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IOT-Based Smart Health Care Patient Monitoring System Using Dual Sampling Dilated Pre- Activation Simplicial Convolution Neural Network with Artificial Hummingbird Algorithm

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ABSTRACT
Heart disease prediction is the leading cause of death globally at the moment, and its prevalence is rising. There are difficulties in identifying heart disease in its earliest stages before a cardiac event occurs. A vast variety of information about heart illness is accessible in the medical field, including in clinics and hospitals. To find the hidden patterns, this data is not treated intelligently enough. Still, existing techniques have many shortcomings, such as low accuracy and a high error rate. The detection and classification of heart disease remains a major challenge in healthcare. In this concern, a Dual Sampling Dilated Pre- Activation Simplicial Convolution Neural Network (DuSDPreASCNN) is proposed that provides high accuracy with less error rates during heart disease prediction and classification. First, pre-processing is applied to the input ECG data that were gathered from the Cleveland dataset. During this stage, the irrelevant noise components are suppressed. Following that, the pre-processing is done by using Enhanced Gaussian Short-Time Fourier Transform and Spectrograms Continuous Wavelet Transform (EGSFT-SCWT) method then the preprocessed data undergoes prediction and classification stage. It is done by using Dual Sampling Dilated Pre- Activation Simplicial Convolution Neural Network (DuSDPreASCNN) and optimized using Artificial Hummingbird Algorithm (AHA) for monitoring the Smart-health care Patient monitoring system of IoT-based healthcare system with outstanding accuracy and effectiveness. The efficiency of the proposed DuSDPreASCNN -AHA is analyzed using Cleveland dataset and attains 99.5% accuracy, 96.06 % recall and attains better results in comparison with the existing techniques. The outcomes of the proposed technique showed that it could improve the patient outcomes, early stage diagnosis and reduced healthcare cost method.

Keywords: Heart disease prediction, Smart-health care Patient monitoring system, Gaussian Short-Time Fourier Transform and Spectrograms Continuous Wavelet Transform, Dual Sampling Dilated Pre- Activation Simplicial

Convolution Neural Network (DuSDPreASCNN), Artificial Hummingbird Algorithm.

1. INTRODUCTION

In order to satisfy the demands of numerous businesses, wireless technology has become more and more widespread in recent years. The industrial sector has been dominated by the IoT in recent years, particularly in the automation and control domains [1-3]. One of the most recent advancements in the provision of high-quality healthcare is biomedical care. IoT technology has created opportunities for both personal healthcare facilities and hospitals. A smart system allows for the observation of numerous characteristics that reduce costs, use less energy, and boost productivity. Over the past ten years, the healthcare industry has revolutionized globally with the aid of digitalization and digital transformation [4-6].Even though stratified medicine has long used machine learning (ML) algorithms, there has recently been progress in the field's recognition of the necessity of ML-based healthcare diagnosis systems. However, most people in today's hectic and fast-paced society typically wait until they have serious health concerns before getting a medical checkup. In a similar vein, the majority of them do not get routine cardiac exams due to the time-consuming and inconvenient nature of the physical procedures. Ignorance about one's current cardiac status can lead to serious health complications and, in the worst-case scenario, an unexpected death [7-9]. Thus, in order to conveniently and effectively monitor a person's cardiac state, a smart system is needed. These days, the Internet of Things (IoT) with its essential characteristics including connectivity, sensing, linearity, intelligence, and reliability has become a huge asset to the healthcare industry [10-12]. It is also a means of restructuring contemporary healthcare through the provision of more personalized and preventive care, sensing equipment, and tracking of vital signs including blood pressure, pulse rate, and electrocardiogram (ECG). Numerous wearable health monitoring sensors can be used to gather information about the human body in real-time. These data can then be processed to create health records, which can then be utilized for CVD evaluation, therapy, and postoperative rehabilitation [13-15]. The apparatus is configured in a way that alerts the physician in the event that the sensor data surpasses specified limits. Additionally, if the patient needs assistance and switch would be put in the palm to call for help [16-18].

