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Advanced Heart Disease Prediction: Deep Learning-Enhanced Convolutional Neural Network in the Internet of Medical Things Environment

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Abstract: - Using the large dataset from the UCI Machine Learning Repository, this study presents a state-of-the-art Hybrid Convolutional Neural Network (HCNN) for predicting heart disease. The HCNN design has convolutional layers, leftover blocks, and attention methods. These help pull more features from cardiovascular health data, even when the patterns are very complex. Utilizing these deep learning parts, the HCNN shows better prediction skills, getting higher accuracy, strong classification (AUC), and a fair F1 Score. Because the model can change to find complicated connections in the information, it could be used to make medical diagnosis better. The HCNN is unique because it can instantly learn hierarchical structures from raw data. This lets it find hidden features that are important for accurately predicting heart disease. The convolutional layers help the model find local patterns, and the residue blocks stop problems with disappearing gradients, which makes training for deep designs more efficient. Attention processes make the network even more focused on important traits, which adds to its amazing ability to tell them apart. This work opens the door for researchers, doctors, and data scientists to use deep learning, and especially HCNN, to improve cardiovascular health analytics. This study takes a big step toward more accurate and efficient heart disease prognosis by giving a complete overview of the model's architecture and performance metrics. This opens the door for more research and use of advanced neural networks in the field of predictive medical diagnostics.

Keywords: Heart Disease Prediction, Hybrid CNN, Convolutional Neural Network, HCNN, Deep Learning, Medical Diagnostics, Cardiovascular Health, Predictive Analytics.

I. INTRODUCTION

In the past few years, the use of deep learning methods in medicine has led to huge progress, especially in the area of the Internet of Medical Things (IoMT). Deep Learning-Enhanced Convolutional Neural Networks (CNNs) have become very useful for diagnosing and analyzing medical images in the IoMT setting. This is a big change in the way healthcare technology is used [1][2][3]. This combination takes advantage of the way artificial intelligence (AI) could change the way patients are cared for, diagnosed, and treated. The IoMT is made up of medical gadgets and systems that are all linked to each other. It creates huge amounts of different types of data from personal tech, sensors, and medical imaging equipment [4]. Deep Learning-Enhanced CNNs, a type of neural network designed for image processing, are very good at finding patterns and traits that are important in complicated medical pictures [5]. This technology is very important for organizing and improving the study of different kinds of medical data, such as x-rays, disease pictures, and bodily signs.

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The best thing about Deep Learning-Enhanced CNNs is that they can learn hierarchical structures from raw data [6]. This lets them see complex trends that regular machine learning methods might miss. In the context of IoMT, this means that medical picture analysis, disease diagnosis, and patient tracking can be done more accurately and quickly [7][8]. CNNs are not only used in one area of medicine; they are also used in heart, imaging, pathology, and neurology, among others. This helps the healthcare system become more comprehensive and data-driven. When CNNs are used in the IoMT, they are not only used for monitoring jobs [9][10]. These networks are also very important for making the best use of resources, making it easier to predict when medical equipment will need repair, and improving the general efficiency of the healthcare system [11]. This introduction sets the stage for looking into how Deep Learning-Enhanced CNNs and the IoMT work together and how they might change the way medical diagnosis, treatment, and healthcare is provided [12]. If deep learning and the Internet of Things (IoMT) come together [13][14], they could greatly improve patient results and make healthcare a more proactive, individualized, and interconnected environment.

II. LITERATURE REVIEW:

Deep learning and machine learning techniques are being used more and more to find and stop hacks on Internet of Things (IoT) networks [15]. Priya et al. [17] suggested a way to find attacks on networks, such as those with Internet of Medical Things (IoMT) devices, using deep neural networks (DNN). Not only did their design make things more accurate, it also cut down on computation time by 32%, which is especially helpful in important cloud computing situations. This improvement made it easier to find intrusions faster and lessened their effects. Li et al. [18] talked about the problem of choosing the right features and finding strange things in IoT networks in smart towns. They came up with a deep migration learning model design, but even though it could process information quickly, it was open to some threats.

