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Automated Heart Disease Diagnosis and Monitoring System using Similarity-Navigated Graph Neural Networks with Leopard Seal Optimization in IoT Healthcare Applications

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***Abstract*— One of the leading causes of death worldwide continues to be heart disease; therefore, early detection and precise diagnosis are essential to better patient outcomes. The conventional methods of diagnosing chemotherapy-induced nail changes involve a great deal of laboratory testing, which is more than exhaustive. In order to tackle these obstacles, this research introduces a novel methodology for the automated diagnosis and continuous tracking of heart diseases in the IoT-based healthcare system, integrated with deep learning algorithms. The proposed system includes several state-of-the art techniques to improve diagnostic reliability and speed. First of all, min-max normalization is used as a pre-processing technique that aims at pre-scaling the data of patients to a consistent level and, as a result, enhancing the performance of the model. The Mud Ring Algorithm is then used for feature selection, whereby the best features are chosen together with the reduction in dimensionality to decrease computational intensity, thus improving diagnostic accuracy. The core diagnostic engine is based on Similarity Navigated Graph Neural Networks (SNGNN) and has been enhanced with Leopard Seal Optimization (LSO), a new meta-method motivated by the hunting patterns of leopard seals. This combination enables the system to relate various features and give the correct prognosis for heart diseases. These techniques, applied within the IoT framework, enable real-time monitoring and diagnosis and therefore have the benefit of being a scalable solution for modern health care systems. The results show that the proposed method for providing diagnosis of heart disease is accurate, timely, and reliable and thus has the potential to revolutionize patient management in healthcare based on the IoT.**

Key words*— Automatic Heart Disease Diagnosis, IoT Healthcare Application, Min-Max Normalization, Mud Ring Algorithm, Similarity Navigated Graph Neural Networks, Leopard Seal Optimization.

I. INTRODUCTION

Heart disease refers to a range of conditions that affect the heart, such as heart failure, coronary artery disease, and heart attacks. It is often the result of lifestyle choices, hypertension, and elevated cholesterol. Improving results and avoiding major issues require early discovery and intervention. Predicting heart illness automatically is among the most important and challenging healthiness issues in actual life [1]. Heart disease affects the structure of blood vessels and increases the risk of arterial infections, which can harm a patient's health, especially in elderly people. Based on information provided by the World Health Organization (WHO), cardiovascular illnesses account for about 18 million deaths worldwide each year [2-3].

Alongside human evolution, science and technology have advanced. Developments in ICT (Information and Communication Technology) have created the groundwork for creative resolutions in a variety of business areas, including healthcare, logistics, agriculture, and transportation [4]. The IoT is a significant factor behind the technological growth of

ICT, guiding future industries toward automation and decentralized intelligence.

Since the beginning of the use of information technology to collect, track, and manage patient status data remotely, applications in healthcare have been driving scientific and technological developments [5]. Therefore, by using wearable technology and sensor networks to collect patient physiological data, IoT is driving and revolutionizing current advancements in healthcare.

Predictive analytics seeks to forecast potential occurrences using current data, whereas healthcare analytics is the methodical examination of data for effective decision-making. For risk assessment, clinical decision assistance, and remote health monitoring, this is essential. Healthcare analytics combines data from several sources to save expenses and improve decision-making. This aids in the early detection of problems and the efficient management of chronic illnesses [6].

Innovative AI (artificial intelligence) and ML (machine learning) algorithms are employed in conjunction with traditional linear models in predictive analytics. DL (deep learning), a branch of ML, provides meaningful insights and answers to complex issues. It is robust and dependable enough to manage and acquire from massive amounts of composite healthcare data [7]. Its implementation in numerous medical presentations has outperformed the outcomes of conventional models.

Novelty and Contribution

- The proposed method integrates Min-Max normalization, the Mud Ring Algorithm, SNGNN, and Leopard Seal Optimization to provide a unique framework for diagnosing heart disease.
- The proposed method presents the Mud Ring Algorithm, a novel approach to feature selection that preserves or enhances diagnostic accuracy while lowering feature dimensionality.
- The proposed method suggests using the cutting-edge SNGNN-LSO technique, which was created especially to diagnose heart problems automatically and improves the functionality of the proposed method.
- The proposed method optimizes feature selection and DL models to increase the efficiency and accuracy of heart disease identification, improving the functionality of IoT-based healthcare systems.
- The proposed method addresses the need for prompt and accurate heart disease monitoring and may even improve patient outcomes by offering a scalable, real-time diagnostic solution for IoT healthcare applications.