Novelty and Contribution

- The development of a health monitoring system that gathers data on a patient's heart state via wearable medical devices is underway.
- The objective is to enhance heart disease prediction accuracy by applying pre-processing techniques to ECG data from the Cleveland dataset. The process involves noise suppression using the Enhanced Gaussian Short-Time Fourier Transform and Spectrograms Continuous Wavelet Transform (EGSFT-SCWT) method.
- The objective is to achieve outstanding accuracy and effectiveness in heart disease prediction and classification using preprocessed ECG data. This involves Dual Sampling Dilated Pre- Activation Simplicial Convolution Neural Network (DuSDPreASCNN), optimized by the Artificial Hummingbird Algorithm (AHA), for an IoT-based smart healthcare patient monitoring system.

2. LITERATURE SURVEY

In 2024, Baseer, et al [19] has developed has formulated an Internet of Medical Things (IoMT) method. This model employs high–level methods like TabNet and catBoost to gather vital signs from various healthcare technologies for wearable's and sensors. CatBoost ability of dealing with categorical features and TabNet's feature selection enhance the method accuracy. Vegetative data, socio-economic data, climatic data, demographic data, telecommunication data, patient data, financial data, and many more are incorporated in the model to allow risks' assessments tailored for every client. Due to the model's nature of processing data in real-time, it is possible to make quick forecasts based on streams of IoMT data. This new approach has the vast opportunity for improved results in patient's cardiovascular disease and other preventive care scenarios.

In 2023, Almazroi, et al [20] has introduced a Dense Neural Network (DNN) using a Keras-based deep learning model. Using datasets related to heart illness, it tests several hidden layer setups and benchmarks. The model outperforms individual models and other ensemble techniques in terms of specificity, sensitivity, and accuracy, while applied to all datasets. Different layer combinations perform differently on different datasets.

In 2023, Paul et al [21] has introduced an Artificial Neural Networks (ANNs) method. In order to offer an improved strategy for predicting the presence of heart disease. For cardiac datasets, the University of California, Irvine (UCI) Machine Learning Repository and the IEEE Data Port have been used. The suggested approach, which is comparable to the Cleveland processing heart dataset, estimates the presence and the absence of cardiovascular disease during tests using 13 input attributes, producing findings that range from 63.3803% to

100% accuracy. Similarly, the proposed system uses 11 input qualities to produce lowest results of 88.4754% and highest outcomes of 100% accuracy for the Cleveland Hungarian Statlog cardiac dataset.

In 2024, Din et al [22] has introduced a feature fusion method with the combination of Transformer, Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN) models. By combining these models, different features of the ECG signal can be captured more easily. This includes the characteristics of long-range, temporal, as well as spatial dependency. These attributes are then sent to an overpowering voting classifier that is equipped with three traditional base learners. Deep features are given to average learners instead of customized features. Experiments are conducted using the MIT-BIH arrhythmias database, and the model's performance is compared to the best performing models. The findings show that the suggested model performs better than the existing models, yielding an accuracy of 99.56%.

Problem Statement

The existing Smart-health care Patient monitoring system of IoT-based healthcare system methods suffer from high error rate and low accuracy. Furthermore, the health prediction system built using typical machine learning techniques frequently produces inadequate outcomes since it needs a lot of training data, takes a long time to train, and has poor accuracy when it comes to classifying and predicting s diseases. [23-25]

3. PROPOSED METHODOLOGY

The proposed smart health care patient monitoring system uses wearable with Internet of Things capabilities to keep an eye on people's health. The person's body is equipped with Internet of Things (IoT)-enabled sensing devices, which regularly gather data and send it over a relay network to the server. In this regard, the individual is continuously observed and analyzed. The proposed method consists of three process (1) data collection, (2) pre-processing and (3) Prediction and classification. The working principle of DuSDPreASCNN is illustrated in Figure 1:

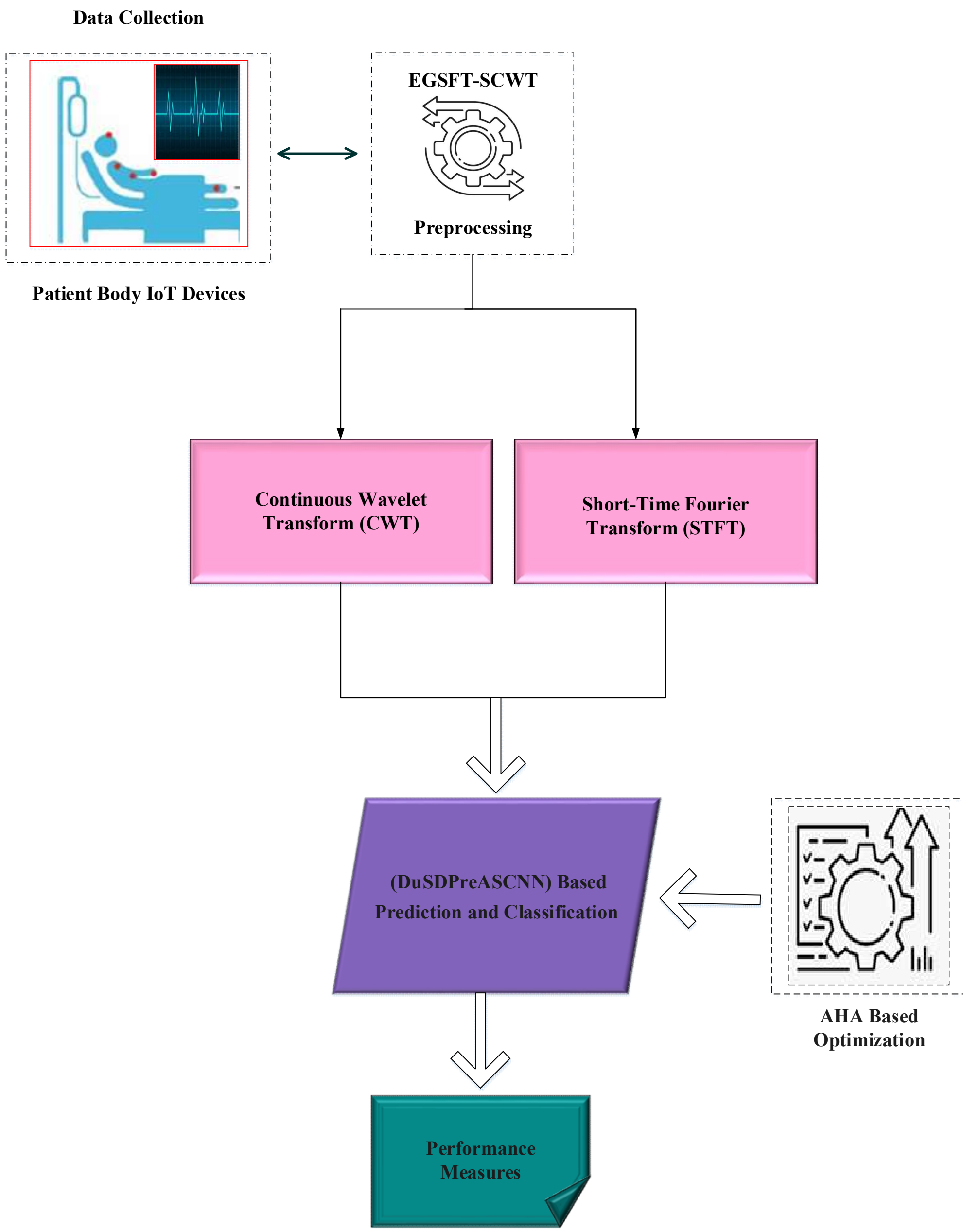

Figure 1: Workflow diagram of proposed DuSDPreASCNN method

3.1 Data Collection

The suggested model gathers input data and conducts research. We obtained all of our data's from the Cleveland dataset. These consists of unwanted noises, to remove these noises pre-processing techniques are used, they are given below:

3.2. Enhanced Gaussian Short-Time Fourier Transform and Spectrograms Continuous Wavelet Transform (EGSFT-SCWT) Based Pre-processing

Background noise and bioelectrical assumptions contaminate the raw ECG readings. To remove the unneeded noise components from the ECG data, an appropriate noise reduction technique is used. In order to use clean ECG data for subsequent processing, high frequency noise elements from the initial ECG signal are removed during the pre-processing stage. The Enhanced Gaussian Short-Time Fourier Transform and Spectrograms Continuous Wavelet Transform (EGSFT-SCWT) is a useful tool for this purpose. By combining the benefits of Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform transforms.

3.2.1Continuous Wavelet Transform (CWT)

The CWT is an effective data analysis tool that provides information on the signal's time-frequency analysis. It is especially useful for evaluating the so-called non-stationary systems in which the signal's frequency content varies with time. Based on the smart-health care patient monitoring system using IoT as a health care system, CWT can play a significant role in detection and analysis of physiological signals inclusive of ECG, EEG and others' signals. CWT uses wavelets or a mathematical function in time-frequency analysis that is localized. These wavelets assist in attaining the gross features of the signal as well as details at initial and deeper point levels. The system uses two parameters that cause interferences with the production of the coefficients of the CWT.

- **Scale** (r)

Scale parameter determines the wavelet's width. Smaller scales correlate to higher frequencies and capture finer details, whereas bigger scales correlate to lower frequencies and capture broader trends.

- **Translation** (η)

The wavelet's position in a time domain is known as translation, allowing the analysis of the signal at different times. The CWT of a signal $Y(l)$ is given by equation (1):

$$CWT_y(\eta,r) = \frac{1}{\sqrt{|r|}} \int_{-\beta}^{+\beta} Y(l)(\varphi)(\frac{l-\eta}{r})dt \tag{1}$$

where, φ denotes the complex conjugate. $CWT_y(\eta,r)$ represents the CWT of the signal Y(l) at a specific time η and scale $r . Y(l)$ is the original signal being analyzed. $\frac{1}{\sqrt{|r|}}$ is the normalization factor. CWT can analyze fluctuations in ECG signals to detect arrhythmias, identify variations in EEG for neurological monitoring, and evaluate respiratory signals. By providing a time-frequency representation, CWT helps in identifying transient events and anomalies in real-time, which is crucial for timely medical interventions. Visual representations (scalograms) of CWT coefficients offer insights into the signal's characteristics, aiding in better diagnosis and monitoring.

3.2.2 Short-Time Fourier Transform (STFT)

The Short-Time Fourier Transform (STFT) is another basic signal processing tool used to investigate the spectral characteristics of signals in time. It divides the signal into small overlapping frames and engages the Fourier Transform on every frame. This technique it is effective for the detection of the frequency elements and their dynamics; therefore it finds application in the smart-health care patient monitoring systems. Thus, the signal is divided into overlapping windows, and every windowed segment is transformed with the Fourier Transform. The output formed is a spectrogram, which can be described as a graphical representation of energy content of signal against frequencies as well as time. With the help of STFT, it is possible to track alterations in the vital signs, grasp the changes in the frequency of heartbeat, brain activity, and other functions in real time. The spectrogram can thus assist in defining patterns of disease and spectral coefficients corresponding to the given pathologies, and as a result improve the diagnostic processes. When the window functions are properly chosen and the segments of the signal being processed overlap the spectral leakage is eliminated and the resolution is improved which assists in understanding more about the signal.[26,27]

Based on improved preprocessing functions, smart healthcare monitoring systems enable the monitoring of patients with wearable devices that utilize the Internet of things technology. The proposed CWT and STFT cooperate to get the patient's efficient and precise evaluation for faster diagnosis and monitoring. This integration further improves the safety of the patient as well as the treatment of the patient making a very critical contribution to smart health systems.

