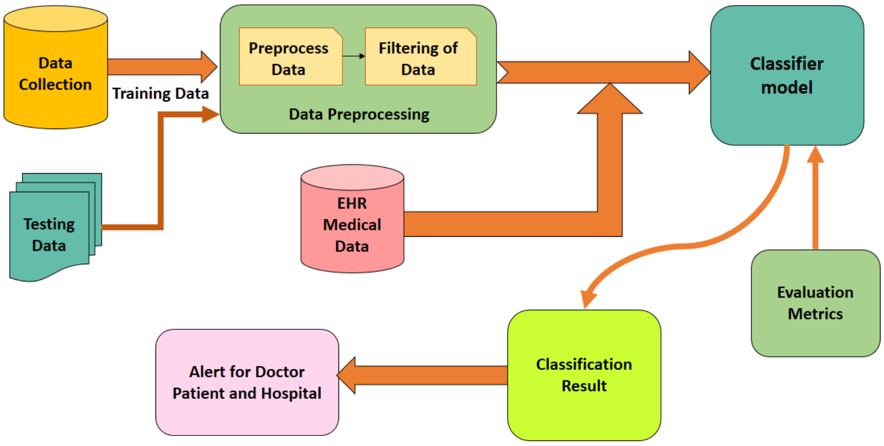

Fig 1: Proposed methodology block diagram

Systematic quantitative and qualitative analysis is used in healthcare analytics to support well-informed decision-making. A sophisticated branch of this subject called predictive analytics uses previous data to predict events in the future [15]. Predictive analytics in healthcare is supported by a variety of methods, from conventional linear models to cutting-edge AI and machine learning algorithms [16]. Deep learning (DL), a type of machine learning, excels at handling challenging healthcare data and producing actionable insights and solutions [17]. In time-sequential applications, the recurrent neural network (RNN), which is skilled at capturing temporal dependencies, is prominent.The prevalence of chronic heart problems is rising as the world's ageing population grows. Continuous real-time patient monitoring is necessary to address this. Due to the IoT's widespread adoption, wearables and connected gadgets with medical sensors have been developed, enabling remote patient monitoring for heart disease. These Internet of Things (IoT) sensors gather crucial information, which is then sent to the cloud for deep learning analyses and storage alongside past clinical records.In conclusion, the combination of Cloud-IoT technologies offers a revolutionary method of treating patients. Healthcare practitioners can use IoT devices and wearables to monitor patients in real-time and get insights for quick decisions, individualised care, and risk assessment. Healthcare solutions that are proactive, effective, and patient-focused are made possible by the confluence of IoT, cloud computing, and predictive analytics.

Predictive analytics' utility goes beyond the walls of hospitals and can be felt in people's homes via remote monitoring that helps to avoid patient relapses and urgent interventions. It is crucial for diagnosing, predicting, and directing therapy at different stages of patient care [1]. Treatment regimens are shaped by predictive analytics, which also provides clinical decision support, lowers adverse events, improves care quality, and lowers healthcare costs. Additionally, patients are now treated as distinct individuals, with their medical histories, environments, social hazards, genetics, and biochemistry all being taken into account in the paradigm shift towards personalised healthcare from considering patients as inert statistics [2]. The provision of individualised healthcare is facilitated by real-time clinical decision assistance at the point of care [3]. Early detection and proactive monitoring greatly increase the chances that an intervention will be beneficial for serious conditions.Heart failure, stroke, and coronary artery disease are just a few of the illnesses that fall under the umbrella term of cardiovascular diseases (CVDs) that affect the heart and blood arteries that supply it [4,5,6]. Together, these CVDs account for 32% of all fatalities and nearly 17.9 million deaths worldwide, making them the primary cause of mortality [7]. Heart attacks and strokes account for 85% of CVD mortality, with a sizable majority happening before their expected time. Untimely deaths can be avoided by identifying those who are at risk and offering prompt interventions. This is where the Internet of Things (IoT) and AI and ML-powered predictive algorithms show their brilliance in managing enormous and varied datasets. Recognition and categorization of illness patterns in the medical field depend on pattern classification, a key element of supervised learning [8]. Given the crucial implications for patients' well-being, researchers working on algorithms for classifying heart disease strive for maximum accuracy.