II. LITERATURE SURVEY

In 2022 Nancy et al. [8] have suggested the heart disease prediction using DL in an IoT-powered smart health system for monitoring. For early intervention and preventative treatment, accurate disease prediction is critical. To achieve this, deep learning models using recurrent neural networks and electronic health information must be used. The recommended method gathers information from predictive analytics is used to electronic clinical data via IoT devices related to patient history that is stored on the cloud.

Ramkumar G et al. (2023) [9] have demonstrated the use of DL, an IoT-based patient tracking system, to forecast cardiac illness. The IoT gathers huge quantities of data, and DL methods have made it possible to identify and detect diseases. The recommended method gathers data from IoT devices and sends electric medicinal records associated with cloud-stored patient histories to predictive analytics. Limited deep learning model interpretability is a drawback of the suggested approach.

Rajkumar G et al. (2023) [10] have introduced the enhanced deep learning technique and IoT-based framework for heart disease prediction: application in medicine. The input dataset for this study has been preprocessed to eliminate erroneous information and absent values. Feature-based selection of results from preprocessed data is done via the Harris Hawk Optimization (HHO) approach. The MDLSTM (modified deep long short-term memory) classifies the selected attributes as abnormal or normal. The ISHO (improved spotted hyena optimization) algorithm modifies the LSTM output. The suggested method's shortcoming is its high level of complexity in both model training and optimization.

In 2022 Nelson I et al. [11] have suggested an effective AlexNet DL architecture for the health system's automatic diagnosis of cardiovascular illnesses. The innovative ABFog system uses cloud framework fog computing to ensure optimal service quality in several configuration modes while integrating devices for edge computing in DL for actual time analysis of heart disease. The suggested method's limited emphasis on response time optimization represents one of its drawbacks.

A. Problem Statement:

Due to the complex and multidimensional nature of medical data, prompt and accurate detection of heart disease is essential but frequently difficult. Traditional methods may not be as precise and may require a lot of time and resources. An automated system is required in order to effectively process, choose, and evaluate pertinent features in order to produce precise diagnoses. The SNGNN-LSO method is a unique methodology that combines Similarity-Navigated Graph Neural Networks with Leopard Seal Optimization to enhance the efficiency and accuracy of computerized heart disease diagnosis by managing intricate feature interactions.

III. PROPOSED METHODOLOGY

The proposed IoT-based health monitoring system is display in the Figure 1. A gateway device is used to obtain physiological data, such as electrocardiogram, blood pressure, and heart rate. Before the data are input into a preprocessed using Min-Max Scaler Normalization then Mud Ring method for feature selection is used to select the relevant features. The Similarity-Navigated Graph Neural Networks with Leopard Seal Optimization (SNGNN-LSO) process the chosen features after that in order to analyze them. Based on the examined data, doctors, hospitals, and patients receive alerts for prompt action.

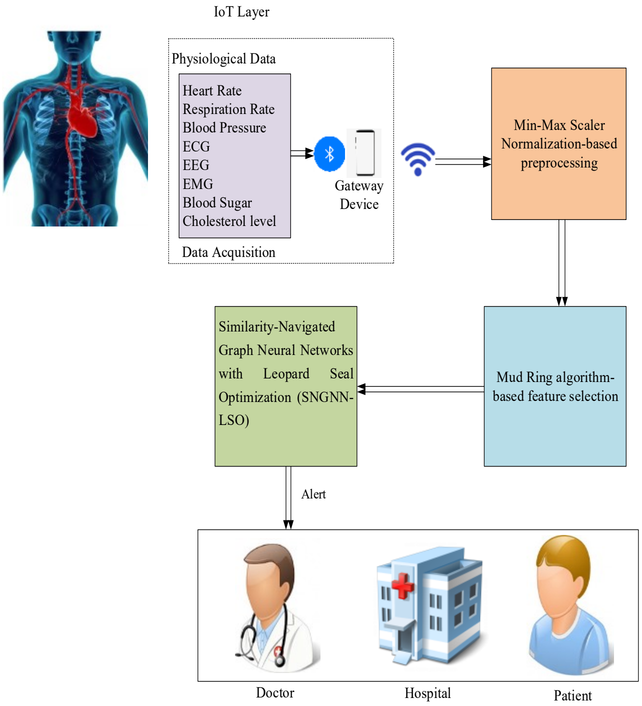

Figure 1: Proposed IoT-based health monitoring system

A. Dataset Acquisition

The physiological information obtained from the routine health check-ups for patients includes their blood glucose/blood sugar level, blood pressure (BP), respiration rate, heart rate, blood oxygen level, activity, cholesterol level, electroencephalogram (EEG), electromyogram (EMG), and electrocardiogram (ECG).

