IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 17 January 2024, accepted 10 February 2024, date of publication 16 February 2024, date of current version 23 February 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3366537

RESEARCH ARTICLE

A Novel Early Detection and Prevention of Coronary Heart Disease Framework Using Hybrid Deep Learning Model and Neural Fuzzy Inference System

B. RAMESH AND KURUVA LAKSHMANNA
School of Computer Science Engineering and Information Systems, Vellore Institute of Technology, Vellore, Tamil Nadu 632014, India
Corresponding author: Kuruva Lakshmanna (lakshman.kuruva@vit.ac.in)

This work was supported by the Vellore Institute of Technology, Vellore, India.

ABSTRACT Diabetes is the ''mother of all diseases'' as it affects multiple organs of body of an individual in some way. Its timely detection and management are critically important. Otherwise, the long run, it can cause several complications in a diabetic. Heart disease is one of the major complications of diabetes.This work proposed an Optimal Scrutiny Boosted Graph Convolutional LSTM (O-SBGC-LSTM), SBGC-LSTM enhanced by Eurygaster Optimization Algorithm (EOA) to tune hyperparameters for early prevention and detection of diabetes disease. This work proposed an Optimal Scrutiny Boosted Graph Convolutional LSTM (O-SBGC-LSTM), SBGC-LSTM enhanced by Eurygaster Optimization Algorithm (EOA) to tune hyperparameters for early prevention and detection of diabetes disease. This method not only captures discriminative features in spatial configuration and temporal dynamics but also explore the co-occurrence relationship between spatial and temporal domains. This method also presents a temporal hierarchical architecture to increase temporal receptive fields of top SBGC-LSTM layer, which boosts the ability to learn high-level semantic representation and significantly reduces computation cost. The performance of O-SBGC-LSTM was found overall to be satisfactory, reaching >98% accuracy in most studies. In comparison with classic machine learning approaches, proposed hybrid DL was found to achieve better performance in almost all studies that reported such comparison outcomes. Furthermore, prevention is better than cure. Additionally, employed fuzzy based inference techniques to enhance the prevention procedure using suggestion table.

INDEX TERMS Diabetes, detection, prevention, coronary heart disease, optimal scrutiny boosted graph convolutional LSTM, deep learning, fuzzy inference systems.

I. INTRODUCTION

The incidence of diabetes has increased over the last decade, posing a new challenge to India's health policymakers. According to the International Diabetes Federation (IDF), approximately 537 million people across the globe were living with diabetes in 2021. The IDF has also projected that this number will increase to 643 million by 2030 [1]. By 2035, Indian diabetic counts are expected to exceed 80 million, making it ''Diabetes Capital'' of the world according to the Diabetes Foundation of India [2]. Diabetes prevalence increased in both rural and urban regions of India between 2005 and 2015 according to an analysis of (National Family Health Survey data) [3]. Overnutrition has been found to be a major risk factor for a number of diseases such as diabetes, hypertension, heart diseases, certain type of cancers, etc. [4], [5]. Overnutrition is one of the potential factors that may generate insulin resistance, which in turn may increase the sugar or glucose content in the blood leading to diabetes [6]. The study [7], finds similar results among married women in

The associate editor coordinating the review of this manuscript and approving it for publication was Yiming Tang.

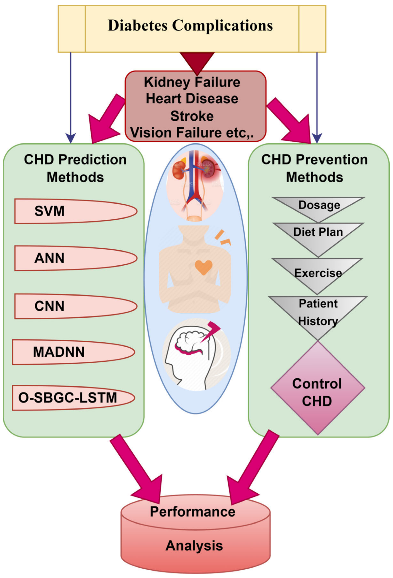

FIGURE 1. Smart Art of the proposed methodology.

Delhi, India. Other factors that may lead to diabetes include smoking, alcohol consumption, high sugar intake, genetic predisposition, etc [8]. Type 2 diabetes mellitus (T2DM) can result in a number of complications, such as macrovascular diseases, for example, cardiovascular disease (CHD), and microvascular diseases, for example, kidney, the retina failure and the nervous system diseases [9]. Even worse, T2DM may cause dementia and cognitive impairment, thereby reducing sensitivity to diabetes complications for T2DM patients. It is known that the incidence of heart disease such as Heart Failure (HF), cardiac dysfunction in individuals with T2DM is much higher than those without T2DM. Specifically, coronary heart disease (CHD) represents one of the most common and severe diabetes complications. Since CHDs have high incidence and fatality rates, it is critical for people to be aware of CHDs. Diabetics have a two to four times higher risk of developing CHDs, and 68% of diabetics older than 65 years with CHDs have died. Numerous approaches, including mathematical models such as Cox regressions and Machine Learning Techniques (MLTs) such as neural networks, have been used to predict CHDs [10], [11].

As shown in Fig 1, this work presented an artificial intelligence-based approach to predict the probability of developing CHDs in persons with T2DM.