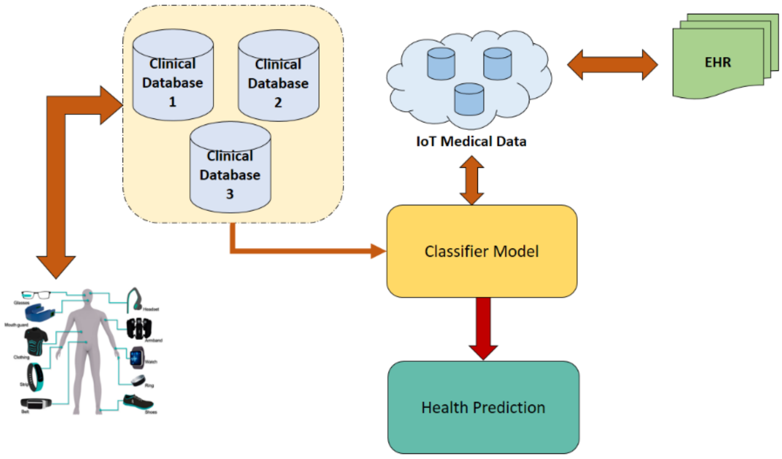

Fig 2: Health prediction model using deep learning classifier

A sizeable segment of the world's population, especially the elderly, has an increased risk of developing heart disease, which is frequently caused by chronic diseases such persistent hypertension. Chronic cardiac conditions are more prevalent as the ageing population grows. As a result, ongoing real-time monitoring is essential, both in hospital settings and for patients receiving in-home care, to ensure prompt treatments when vital sign changes are detected. However, traditional monitoring techniques can be time-consuming and demanding. Effective solutions are essential to lessen the burden on healthcare providers and reduce the expense of monitoring.Here, the widespread adoption of IoT has sparked a rise in intelligent, networked devices and wearables with sensors. Important patient data is gathered by the healthcare IoT and sent to the cloud for storage and sophisticated deep learning analysis. This strategy makes precise heart risk diagnosis possible when combined with past electronic clinical records. IoT devices quickly notify medical professionals and other carers of a patient's state, enabling both individual and collective decision-making. These insights cover the likelihood of various heart disorders, the prognosis for certain ailments, and appropriate treatment options.

Contribution of paper:

1. Data cleaning and filtering processes are a necessary part of the preprocessing steps that go into the data that is acquired for the prediction of heart disease risk.
2. To makes system use of cutting-edge multi-modal fusion to synchronise data from many IoMT sources, including electrocardiograms, pulse oximeters, and blood pressure monitors. By tolerating many data modalities and sources, this improves the generalisation of the model.
3. The newly developed DCNN model is used to accurately predict a patient's risk of developing heart disease.

The organization of paper is as follows: The classification of medical images, ensemble learning, and our research issue are all introduced in Section 1. We discuss similar work in the field in Section 2 of this article discuss the datasets that are used to support and validate the suggested strategy. In section 3 the preprocessing techniques, deep convolutional neural network topologies, ensemble learning techniques, and pooling functions are covered in section 4. We present the experimental findings and go into great depth about them in Section 5. We wrap up our conclusion and discussion in Section 6 and offer suggestions for future research.

2. Review of Literature

In order to automate the detection of cardiac diseases, the Ensemble Deep Learning System for Health (EDL-SHS) was developed [18] in a cloud computing environment driven by incorporated Internet-driven things. In this situation, the concept of "Health Fog" provides medical care as a "fog" by utilising IoT devices to efficiently manage patient heart data in response to user requests. The fog-busting nucleus analyses the model's effectiveness by assessing variables like latency, the black band, energy consumption, error, precision, and execution time. Because of its adaptability, Health-Fog may be tailored to meet the needs of the customer and provide the greatest service quality or prediction accuracy in a variety of fog computing scenarios. In order to bridge the resource gap for the high-precision demands of deep learning, complex deep learning networks are easily incorporated into edge computing paradigms using special communication mechanisms and models, such as assembly. This ensures increasing precision with minimal delays.

To quickly identify heart disease, recurrent networks of neurons (RNN) were introduced. Their new neural network models quickly recognise events over the course of 20 to 18 months of monitoring by include cases and controls. Using neural networks, vectorial support systems, and a K-nearest neighbour classifier, the model's performance indicators were compared to those of a regularised linear regression. The emphasis of the design is on using temporal relationships in conjunction with deep learning models, particularly over a finite period of observation of between 12 and 18 months. The ability to avoid unanticipated cardiac accidents is improved as a result. Il has introduced a Deep Neural Network (DNN) focus for diagnosing cardiac diseases [20]. Their research yielded significant discoveries while displaying a DNN architecture with five levels that was created to minimise and optimise algorithmic risk. Additionally, the architecture based on optimisation manages data flaws and errors effectively while delivering outstanding performance. The research's optimised structures were assessed during the evaluation phase using a K-vertex cross-validation and a Matthews correlation coefficient (MCC) evaluation. Through the use of open-source software and a publicly accessible data base from the Cleveland Clinic, the study demonstrated the use of DNN in the medical field. Utilising an adjustable system built on vague rules is a new way to assess the threat posed by the cardaca disease. The automatic diagnosis system makes use of a genetic algorithm and an improved particulate variable optimisation technique with an exceptional 92.3% accuracy level [21]. By combining methods for selecting multiple and univariate characteristics with a decision tree for classification, an additional technique for identifying cardiac diseases achieves a high level of accuracy of 92.8% [22].