1. Dataset

In this proposed method, the Hungarian and Cleveland datasets from the UCI machine learning repository are used to identify the existence of heart illness from cardiac patient data. Data input is fed to the preprocessing stage.

B. Min-Max Scaler Normalization-based Preprocessing

The input data are preprocessed through the Min-Max Scaler Normalization-based preprocessing technique, which scales and normalizes feature values in datasets to ensure consistency and relevance for precise analysis. Due to the wide variations in feature values in heart disease diagnosis caused by different diagnosis techniques and data sources, this strategy works especially well with high-dimensional data [12]. The Min-Max scaler normalizing algorithm is described by equations (1) and (2).

$$A_{Std} = \frac{(A - A.Min)}{(A.Max - A.Min)} \tag{1}$$

$$A_{Scaled} = A_{Std} * (A.Max - A.Min) + A.Min \tag{2}$$

In order to ensure consistency, preprocessing normalizes the dataset's min and max feature values. Subsequently, the preprocessed data is used to select the pertinent features once these values have been fitted and transformed for model testing. The pre-processed data's are given to feature selection.

C. Mud Ring algorithm-based Feature selection

Following pre-processing, feature selection occurs. The automatic diagnosis of heart disease uses the Mud Ring algorithm-based feature selection to select the relevant features. Marine creatures called bottlenose dolphins can dive up to 260 meters in search of food. They can make sounds like whistles, burst pulses, and echolocation clicks. Together, they optimize hunting through the application of prey- and environment-based techniques, such as mud ring feeding [13]. It identifies the most relevant characteristics since it continually reduces the feature set based on its performance measurements. In addition to lowering computational intensity, both of these techniques increase diagnostic accuracy.

- *Initialization*

Inspired by the behavior of dolphins, the Mud Ring Algorithm's initialization formula is represented as follows:

$$d_i = d_{\min} + (d_{\max} - d_{\min}) \times rand(i) \tag{3}$$

Where $i \in [1,2,..., n]$, $d_{\min}$ and $d_{\max}$ are the population's minimum and maximum boundaries, and $rand(i)$ is assigned to every dolphin at random.

- *Fitness function*

Considering the circumstances of automatic diagnosis of heart disease, the fitness function of the Mud Ring Algorithm might be created to assess the degree to which a given feature subset improves the accuracy of disease prediction. The objective of fitness is:

$$Fitness\ function = \alpha \cdot acc(d_i) + \beta \cdot \left(1 - \frac{|d_i|}{|d_{total}|}\right) \tag{4}$$

Where $acc(d_i)$ is the model's accuracy at classifying data using the chosen features d_i, $|d_i|$ is the number of selected features, $|d_{total}|$ denotes the total number of features available.

- *Exploration*

The study uses virtual dolphins to find prey in a $D-$space of dimensions in parameters. The dolphins exploration randomly, using a random $|\vec{g}| \geq 1$ value. This selection mechanism inspires exploration and allows the MRA algorithm to conduct a worldwide search. Criteria for updating positions and velocity are provided. Based on the velocity $\vec{v}^f$ and time step f, the workability $\vec{d}^f$ is supplied by

$$\vec{d}^f = \vec{d}^{f-1} + \vec{v}^f, \tag{5}$$

Where a random vector v is initialized. Initially, according to the extent of the relevant issue, an arbitrary speed from $[v_{\min}, v_{\max}]$ is assigned to each dolphin.

- *Exploitation*

The MRA method involves dolphins detecting and surrounding prey, the intended prey being the most effective remedy at the moment. Various dolphins update their locations based on the finest search engine representative.

$$\vec{b} = \left| \vec{h}\,\vec{d}^{*f-1} - \vec{d}^{f-1} \right| \tag{6}$$

$$\vec{d}^t = \vec{d}^{*f-1} \cdot \sin(2\pi l) - \vec{g} \cdot \vec{b} \tag{7}$$

Where 1 denotes the random number, $\vec{g}$ denotes the coefficient vector, $\vec{d}$ denotes the position vector of dolphins, and $\vec{d}^*$ denotes the position vector of the ideal dolphin position that has been attained to date.

- *Termination*

The Mud Ring Algorithm for diagnosing heart disease terminates when a stopping condition is satisfied. This can be when improvements in fitness values become insignificant over successive generations, when the number of iterations reaches a maximum, or when the classification accuracy reaches a desired level. Once an ideal or satisfactory solution is found, these criteria guarantee the algorithm ends. Then the selected features are given to classification.