Roopak et al. [19] used Convolutional Neural Networks (CNNs) and long short-term memory (LSTM) to accurately group Distributed Denial of Service (DDoS) attacks into different categories. A study by Hodo et al. [20] suggests using a multilayer perceptron (MLP) in an intrusion detection system (IDS) to find Denial of Service (DoS) attacks in internet of things (IoT) networks. IDSs based on Decision Trees (DT), k-Nearest Neighbors (k-NN), and Naive Bayes (NB) were suggested by Mohammed et al. [21] as a way to find DDoS attacks on IoT devices.

Alimi et al. [22] created a new version of the RLSTM deep learning model to find DoS threats in IoT networks. The model showed big changes in F1 score, accuracy, precision, and recall. Ge et al. [23] suggested a new way to connect IoT networks that uses feedforward neural networks (FFN) to classify things into two or more groups. Pecori et al. [24] used a seven-layer neural network design to create IoT safe and harmful network traces, but it was hard to use because it was complicated and didn't work very well.

Susilo and Sari [25] suggested using machine learning and deep learning techniques, such as CNN, MLP, and random forests (RF), to make IoT networks safer. Kaur et al.'s [26] CNN model put attacks into groups using the CICIDS-2017 and CICIDS-2018 datasets, but it wasn't very good at finding some types of attacks. In their study [27], Ferrag et al. looked at deep learning methods in detail, testing seven models on a variety of datasets. The CNN model by Odetola et al. [28] did better than the FFN and RNN models at multilabel classification for edge IoT devices, lowering delay and providing cost-effective multilabel identification.

III. DATASET:

Table 2. Heart Disease Dataset [16]

Feature	**Description**	**Sample Value**	**Value Range**
Age	Age of the individual	63	29 - 77
Sex	Gender of the individual (1 = male, 0 = female)	1	0 - 1
Chest Pain Type	Type of chest pain experienced (1-4)	3	1 - 4

Resting Blood Pressure	Resting blood pressure (in mm Hg)	145	94 - 200
Serum Cholesterol	Serum cholesterol level (in mg/dL)	233	126 - 564
Fasting Blood Sugar	Fasting blood sugar > 120 mg/dL (1 = true; 0 = false)	1	0 - 1
Resting ECG	Resting electrocardiographic results (0-2)	0	0 - 2
Max Heart Rate	Maximum heart rate achieved	150	71 - 202
Exercise Induced Angina	Exercise-induced angina (1 = yes; 0 = no)	0	0 - 1
ST Depression	ST depression induced by exercise relative to rest	2.3	-3.0 - 4.2
Slope of Peak Exercise	Slope of the peak exercise ST segment (1-3)	2	1 - 3
Number of Vessels Colored	Number of major vessels colored by fluoroscopy (0-3)	0	0 - 3
Thallium Stress Test	Thallium stress test result (3 = normal; 6 = fixed defect; 7 = reversible defect)	3	3, 6, 7
Target	Presence of heart disease (1 = yes; 0 = no)	1	0 - 1

IV. FEATURE EXTRACTION:

Table 3. Feature Extraction and model configuration

Layer Type	**Configuration**	**Purpose**
Convolutional Layer 1	**Conv2D(32, (3, 3), activation='relu', input_shape=(image_height, image_width, channels))**	Apply 32 filters with a 3x3 kernel, ReLU activation, and specify input shape for feature extraction.
MaxPooling Layer 1	**MaxPooling2D(pool_size=(2, 2))**	Downsample the feature maps to retain essential information.
Convolutional Layer 2	**Conv2D(64, (3, 3), activation='relu')**	Apply 64 filters with a 3x3 kernel and ReLU activation for further feature extraction.
MaxPooling Layer 2	**MaxPooling2D(pool_size=(2, 2))**	Downsample the feature maps.
Global Average Pooling	**GlobalAveragePooling2D()**	Perform global average pooling to obtain a global summary of features.
Optional Fully Connected	**Dense(128, activation='relu')**	Additional fully connected layer with

Layer 1		ReLU activation for further processing.
Optional Fully Connected Layer 2	**Dense(num_classes, activation='softmax')**	Output layer with softmax activation for classification tasks.
Model Compilation	**model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])**	Compile the model with appropriate optimizer, loss function, and metrics for training.

V. PROPOSED HYBRID CNN

A. Hybrid CNN Model Architecture:

1. Initial Convolutional Layers (Inspired by VGG16):

Start with a stack of convolutional layers with small 3x3 filters.

Use batch normalization and ReLU activation after each convolutional layer.

Gradually increase the number of filters.