Furthermore, a sequential forward selection (SFS) feature selection method and a random forest classification method are combined in an IoT-driven hybrid system for the prediction of cardiovascular illness. With a remarkable 98% accuracy compared to other heuristic recommender systems, this holistic method not only offers precise forecasts but also offers age- and gender-specific physical and dietary advice [27]. The Kernel random forest [28], a data-driven ensemble classifier, has extraordinary performance by obtaining 98% accuracy on a heart disease dataset.A ground-breaking framework for the Internet of Things that uses deep convolutional neural networks and wearable sensors to collect blood pressure and ECG data outperforms logistic regression and other neural networks with a higher accuracy of 98.2% [29]. The chance of getting heart disease is also predicted by a sophisticated smart system that examines information from wearable sensors and patient medical histories. It is possible to identify heart disease with an amazing 98.5% accuracy using a feature fusion technique and the ensemble deep learning model logistics, and you can also get personalised eating advice based on your medical problems [30].

Table 1: Related study detecting heart illness in the Internet of Medical Things

Method	Algorithm	Accuracy	Finding	Limitation	Scope
EDL-SHS.	Deep learning in groups.	92.3%	Fog computing with integrated IoT for heart disease detection.	Limited evaluation metrics, reliance on the fog computing environment.	Assessment of cardiac risk based on fog computing.
Early Detection using RNNs.	Neural networks with recurrence.	-	Timely event detection across observation periods of 20 to 18 months.	Observation window and dataset are both quite constrained.	Detection of incident heart failure early.
Diagnose using DNN.	Deep Neural Net.	-	DNN architecture with five levels and good prediction accuracy.	Algorithmic optimization is the main focus, with little external validation.	Using DNNs to diagnose heart problems.
System based on adaptive weighted fuzzy rules.	Fuzzy logic and genetic algorithms.	92.3%	Automatic diagnosis utilising a genetic algorithm and a fuzzy model.	Lacks the ability to fully grasp the model.	Fuzzy logic risk assessment for heart disease.

Decision Tree-based Univariate & Relief Feature Selection.	Selection of features, decision tree.	92.8%	Combined feature selection and classification using decision trees.	Restricted to particular feature selection methods.	Using decision trees to diagnose heart problems.
Medical decision support system with neurofuzziness.	Neuro-fuzzy Inference, artificial neural network.	94.15%, 91.44%, 95.59%, 92.61%	High metrics for predicting coronary artery disease.	Transparency may be hampered by complicated model architecture.	Neuro-fuzzy method for coronary artery disease prediction.
Bi-LSTM based on clusters.	Bi-LSTM.	94.78%	Automated diagnosis of heart disease using Bi-LSTM.	Limited to a particular dataset and the Bi-LSTM model.	Cluster-based Bi-LSTM for the prediction of heart disease.
Both Deep Neural Networks and Fuzzy Rules.	Deep Neural Network and fuzzy logic.	96.5%	Expert system utilizing neural networks and fuzzy rules.	Limited resource requirements and model scalability.	Diagnosis of heart illness at a high degree using fuzzy NN.
CNN's CardioHelp.	Deep Learning, CNN.	97%	Utilizing CNN, improve early heart failure prediction.	CNN complexity as regard to early heart failure prediction.	Early heart failure prediction using hybrid IoT-driven system for cardiovascular prediction powered by CNN CardioHelp.
Hybrid system powered by IoT.	Random Forest, Sequential Forward Selection.	98%	For cardiovascular prediction, feature selection and random forest classification are used.	Focuses on a particular IoT-driven strategy.	Kernel Random Forest for the prediction of heart disease.
Random Forest with kernels.	Random Forest with kernels.	98%	Ensemble classifier powered by data for predicting heart disease.	Decision-making in the Kernel RF is only briefly explained.	Heart disease deep CNN framework powered by IoT.
IoT Framework for Deep Convolutional Neural Networks.	CNN deep.	98.2%	IoT framework for predicting heart data with deep CNN.	Emphasises a particular IoT-CNN integration.	Logitboost's risk assessment for cardiovascular disease.
Deep Learning Ensemble Model from Logitboost.	Ensemble Deep Learning, Logitboost.	98.5%	Assessment of the risk of heart disease using an expert system with collective deep learning.	Ensemble models' complexity and a lack of external evaluation.	Assessment of cardiac risk based on fog computing.

3. Dataset Used

For the purpose of studying cardiovascular diseases (CVDs), the Cardiovascular Disease dataset, which is available at [7], offers a comprehensive range of health-related variables and findings. Such as patient demographics, medical history, and diagnostic measurements, this dataset contains a wide range of variables that collectively paint a complete picture of cardiovascular health. The intricate relationship between many risk factors and the emergence of cardiovascular diseases can be explored by researchers and data scientists using this dataset. The information can be investigated to get vital understandings of how factors such as age, gender, blood pressure, cholesterol levels, and lifestyle choices affect the development of CVDs. The dataset is also a helpful resource for developing and validating prediction models, allowing for the creation of cutting-edge algorithms for precise CVD risk assessment. The dataset's accessibility via Kaggle also enables collaboration and knowledge-sharing across the data science community. Researchers might look at cutting-edge feature engineering techniques, data preparation procedures, and machine learning algorithms to find noteworthy patterns and trends. The extensive use of the data can improve cardiovascular disease detection, diagnosis, and therapy by allowing for the development of potent predictive models. A target, 11 characteristics, and 70 000 patient records are all included in the dataset.