D. Similarity-navigated graph neural networks with Leopard seal optimization

Following feature selection, heart disease prediction occurs. Similarity-Navigated Graph Neural Networks (SNGNN) is used in automated heart disease diagnosis and monitoring to evaluate and understand complex heart disease data. This technique improves Graph Neural Network's (GNN) capacity to spot trends and connections linked to cardiac disease, enabling prompt diagnosis and ongoing observation [14]. The Graph Convolutional Network's (GCN) matrix-based propagation and aggregation principles lead to equation (8).

$$F^{(l)} = \sigma\left(\widetilde{C}^{-\frac{1}{2}} \widetilde{B} \widetilde{C}^{-\frac{1}{2}} F^{(l-1)} W^{(l-1)} \right), \tag{8}$$

Where, $\widetilde{C}^{-\frac{1}{2}} \widetilde{B} \widetilde{C}^{-\frac{1}{2}}$ is an adjacency matrix with symmetry and normalization with $\widetilde{B} = B + X$ and $\widetilde{C}$ is the degree matrix of $\widetilde{A}$. The normalized adjacency matrix, which is essentially a weight matrix W, is used for aggregation in a statistical and non-adaptive manner. The normalized adjacency matrix is replaced by the similarity matrix in SNGNN, which dynamically characterizes neighborhood data. It is possible to adjust the aggregation and propagation procedures accordingly, i.e.,

$$F^l = \sigma\left(R^{(l)} F^{(l-1)} W^{(l-1)} \right), \tag{9}$$

Utilizing Similarity-Navigated Graph Neural Networks (SNGNN) enables the avoidance of over-smoothing, which becomes a significant problem when applied to automated heart disease detection and monitoring and may obscure some of the features. In this way, the weighted ego-feature (derived from the mean neighbor-feature) of SNGNN maintains the quality of the significant variables linked with critical heart disease. By applying a more robust method to analyze key patterns in patient data sets, the methodology improves the model's interpretability when related to classical approaches like AGNN. The result is an increased level of accuracy in the system's diagnosis and treatment of cardiac illnesses through the custom of DL techniques. The identified data are subjected to optimization in order to maximize the neural network's weight matrix.

1. Leopard seal optimization (LSO)

LSO imitates the non-intrusive hunting techniques of leopard seals. These sentient creatures work together for the good of all, frequently hunting prey even when they are not hungry. There are three stages in which leopard seals search, encircle, and attack. They hunt separately during the search phase, alert other herd members in the area with an "encircle message," and then encircle the prey. The attack phase begins when the prey becomes motionless [15]. LSO is used to optimize the weight matrix of SNGNN. The fitness function is given in equation (10):

$$Fitness\ function = Min(W) \tag{10}$$

Where W denote s the weight matrix of SNGNN.

The IoT-based health monitoring system uses advanced techniques like Min-Max Scaler Normalization Mud Ring algorithm-based feature selection and SNGNN-LSO to provide timely alerts for patient care, enabling early detection of critical health issues and improving patient outcomes.

IV. RESULTS AND DISCUSSION

The efficiency of the methodology is demonstrated in the results and discussion section, which provides a detailed comparative performance comparison between the suggested method and current methods. Python is used to implement the proposed method, allowing for flexible experimentation and fine-tuning.

A. Dataset Description

The Hungarian and Cleveland heart disease datasets are used in the method, which makes use of the University of California, Irvine's (UCI) online machine learning. 14 features are included in 303 and 294 records, respectively, from the original heart disease datasets from Hungarian and Cleveland. The endurance of the proposed DL model was tested by increasing these records to 100,000 entries utilizing the dataset-generating tool Mockaroo. Hence, 100,000 entries divided into 70% for training and 30% for testing are used to determine the method.

B. Performance comparison with existing methods

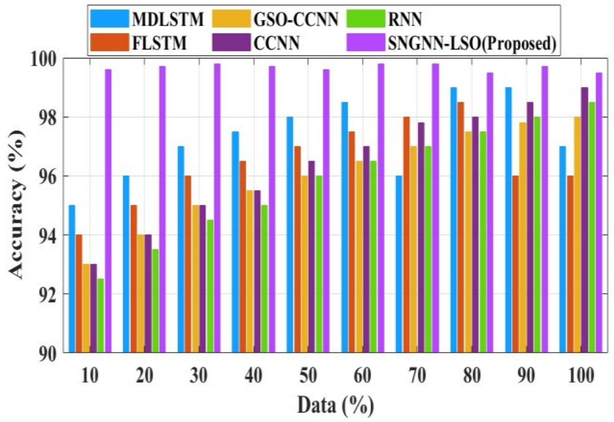

Figure 2: proposed method accuracy comparison on existing approaches

The accuracy comparison of six approaches is displayed in the figure 2: SGNN-LSO, CCNN, GSO-CCNN, RNN, MDLSTM, and FLSTM. At 70% data, the approximate values of MDLSTM are slightly over 96%, FLSTM is approximately 95%, GSO-CCNN is approximately 94%, CCNN is slightly above 94%, RNN is approximately 96%, and SGNN-LSO is almost 98%. Across all data percentages, SNGNN-LSO consistently has the highest accuracy.