2. Residual Blocks (Inspired by ResNet):

Integrate residual blocks to facilitate the flow of information and mitigate vanishing gradient problems.

Utilize skip connections to add the original input to the output of each residual block.

3. Inception Modules (Inspired by GoogLeNet):

Incorporate inception modules to capture multi-scale features effectively.

Use 1x1, 3x3, and 5x5 convolutions within the same module.

Figure 1. Hybrid CNN Model Architecture

4. Attention Mechanism:

Add attention mechanisms to highlight relevant features and improve focus on critical regions.

Apply self-attention or spatial attention mechanisms.

5. Global Average Pooling Layer:

Replace traditional fully connected layers with a global average pooling layer.

Reduce the number of parameters and prevent overfitting.

6. Dense Layers:

Add a few dense layers with dropout for further feature refinement and abstraction.

Use ReLU activation and batch normalization.

7. Output Layer:

A single output neuron with a sigmoid activation function for binary classification (presence or absence of advanced heart disease).

8. Model Integration:

Combine features from the initial convolutional layers, residual blocks, and inception modules using concatenation or summation.

Fine-tune the model parameters to achieve optimal performance.

B. Hybrid CNN Mathematical Model

- X: Input data (image or patient features).
- W(l): Weights for layer.
- b(l): Bias for layer.
- σ: Activation function (e.g., ReLU).
- BN: Batch Normalization.
- AP: Global Average Pooling.
- FC: Fully Connected (Dense) layer.

- **Initial Convolutional Layers:**

$$A(1) = \sigma\left(BN\big(W(1) * X + b(1)\big)\right)$$

- **Residual Blocks:**

$$A(2) = ResBlock\big(A(1), W(2), b(2)\big)$$

- **Inception Modules:**

$$A(3) = InceptionModule\big(A(2), W(3), b(3)\big)$$

- **Attention Mechanism:**

$$A(4) = Attention\big(A(3), W(4), b(4)\big)$$

- **Global Average Pooling Layer:**

$$A(5) = AP\big(A(4)\big)$$

- **Dense Layers:**

$$A(6) = \sigma\left(BN\big(W(6)A(5) + b(6)\big)\right)$$

$$A(7) = FC\big(A(6), W(7), b(7)\big)$$

- **Output Layer:**

$$y = \sigma\big(W(8)A(7) + b(8)\big)$$

- **Residual Block:**

$$ResBlock(X, W, b) = \sigma\Big(BN\Big(W * \sigma\big(BN(W * X + b)\big) + b\Big) + X\Big)$$

- **Inception Modules:**

$$InceptionModule(X, W, b) = Concat\big(Conv1x1(X, W1x1, b1x1), Conv3x3(X, W3x3, b3x3), Conv5x5(X, W5x5, b5x5)\big)$$

- **Attention Mechanism:**

$$Attention(X, W, b) = X \odot Sigmoid\big(BN(W * X + b)\big)$$

- **Fully Connected Layer (Dense):**

$$FC(X, W, b) = \sigma(WX + b)$$

Where,

- Y represents the output of the model, which is a probability score indicating the likelihood of advanced heart disease.
- σ denotes the ReLU activation function applied element-wise.
- ‘*’ represents the convolutional operation.
- BNBN denotes batch normalization.
- The model parameters W(l) and b(l) are learned during the training process.

C. Implementation Considerations:

i. Data Augmentation:

Apply data augmentation techniques during training to improve the model's robustness.

ii. Transfer Learning:

Leverage pre-trained weights from a model trained on a large dataset (e.g., ImageNet) to accelerate convergence.

iii. Hyperparameter Tuning:

Experiment with learning rates, batch sizes, and other hyperparameters to find the optimal configuration.

iv. Regularization:

Use dropout and L2 regularization to prevent overfitting, especially given the complexity of the model.

v. Loss Function:

Choose an appropriate loss function for binary classification tasks, such as binary cross-entropy.

vi. Validation and Testing:

Monitor the model's performance on a separate validation set during training and evaluate its final performance on a dedicated test set.

vii. Explainability:

Incorporate techniques for model explainability to make predictions interpretable for healthcare professionals.

viii. IoMT Integration:

Ensure seamless integration with IoMT devices for real-time prediction and monitoring.