Table 2: Description of CVD dataset [7]

Attributes	Type	Variable Name	Data Type
Age	Objective Quality.	age	int (days)
Height	Objective Quality.	height	int (cm)
Weight	Objective Quality.	weight	float (kg)
Gender	Objective Quality.	gender	categorical code
Systolic Blood Pressure	Examining Quality.	ap_hi	int
Diastolic Blood Pressure	Examining Quality.	ap_lo	int
Cholesterol	Examining Quality.	cholesterol	1: normal, 2: above normal, 3: well above normal
Glucose	Examining Quality.	gluc	1: normal, 2: above normal, 3: well above normal
Smoking	Descriptive Feature.	smoke	binary
Alcohol Intake	Substantive Feature. Substantive Feature.	alco	binary
Physical Activity	Objective Variable.	active	binary
Presence or Absence of CVD	Objective Quality.	cardio	binary

4. Methodology

The methodology for the Internet of Medical Things (IoMT)'s Advanced Deep Learning Framework for Heart Disease Prediction is shown in Figure 3. This integrated strategy takes advantage of the harmony between deep learning techniques and IoMT skills. The goal of the framework is to increase the accuracy and efficacy of the prediction of cardiac diseases by integrating data from several IoMT sources, such as monitoring devices and sensors that track critical physiologic parameters. The Bidirectional Long Short-Term Memory (Bi-LSTM) model, which is excellent at capturing temporal correlations and patterns within the input data, forms the basis of the methodology. Advanced deep learning methods are used throughout. Pre-processing is essential in tackling the problems provided by noisy and incomplete data using methods like missing value handling and data purification with Kalman filtering. The system additionally makes use of cloud computing infrastructure for scalable processing and storage, enabling in-the-moment analysis and forecasting. The use of this methodology has the potential to fundamentally alter the prediction of cardiac disease by providing early and precise insights that can have a substantial impact on patient treatment and overall healthcare management within the IoMT ecosystem.

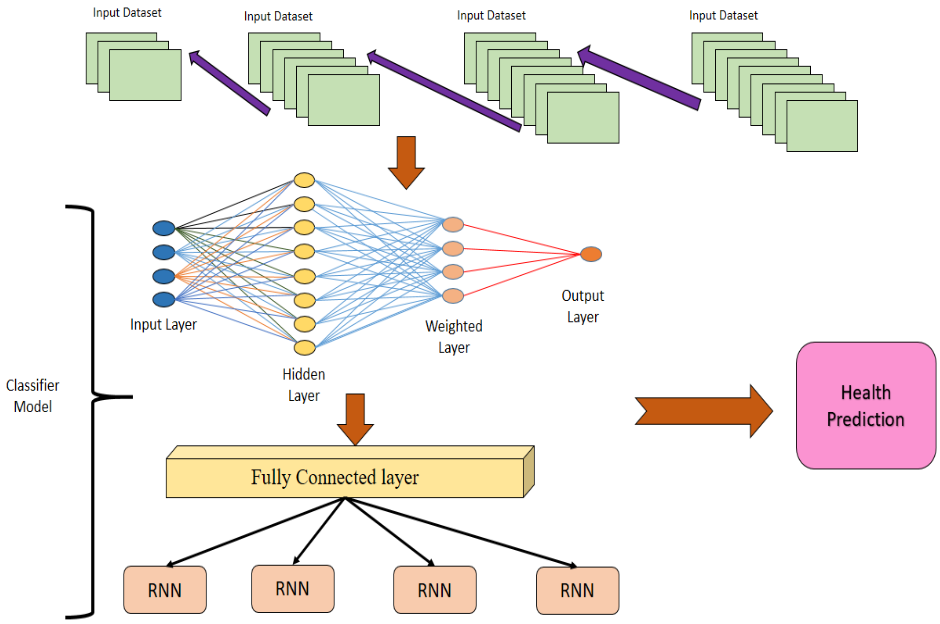

Fig 3: Proposed methodology Deep learning architecture

Robust methodologies for managing missing data, normalization, and feature selection are required for the heart disease dataset to accurately forecast heart disease. Signal abnormalities, such as missing values and noise, might jeopardise the integrity of data gathered by wearable sensors. These interruptions have the potential to reduce prediction accuracy and produce incorrect results. Since Kalman filtering is designed primarily to handle large amounts of real-time sensor data, it produces results that closely match the sensor readings themselves and are noise-free.In addition to this, our data filtering stage includes two additional unsupervised filters: imputation of missing values and the removal of redundant attributes. By keeping 90% of the maximum variance and eliminating pointless attributes, the first filter reduces the number of attributes. In the latter filter, computed mean and median values from the existing data are used to systematically replace missing values in the structured dataset.