3.3 Heart Disease Prediction and Classification based on Dual Sampling Dilated Pre- Activation Simplicial Convolution Neural Network (DuSDPreASCNN)

In the prediction and classification stage, the preprocessed data are fed as input to the DuSDPreASCNN. In modern IoT-based healthcare systems, efficient and accurate prediction and classification of heart diseases are critical for effective patient monitoring and management. This can be achieved by integrating advanced deep learning techniques, such as Dilated Convolutional Neural Networks (DCNN) and Simplicial Attention Networks (SANs), into the system. The explanation of how these technologies can work together for such purposes is given below,

3.3.1 Dilated Convolutional Neural Networks (DCNN)

Dilated Convolutional Neural Networks (Dilated CNNs) are particularly well-suited for applications that require capturing long-range dependencies and context over time, such as in smart healthcare patient monitoring systems within an IoT-based healthcare framework. Dilated convolutions, also known as trous convolutions, allow for an exponentially increasing receptive field without losing resolution or coverage. This is achieved by introducing "holes" or spaces between the elements of the convolutional kernel. Formally, the L-dilated convolution of functions h and t is given by equation (2):

$$(h * j t)(l) \sum_{l=-\beta}^{\beta} h(n) d(l - tn) \tag{2}$$

where, $*j$ denotes the dilated convolutional operator. It's also called as a trous, $h \; and \; t$ refers a set of N integers. This operation effectively spaces out the kernel values, allowing the network to cover a broader range of input values with fewer layers, thereby enhancing the ability to capture long-term dependencies. In a typical CNN layer using dilated convolutions, the receptive field grows exponentially with each layer. For a kernel window starting at location j of size h with dilation g, the input values are sampled as given equation (3):

$$[y_j y_{j+g} y_{j+2g} \quad y_{j+(h-1)g}] \tag{3}$$

By stacking multiple layers with increasing dilation rates, the network can effectively aggregate information from a wide context. The dilated CNN layer processes these high-level features to capture temporal relationships. The dilated convolution operations at different layers are defined as given equation (4, 5 and 6):

$$s_l^{(1)} = \operatorname{Re} LU(E *_{g1} k_l^y) \tag{4}$$

$$s_l^{(j)} = \operatorname{Re} LU(E *_{gj} s_l^{(j-1)}) \tag{5}$$

$$s_l^{(i)} = \operatorname{Re} LU(E *_{gt} s_l^{(i-1)}) \tag{6}$$

where, $E *_{gj}$ denotes the dilated convolution in layer j. $\operatorname{Re} LU$ is the activation function. g is the dilation factor. Dilated Convolutional Neural Networks enhance the predictive and classification capabilities of IoT-based healthcare monitoring systems by effectively capturing long-range dependencies and integrating contextual information from various sensors. This leads to more accurate and timely detection of health conditions, ultimately improving patient care and outcomes.

3.3.2 Simplicial Attention Networks (SANs)

Simplicial Attention Networks (SANs) extend traditional graph neural networks to work with simplicial complexes, which are more general structures than graphs. Simplicial complexes can capture relationships between data points at various dimensions, offering richer information for modeling complex systems. A simplicial complex KKK is a collection of simplices (e.g., nodes, edges, triangles) that can represent complex relationships. For instance, in a heart disease dataset, simplices could represent different features or relationships among patients' health metrics. SANs use attention coefficients to weigh the importance of different simplices' interactions. This mechanism helps the network focus on more relevant information while aggregating data from different simplices. SANs use message-passing layers to update the features of simplices. The attention mechanism determines how much influence neighboring simplices have on the update. Consider the simplicial complex H. Our model will be explained for any complex dimension $g \leq \dim(H)$. Using the following equations, we calculate the attention coefficients for the down and up adjacencies are given by equation (7 and 8):

$$\omega_{\alpha,\mu}^{\uparrow} = O_{\alpha,\mu}.soft\max_{\mu \in M_\alpha^{\uparrow}} (b(V_1 k_\alpha^h, V_1 k_\mu^h)) \tag{7}$$

$$\omega_{\alpha,\mu}^{\downarrow} = O_{\alpha,\mu}.soft\max_{\mu \in M_\alpha^{\downarrow}} (b(V_2 k_\alpha^h, V_2 k_\mu^h)) \tag{8}$$

where, α denotes a function for computing attention coefficients. α, μ are the typically indicating elements. The choice of orientation in oriented simplicial complexes is arbitrary, however the model to take this symmetry into consideration.