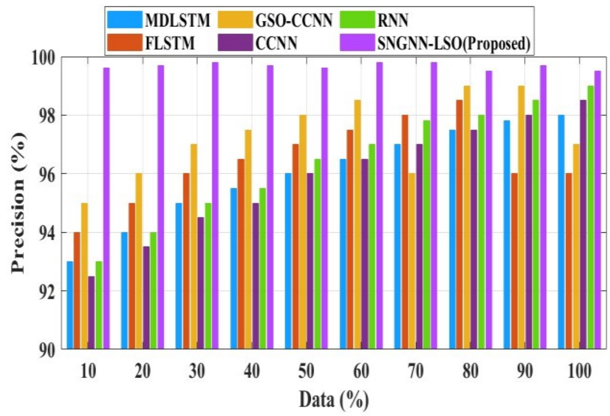

Figure 3: Proposed method precision comparison on existing approaches

Five techniques for automated heart disease diagnosis are shown in the Figure 3: SGNN-LSO, CCNN, GSO-CNN, FLSTM, and MDLSTM. The MDLSTM is a little over 96%, the FLSTM is approximately 95%, the GSO-CNN is approximately 94%, the CCNN is slightly over 94%, and the SNGNN-LSO (proposed) is almost 98% at 70% data. SNGNN-LSO is the most precise method in all data percentages.

TABLE I: Performance comparison on existing approaches

Methods	Accuracy	Precision	Recall	Specificity	F1-score
MDLSTM	92	91	90	91	91
FLSTM	93	92	91	92	92
GSO-CNN	95	94	93	94	94
CCNN	94	93	92	93	93
RNN	96	95	94	95	95
SNGNN-LSO	99	98	97	98	98

Table 1 displays the performance comparison on existing approaches. With the highest accuracy (99%), precision (98%), recall (97%), specificity (98%), and F1-score (98%), SNGNN-LSO performs better than other approaches. RNN comes in second with 96% accuracy, followed by GSO-CNN, CCNN, FLSTM, and MDLSTM, all of which score worse on all parameters.

Overall performance comparison with existing approaches

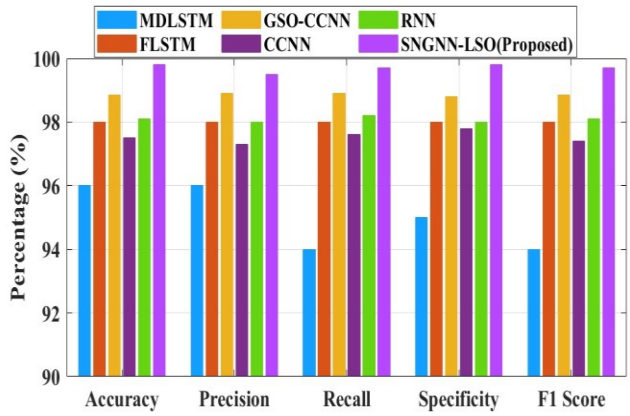

Figure 4: Overall performance comparison with exiting methods

The six methods (MDLSTM, FLSTM, GSO-CCNN, CCNN, RNN, and SGNGN-LSO) are compared in the Figure 4 based on five different performance metrics: Recall, Accuracy, F1 Score, Precision, and Specificity. With the highest accuracy (99%), precision (98%), recall (97%), specificity (98%), and F1 score (98%), SNGNN-LSO is the most successful. With MDLSTM and FLSTM performing the lowest, other algorithms range in performance between 90% and 96% across these metrics.

V. CONCLUSION

The IoT-based monitoring system for health efficiently combines sophisticated gathering data, preparing it, choosing features, and analysis methods to deliver timely alerts for patient treatment. The application of Min-Max Scaler Normalization-based preprocessing and Mud Ring guarantees precise feature selection, which is subsequently handled by Similarity-Navigated Graph Neural Networks with Leopard Seal Optimization (SNGNN-LSO). By utilizing a comprehensive strategy, patients, physicians, and hospitals may identify key health issues early and take appropriate action, leading to better patient outcomes. Future work will concentrate on making the system more capable of handling predictive analytics for the management of chronic diseases and on making it more scalable to accommodate a wider variety of physiological data.

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