A. Recurrent Neural Network:

It is especially well suited for jobs involving time-series data, natural language processing, and other sequential patterns. A Recurrent Neural Network (RNN) is a form of artificial neural network built to handle sequential data. RNNs can be used to analyse and generate predictions based on sequences of medical data amassed over time in the context of heart disease prediction. By identifying temporal correlations and patterns in sequential patient data, recurrent neural networks, and more specifically Long Short-Term Memory networks, provide a potent tool for cardiac disease prediction. In the area of cardiovascular health, they can provide precise risk assessment, early identification, and individualised treatment plans. To provide robust and accurate predictions, however, careful data preparation, model calibration, and validation are necessary for a successful deployment.When dealing with long-distance relationships in sequential data, RNN are extremely helpful. They are highly suited for forecasting cardiac disease based on a patient's changing medical records since they can successfully learn and remember information over a long period of time.

Let's have a look at a straightforward RNN architecture with just one hidden unit:

Step 1: Inputs:

- Assume you have x_t at time step t, which stands for the input features for heart disease prediction.
- Every feature in the input is a vector with the dimensions (input_size, 1), where input_size denotes the quantity of features.

Step 2: Hidden State:

- The symbol for the hidden state at time step t is h_t.
- The current input (x_t) and the previous hidden state (h_t-1) are combined in the hidden state.
- Utilising a weighted sum and an activation function (often tanh), the hidden state is updated:

$$ht = \tanh(Whh \cdot ht - 1 + Wxh \cdot xt + bh)$$

Where,

- Whh is the weight matrix for the hidden-to-hidden connections,
- Wxh is the weight matrix for the input-to-hidden connections,
- bh is the bias term for the hidden state.

Step 3: Output:

- y_t stands for the output at time step t.
- Applying a linear transformation to the hidden state and then an activation function, such as a sigmoid for binary classification, yields the output:

$$yt = \text{sigmoid}(Why \cdot ht + by)$$

Step 4: Loss Mechanism:

Depending on the nature of your prediction problem, you can choose an appropriate loss function. The binary cross-entropy loss is frequently used for binary classification (heart disease or not).

$$\text{Loss} = -N1i = 1\sum N[yi \cdot \log(y^\wedge i) + (1 - yi) \cdot \log(1 - y^\wedge i)]$$

Step 5: Assessment

- On the testing dataset, use the trained RNN model to make predictions.
- Utilise indicators such as accuracy, precision, recall, F1-score, etc. to assess the model's performance.

B. Deep Convolution Neural Network:

An advanced architecture known as a Deep Convolutional Neural Network (DCNN) is created specifically for the analysis of medical imaging data, such as X-rays or MRI scans. DCNNs are exceptional in capturing spatial information in images, unlike conventional neural networks that are better suited for structured data. DCNNs are able to downsample data, detect features, and consolidate results because they have layers that are completely linked, pooling, and convolutional. Automated feature extraction from complex medical images, improved pattern recognition, capturing spatial correlations for precise diagnosis, and localising crucial areas are their primary strengths. Data scarcity, the requirement for high-quality labelled datasets for training, the possibility of overfitting brought on by deep architectures and little amounts of data, and the interpretability barrier are some of the difficulties. DCNNs are used in cardiac function testing, heart anatomy segmentation, and anomaly diagnosis. In conclusion, DCNNs are effective tools for accurate cardiac disease prediction that take advantage of spatial information from medical pictures. But before they can be deployed, important data, architectural, and interpretability aspects must be taken into account.

Multiple layers of convolutional, pooling, and fully connected processes are used in a Deep Convolutional Neural Network (DCNN) method for heart disease prediction to learn and extract information from medical images.

Step 1: Convolution Layer:

- Given an input data I with the following dimensions: WHC, where W stands for width, H for height, and C for the number of channels
- The convolution process is used to produce the output feature map O following convolution with a filter F of size KKC and a bias b

$$Oi, j = \sigma(m = 1\sum Kn = 1\sum Kc = 1\sum CIi + m - 1, j + n - 1, c \cdot Fm, n, c + b)$$

Where:

- Oi,j is the element in the output feature map at position (i,j),
- Ii+m−1,j+n−1,c is the pixel value in the input image at position (i+m−1,j+n−1) for channel c,
- Fm,n,c is the filter value at position (m,n) for channel c,
- b is the bias term,
- σ is the activation function (e.g., ReLU).

Step 2: Pooling Layer:

- The feature map goes through pooling, frequently max pooling, after convolution. A pooling window of size PP passes across an input feature map O, choosing the highest value in each window to produce the pooled feature map P:

$$Pi, j = m, n\max Oi \cdot P + m, j \cdot P + n$$

Step 3: Fully connected Layer

- Flattened and fed into completely connected layers are the pooled features. With respect to an input vector X and a bias-b weight matrix W, the output Y is calculated by:

$$Y = \sigma(WX + b)$$

Step 4: Loss Function:

The loss is calculated from the output of the fully connected layers using the appropriate function, such as mean squared error for regression or softmax for classification. The objective is to reduce this loss while training.