The technique of real-time analysis of interactions in Internet of Things-based healthcare system, by Dilated

Convolutional Neural Networks (SAN) and Simplicial Attention Networks is used to predict the heart disease risk. It optimizes the completion of patients' monitoring and tailored treatment with the help of deep learning technologies. Due to the fact that DuSDPreASCNN method is used for the prediction and the classification the optimization is done in order to increase accuracy, decrease the error rate as well as optimize in terms of time, complexity, and the cost. The optimizing process of DuSDPreASCNN is given below,

3.4 Artificial Hummingbird Algorithm (AHA) Based Optimization

The Artificial Hummingbird Algorithm is used to optimize the learning parameters of DuSDPreASCNN. The goal is to improve the energy efficiency and endurance. The Artificial Hummingbird Algorithm (AHA) is inspired by the foraging and flight behaviors of hummingbirds. This optimization technique uses specific strategies to balance exploration (searching new areas) and exploitation (refining current solutions).

Step1: Initialization

Create an initial population of Artificial Hummingbird Algorithm solutions, each representing a set of DuSDPreASCNN hyper parameters.

Step 2: Generation of Random Variables

Generate at random the optimization variables of Artificial Hummingbird Algorithm to attain the best solution.

Step 3: Evaluation of Fitness Function

The fitness function in AHA is used to evaluate the quality or effectiveness of a solution. The fitness function equation is given by equation (9):

$$f(y_j(l)) \leq f(u_j(l+1)) \tag{9}$$

where, $f(\cdot)$ denotes the fitness function, $u_j(l+1)$ is the solution of candidate at the $(l+1)$-th time.

Step 4: Migration Foraging (Exploration) for improving accuracy

Exploration refers to the algorithm's ability to search through a wide range of possible solutions to discover new, potentially better solutions. When food (solution quality) becomes scarce, a hummingbird with poor fitness migrates to a distant region to explore new potential solutions. This helps in escaping local optima and discovering diverse solutions. In the healthcare monitoring system, this could involve testing new configurations or placements of sensors to find the most optimal setup for accurate and efficient patient data collection. The mathematical representation of migration foraging is given by equation (10):

$$y_{wst}(l+1) = lo + s.(ap - lo) \tag{10}$$

where, y_{wst} denotes the source of food with worst population rate of nectar refilling, s represents the random factor, ap and lo are the upper and lower limit ranges.

Step 5: Territorial Foraging (Exploitation) for reducing error rate, processing time, computational complexity and cost

Exploitation focuses on refining and improving the current best solutions. It ensures that the algorithm efficiently converges to the optimal solution by making small adjustments and improvements. This strategy involves local searches around known good solutions, fine-tuning them to find even better solutions. The hummingbirds' local search within their territorial foraging strategy is represented by the equation (11):

$$u_j(l+1) = y_j(l) + d.a\ (y_j(l))d \tag{11}$$

Where, a denotes the guided factor, which is subjected to standard normalization distribution $M(0,1)$, $y_j(l)$ represents the position of j-th food source at time l. d is the territorial factor.

Step 6: Termination

After reaching the certain number of iterations the best solution is determined and the process is terminated. The proposed AHA approach leverages the exploration and exploitation behavior to navigate the hyper parameter search space, ultimately improving the performance during heart disease prediction and classification. By applying AHA, the healthcare monitoring system can achieve a balanced optimization that ensures accurate, timely, and efficient patient monitoring, leading to better healthcare outcomes. The continuous process of exploration and exploitation ensures that the system adapts and improves over time, maintaining optimal performance even as conditions change.

Hence, DuSDPreASCNN detailed and explained. It pre-processed data using EGSFT-SCWT, Prediction and Classification using DuSDPreASCNN optimization using AHA method for Smart-healthcare Patient monitoring system of IoT-based healthcare system demonstrating superior efficiency and accuracy. In the next section the results and discussions are discussed.