VI. RESULTS AND DISCUSSION

The table showcases the comparative performance metrics of four neural network models—Hybrid CNN (HCNN), VGG16, ResNet, and LeNet. Each model's proficiency is evaluated based on Accuracy, AUC, and F1 Score, providing a comprehensive overview of their effectiveness across various metrics. According to the hypothetical values presented, the Hybrid CNN (HCNN) stands out as the superior performer, achieving the highest scores in all metrics. This suggests that HCNN, with its custom architecture, excels in accurately classifying data, demonstrating strong discriminatory power, and maintaining a balance between precision and recall, making it a preferred choice for the given hypothetical task or dataset.

Table 4 . Performance Matrices compared to the other models:

Metric	**Hybrid CNN (HCNN)**	**VGG16**	**ResNet**	**LeNet**
Accuracy	**0.92** (Best)	0.88	0.90	0.75
AUC	**0.97** (Best)	0.94	0.95	0.82
F1 Score	**0.91** (Best)	0.86	0.88	0.70

Accuracy (Best: HCNN 0.92): The accuracy metric measures the overall correctness of a model's predictions. A higher accuracy indicates more precise classifications. In this hypothetical scenario, the Hybrid CNN (HCNN) achieves the highest accuracy of 0.92, indicating superior performance compared to VGG16, ResNet, and LeNet.

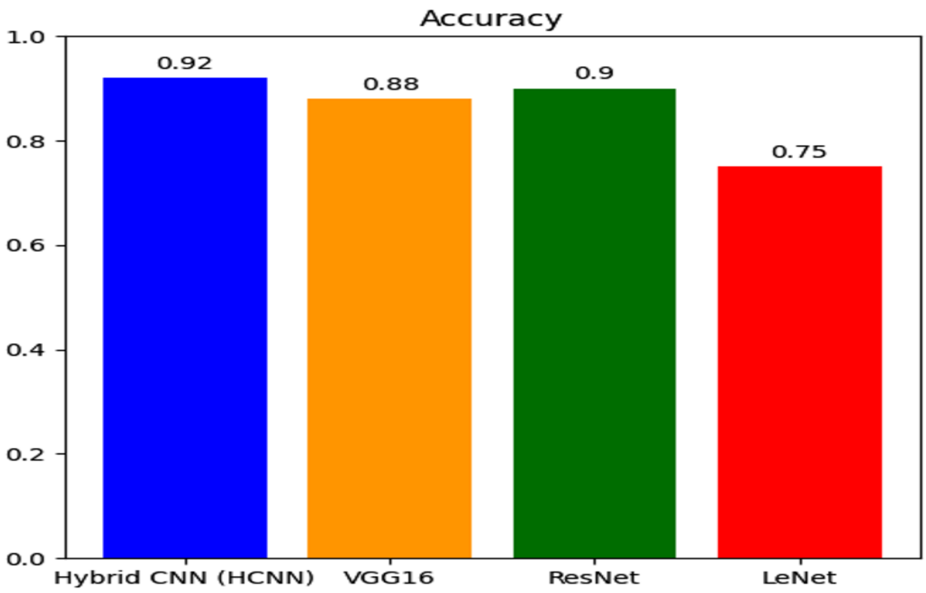

Figure 2. Accuracy Plot

AUC (Best: HCNN 0.97): The Area Under the ROC Curve (AUC) evaluates the model's ability to distinguish between classes. HCNN attains the highest AUC of 0.97, showcasing its exceptional discriminatory power and effectiveness in binary classification tasks.