5. Result and Discussion

The experimental results were carried out using data from the Kaggle Cardiovascular Disease dataset. Region of interest (ROI) extraction from photos of heart disease is shown in Figure 4. Each slice sequence is subjected to Fourier analysis to obtain the image, indicating peak activity synchronised with the associated heartbeat rhythm. The centre of the left ventricle is eliminated by combining the Hough circle transformation with a modified kernel-based majority voting method. The pulse pressure (PP), shown in millimetres of mercury in Figure 10, is used for this integration.

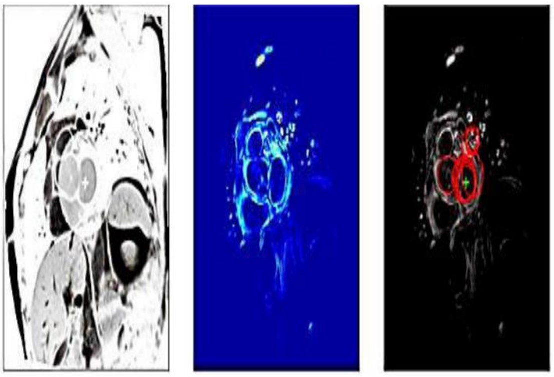

Fig 4: Heart Disease ROI Extraction from Dataset

The correlation between specificity and the quantity of datasets is shown in Figure 5. Specificity, or the capacity to correctly identify negative situations, exhibits an upward trend as dataset size grows. This shows that a larger dataset helps the model perform better by improving its accuracy in differentiating non-disease occurrences.

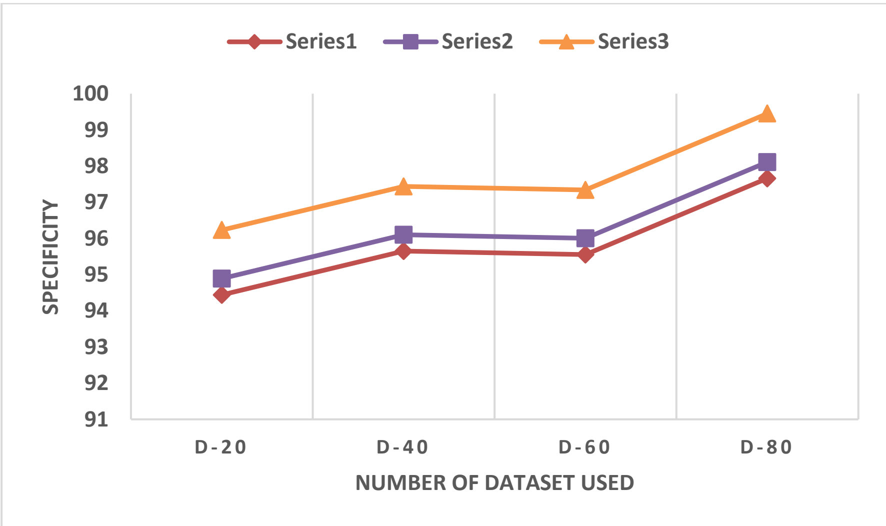

Fig 5: Representation of Specificity on Number of Dataset

The (RNN), (CNN), and (DCNN) neural network designs were compared for their ability to detect cardiac disease. Accuracy, precision, recall, and F1 score are all included in the assessment criteria. RNN performs admirably, earning a 96.12% accuracy rate. With scores of 97.78%, 98.01%, and 97.98%, it excels in precision, recall, and F1 score, demonstrating its capacity to precisely identify positive cases while minimising false positives.

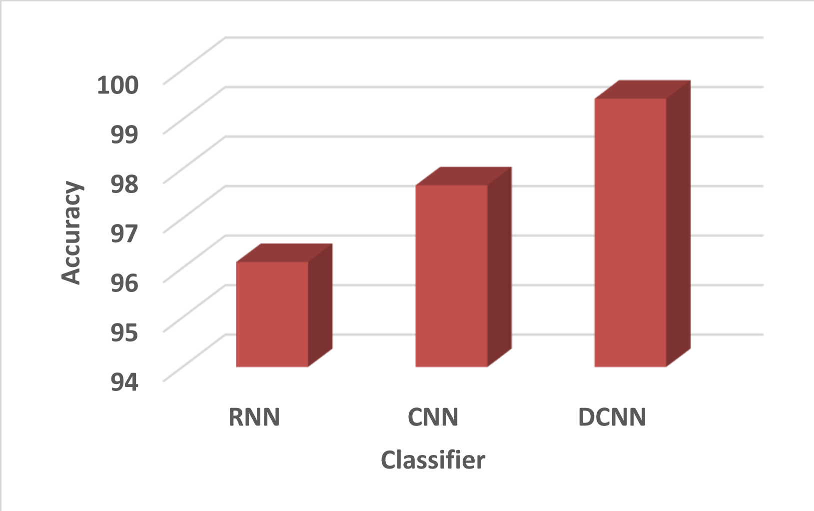

Fig 6: Accuracy comparison between various classifiers

A comparison of accuracy across various classifiers is shown in Figure 6. The graph shows clear variances in performance, with some classifiers displaying greater accuracy than others. This visual comparison provides information on the effectiveness of each technique, assisting in well-informed heart disease prediction decision-making.