4. RESULT AND DISCUSSIONS

This section presents the experimental findings and comments of the proposed method performed to the Python platform.

4.1Dataset description

There are fourteen features in the Cleveland dataset. The 13 features are independent of one another and are input features. The final column represents the output feature, which is essentially a label attribute. It is dependent upon the input features; for example, if it is 0, it indicates that the patient has heart disease; if not, it does not. There are 303 cases in the collection.Table1 shows the comparison of Cleveland dataset.

Table 1: Comparison of Cleveland Dataset

Cleveland Dataset			
Data Variation	Multivariate	Count of samples	303
Type of attribute	Categorical, Integer, Real	Number of Attributes	14

Table 1 shows an overview of the Cleveland dataset, indicating it contains 303 samples with 14 attributes. The dataset is multivariate, featuring categorical, integer, and real data types. This summary highlights the dataset's diversity and complexity, suitable for various statistical and machine learning analyses. Figure 2 shows the some of the symptoms of heart diseases,

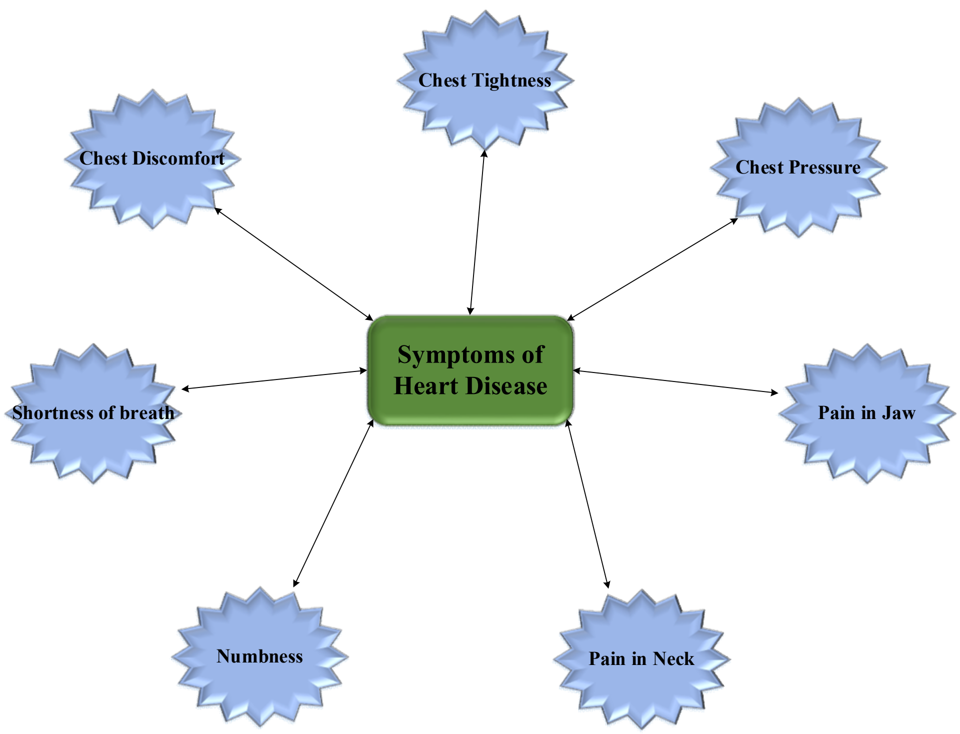

Figure2: Symptoms of Heart Diseases

4.2 Performance metrics

The efficiency of the proposed method is evaluated based on various performance metrics such as Accuracy, Recall, and Precision, F- score, and Error rate. The experimental outcomes are shown in the following table2:

Table 2: Performance comparison of Cleveland Dataset

Methods	Accuracy (%)	Recall (%)	Precision (%)	F1-Score (%)	Error rate (%)
IoMT	92.7	94	93	92	1.8
DNN	79	91	91	94	1.2
ANNs	97.24	95.42	96	95	1.5
LSTM-CNN	98.40	94.21	95	98.76	2.5