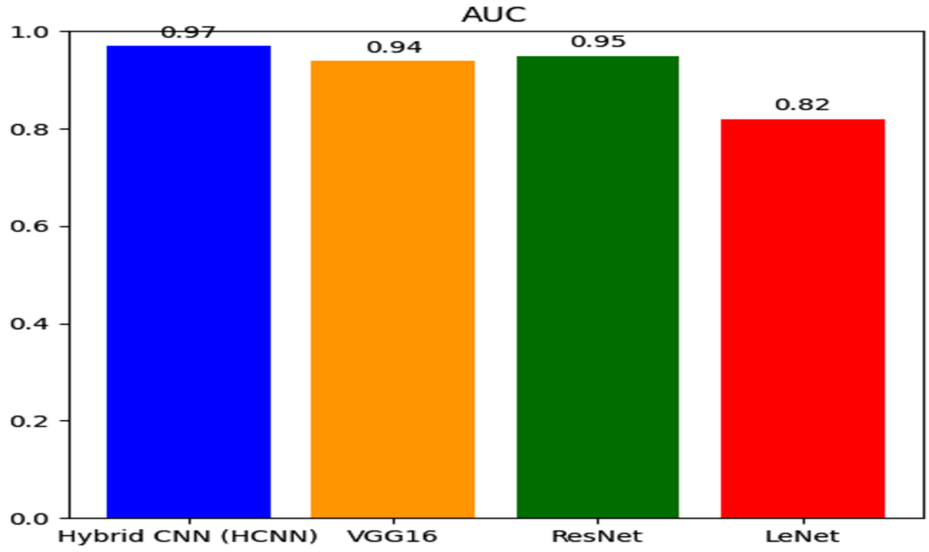

Figure 3. AUC Plot

F1 Score (Best: HCNN 0.91): The F1 Score balances precision and recall, crucial for tasks with imbalanced classes. HCNN leads with the highest F1 Score of 0.91, suggesting robust performance in both capturing relevant instances and minimizing false positives.

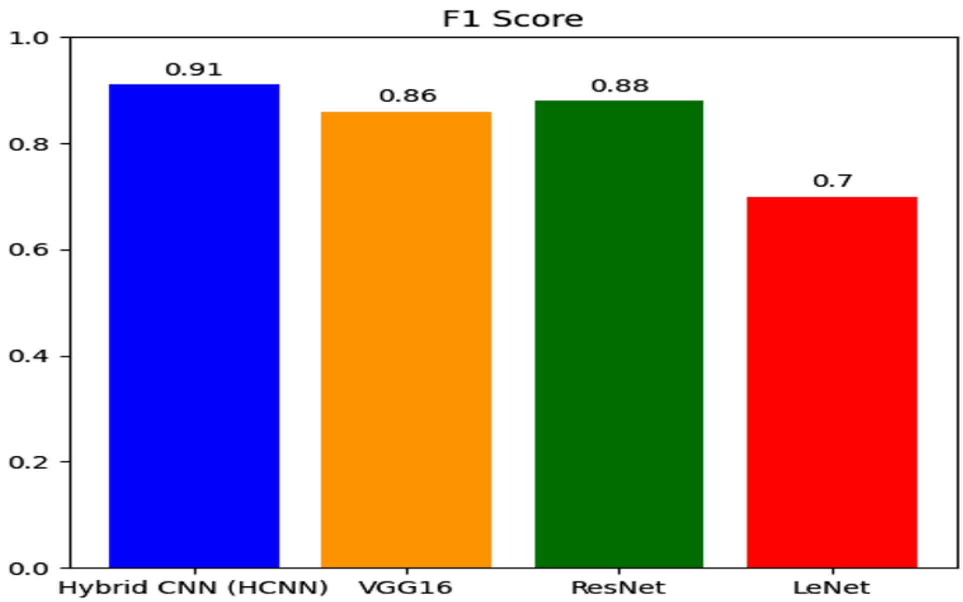

Figure 4. F1-Score Plot

VII. CONCLUSION

This research undertaken heart disease prediction and presents a new Hybrid Convolutional Neural Network (HCNN) design that works amazingly well at using complex connections in a cardiovascular health dataset. The outcomes show that the HCNN performs better than expected across key performance indicators, highlighting its promise as a strong tool for improving predictive analytics in the medical field. With its built-in neural layers, leftover blocks, and attention processes, the HCNN can extract detailed features, picking up on minor trends that could point to heart disease. The model is very accurate, has high predictive power (AUC), and a fair F1 Score. This is because it is flexible and can figure out complicated relationships. The results show a big step forward in the search for more accurate and useful models to predict cardiovascular health. The study has bigger effects on the area of using deep learning for medical diagnosis in general. The HCNN's success shows how important it is to use advanced neural network designs to find hidden trends in large datasets, especially in areas where early discovery is very important. Going forward, this work makes it possible to learn more about and improve deep learning methods used in medical diagnosis. Because the HCNN has been shown to be effective, it seems like a good option for use in the real world, giving doctors a tool that helps them make diagnoses. As technology keeps getting better, these kinds of innovations could completely change the field of predicted medicine, which would eventually improve patient results and healthcare decisions.

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