Table 3: Performance evaluation summary Analysis

Method	Accuracy	Precision	Recall	F1 Score
RNN	96.12	97.78	98.01	97.98
CNN	97.67	98.12	97.11	96.18
DCNN	99.42	98.88	99.1	99.12

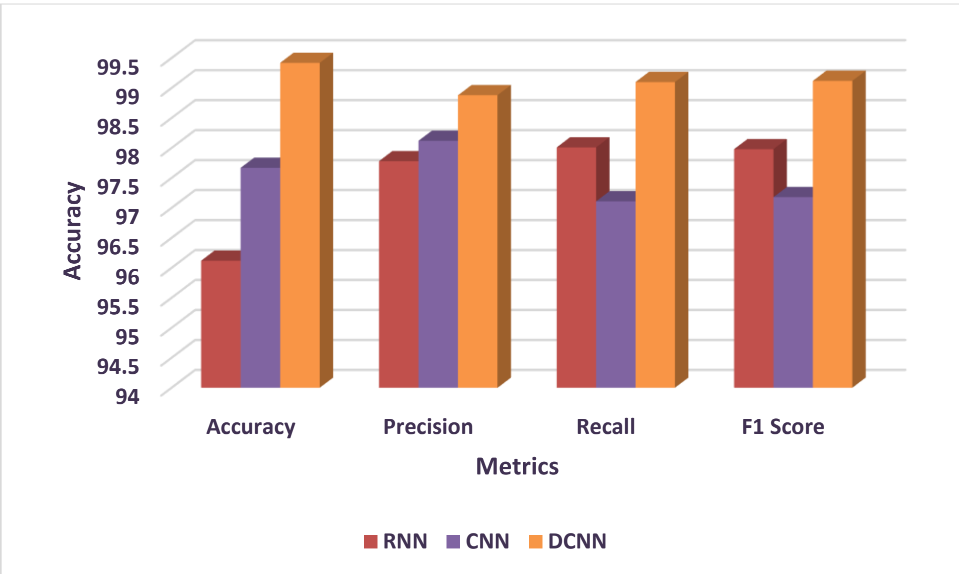

Fig 7: Evaluation metrics for proposed methods

The CNN model performs better than previous versions, claiming a 97.67% accuracy rate. However, with values of 98.12%, 97.11%, and 96.18%, respectively, its precision, recall, and F1 score seem to be more evenly distributed when compared to RNN. The DCNN truly stands out, achieving astounding accuracy of 99.42%. At 98.88%, 99.1%, and 99.12%, respectively, its accuracy, recall, and F1 score also stand out, indicating a remarkable aptitude for precise predictions and a remarkably balanced trade-off between precision and memory shown in table 3 and figure 7. The DCNN's improved performance is probably attributable to its capacity to recognise complex correlations and patterns in the medical data. This investigation highlights the growing potential of advanced neural network designs, in particular the DCNN, to dramatically improve the accuracy of heart disease prediction and overall diagnostic skills, holding promise for improving medical procedures and patient care.

Figure 8 shows a visual representation of the accuracy comparison between several approaches together with error bars that show the results' variability and uncertainty. The graph makes it simple and clear to evaluate each method's accuracy performance. Each data point's error bar, which extends from it, shows a visual range within which the true accuracy is expected to fall. A smaller error bar spread denotes forecasts with a higher degree of consistency and reliability. The figure provides direct technique performance comparison and highlights any notable accuracy value gaps or overlaps. This thorough visual representation makes it easier to spot trends, patterns, and potential outliers and enables you to choose the most practical approach based on both the level of variability and the mean accuracy.