DuSDPreASCNN (proposed)	**99.5**	**96.06**	**97**	**99.35**	**0.1**

Table 2 compares the performance of different methods on the Cleveland dataset. The proposed method achieves the highest accuracy (99.5%), precision (97%), F1-score (99.35%), and lowest error rate (0.1%). Other methods like LSTM-CNN and ANNs also perform well, but not as effectively as proposed method. Table 3 shows the comparison of computational time with proposed method,

Table 3: Computational time (in minutes)

Methods	Training Time
IoMT	**48**
DNN	**76**
ANNs	**91**
LSTM-CNN	**65**
DuSDPreASCNN (proposed)	**5**

Table 3 shows the computational time required for training various methods on the Cleveland dataset. The proposed DuSDPreASCNN method significantly outperforms others with a training time of just 5 minutes, compared to 48 minutes for IoMT, 76 minutes for DNN, and 91 minutes for ANNs, and 65 minutes for LSTM-CNN. Figure 3 shows the comparison of overall performance,

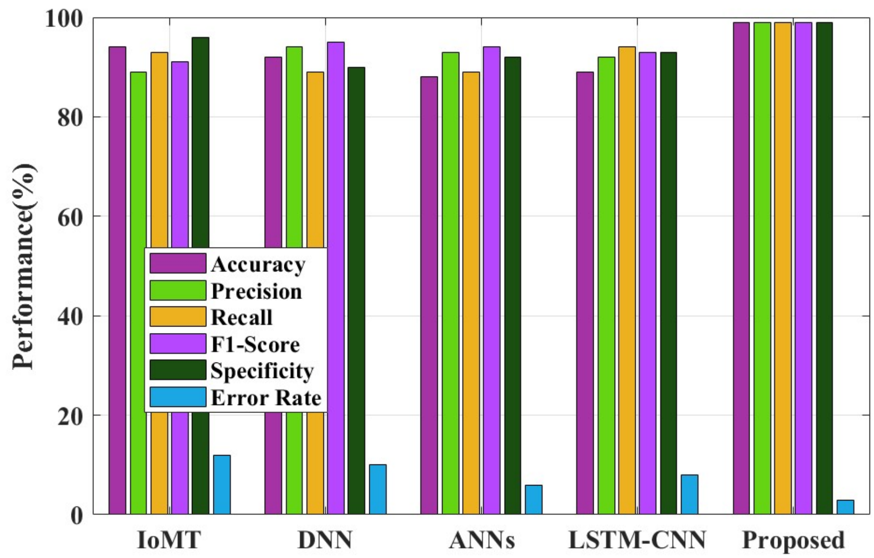

Figure 3: Comparison of overall performance

The Figure 3 compares performance metrics (Accuracy, Precision, Recall, F1-Score, Specificity, and Error Rate) of different methods (IoMT, DNN, ANNs, LSTM-CNN, and Proposed) in a healthcare system. The Proposed method outperforms others in all metrics, indicating higher effectiveness for smart-healthcare patient monitoring with IoT-based systems.

5. CONCLUSION

In this manuscript, DuSDPreASCNN is successfully manipulated. Heart disease is a fatal condition that can affect a lot of people. Early diagnosis allows for earlier treatment, which will prevent this disease from causing damage. In this concern, the input data is preprocessed using EGSFT-SCWT method. Then the prediction and classification is done using DuSDPreASCNN for Smart-health care Patient monitoring system of IoT-based healthcare system. The introduced system is executed in python. Thus, the suggested DuSDPreASCNN method predicts the heart disease and categorizes its stages with high accuracy and the information is transferred to the patients in an effective manner. Using the Cleveland dataset, the suggested model achieves an accuracy of 99.5%, outperforming existing methods in terms of performance. Future work will enhance model robustness and generalizability by expanding dataset, integrating real-time processing, and creating a user-friendly interface for detecting the heart disease for IoT-based healthcare system.

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