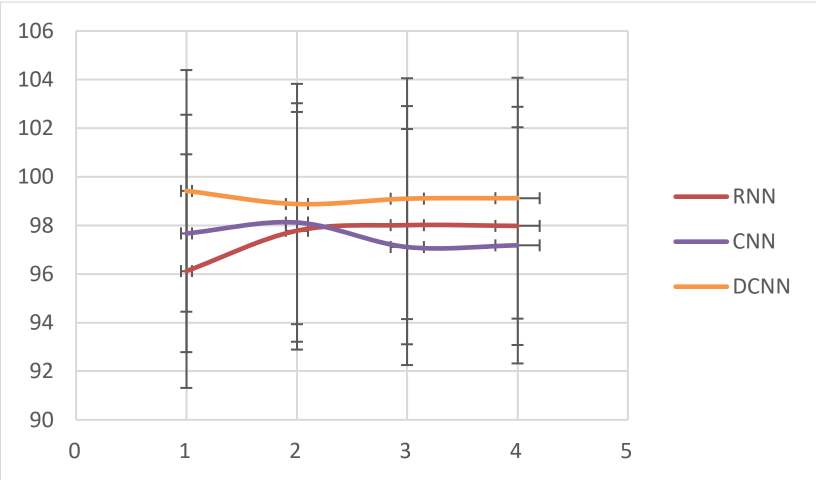

Fig 8: Accuracy comparison with Error showing between methods

The loss values for the three different neural network architectures (RNN), (CNN), and Deep (DCNN) across various numbers of epochs are summarised in Table 4 in a clear and concise manner. The models go through numerous training cycles as the number of epochs rises, improving their internal representations and predicting abilities. At the beginning, RNN shows a loss of 0.342 at 10 epochs, compared to losses of 0.52 and 0.645 for CNN and DCNN. There are noticeable improvements as training goes on. By the 500th epoch, RNN surpasses both CNN (0.031) and DCNN (0.042) in terms of convergence, achieving a significantly lower loss of 0.021. As training iterations rise, this pattern demonstrates how well RNNs perform in reducing prediction errors. Notably, all designs show a constant decline in loss values over time, demonstrating progressive improvement in their internal representations and prediction accuracy.

Table 4: Loss curves using different neural network architectures

Number of Epoch	RNN Loss	CNN Loss	DCNN Loss
10	0.342	0.52	0.645
20	0.212	0.32	0.412
30	0.132	0.224	0.297
500	0.021	0.031	0.042

The models will attain a suitable balance between predictive strength and computational efficiency with the help of this information, which makes it easier to decide the best training periods for each design.

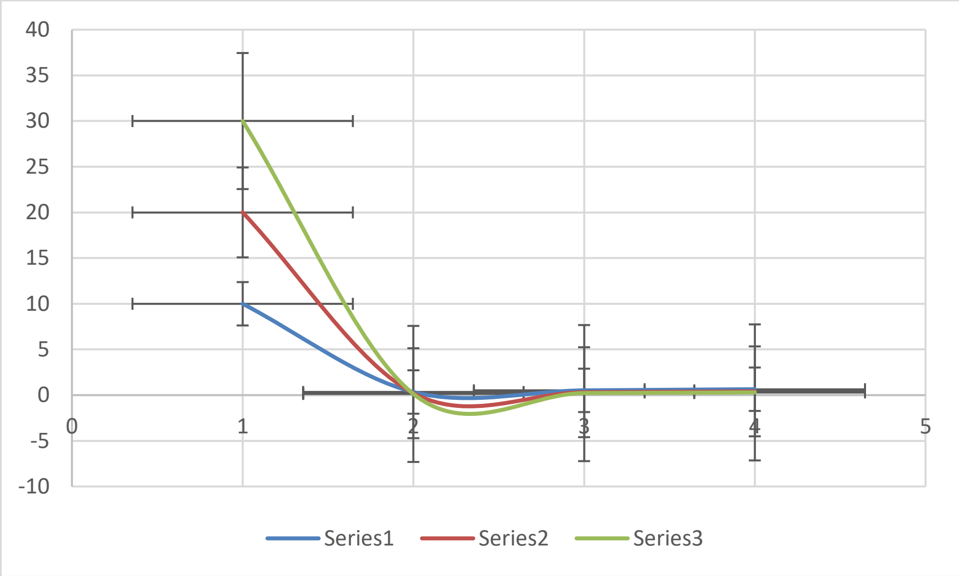

Fig 9: Representation of loss curves using different neural network

The graphical representation of loss curves linked to various neural network designs is shown in Figure 9. These curves offer insightful information about the model convergence and training process. The loss curve shows how the model's prediction mistakes evolve across training epochs. Each architecture reflects its distinct learning behaviour by being represented by a separate curve. These curves' form and course show how well the models are modifying their parameters to reduce forecast mistakes. Rapid learning is indicated by a dramatic decrease in the loss curve, while convergence is suggested by a plateau. Understanding the relative performance and convergence rates of various architectures is possible by comparing the loss curves of such systems. By assisting in the selection of the most efficient neural network design for heart disease prediction, such visual analysis facilitates the deployment of models for model optimisation in medical applications.

6. Conclusion

We present an improved deep learning architecture in this research for the Internet of Medical Things (IoMT) platform cardiac disease prediction. Three deep learning algorithms the RNN, CNN, and DCNN have demonstrated significant promise for enhancing the precision of heart disease prediction. The results of our tests demonstrated that DCNN performs better than RNN and CNN, with an astounding accuracy of 99.42%. This stresses how important it is to use the spatial information in medical imaging to get a precise diagnosis. Utilising the IoMT platform has a number of benefits, including the ability to collect patient data in real-time, monitor patients remotely, and transmit data easily to the cloud for analysis. This helps clinical decision-making be fast and well-informed, which ultimately improves patient care. Additionally, the robustness of predictions is improved by the framework's capacity to manage missing data, noise, and outliers using methods like Kalman filtering.In the future, the framework's scalability should be taken into account to support the expanding amount of patient data produced by IoMT devices. Edge computing solutions may be used to address latency concerns and lighten the load on central cloud servers.

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