Problem Statement:

1. Deep learning-based model to predict the risk of developing CHD for individuals with T2DM. The data is pre-processed, and then feature extraction and classification are achieved O-SBGC-LSTM classifier to diagnose disease. The EOA is combined with SBGC-LSTM to create the O-SBGC-LSTM.

2. After detecting CHD in diabetic patient with the help of O-SBGC-LSTM classifier, to control the disease by applying prevention methods like diet control, fitness of the body, dosage of medicine, and patient medical history.

Major Contribution of the Study: propose an advanced hybrid deep learning system for predicting coronary heart disease (CHD) for individuals with T2DM as shown in Fig. 1. The system seamlessly integrates multiple layers to handle preprocessing, feature extraction, and model classification. Additionally, we introduce a novel approach called O-SBGC-LSTM, which combines EOA with SBGC-LSTM. Furthermore, fuzzy inference techniques are employed to enhance the prevention process. Testing accuracy for training samples show suggested technique to perform better with values of 0.952, by Kaggle dataset (https://www.kaggle.com/datasets/sulianova/cardiovascular-disease-dataset). In addition, a risk contribution model was built to quantify the importance of each feature for a given T2DM individual. DL models have since been used in the prediction of many common diseases, including the prediction of diabetes, detection of hypertension in diabetic patients, and classification of patients with CHD among diabetic patients.

A. INTRODUCTION TO PREVENTION MODEL

Although any type of sickness requires early prediction for disease prevention, because prevention is better than cure, it leads to a healthy life. This lowers the treatment cost and saves time. The most important aspect of this study is that it also identifies illness-related complications. After determining the status of the disease, a patient and a doctor may take appropriate action to avoid the seriousness of the disease.

After detecting CHD in diabetic patient with the help of O-SBGC-LSTM classifier, to control the disease by applying prevention methods like diet control, fitness of the body, dosage of medicine, and patient medical history. The statement from the doctors is that if the patents control his/her sugar level in blood, it can control CHD complications. Through these techniques the patient may increase life span time even under diabetes treatment. Here prevention methods considering fuzzy logic with minimal data from the IoT Tracker.

The rest of the paper is structured as follows: Section II discussed review work and existing methods related to CHD in diabetes mellitus. The proposed methodology for heart disease caused by diabetes: detection and prevention methods is described in Section III. The experimental results of the prediction and prevention are discussed in Section IV. Finally, conclusions and future work are presented in Section V.

II. RELATED WORK

Nahar et al. [12], examined men and women with different risk factors for CHDs. These components were discovered using the computational intelligence tool Association rule mining (ARM) on the biological database Cleveland dataset at UC Irvine. Additionally, the Apriori, Predictive Apriori, and Tertius rule-generating algorithms were considered. The slopes increased, the number of colored vessels was zero, and the old peaks were greater than or equal to 0.56, indicating that both sexes were in good health. On the other hand, normal or hypertensive resting ECGs and flat slope were probable high-risk characteristics for women alone.

Ravaji and Moghe [13], created a deep maxout network based on cat swarm optimization (CSChO) for diagnosing heart problems using medical data. Cat swarm optimization (CSO) and chimp optimization algorithm (ChOA) were combined to generate CSChO. Preprocesses of missing data imputations and log transformations were utilized. The Kendall tau distance metrics with (deep belief network) classifier executed feature fusions. The obtained characteristics were used to diagnose sickness using their suggested CSChO algorithm-trained deep-maxout networks. The training samples demonstrated that their recommended approach outperformed other methods on the Hungary dataset, with values of 0.948, 0.949, and 0.919 for testing accuracy, sensitivity, and specificity, respectively. However, this is still a developing topic, and additional studies into various risk assessment techniques are needed with a focus on improving clinical evaluations.

Karaolis et al. [14], created a data-mining approach for assessing cardiac event-related risk variables with the goal of reducing CHD incidents. The following risk factors were examined:1) Before events: age, sex, and family history of premature CHDs, along with smoking, hypertension, and diabetes history. 2) Smoking, systolic, diastolic, total cholesterol, high-density lipoprotein, low-density lipoprotein, triglyceride, and glucose levels post-event. However, more extensive studies using larger datasets are required. Longato et al. [15], used 214,676 diabetic individuals' data from Veneto region of North Eastern Italy to construct a DLM for forecasting MACE (major adverse cardiovascular events). Their data included pharmaceutical and hospitalization claims along with basic patient information and estimated mortality, heart failure, myocardial infarction, and stroke for up to 5 years. The study treated data as multi-label (1-5 years) and multi-outcome (4P-MACE) classifications. This study contributes to the early forecasts of mortality in people with diabetes. The secondary use of this data in an institutional setting is constrained by the challenges associated with their collection and evaluation.

Sarmah [16], Introduced observe system for person by cardiac attack though IoT (Internet of Things) and Deep learning modified NNs (DLMNNs) to give proper diagnosis and medication supervisor. There are three methods for maintaining authentication: encryption and classification. Most hospitals follow substitute ciphers and SHA-512 authentication for cardiac-disease effectors. Usually, a patient has sensor devices that can collect the required data from the body and store them in a cloud database. The DLMNN subsequently classified the decrypted data to identify normal and aberrant data and two separate forms found in the categorized findings.

Ilango and Ramaraj [17], the researchers were discussed about heart prediction as well as prevention with the study of Neural Fuzzy Inference System (NFIS). In this proposed model, all attributes were combined dependable and no dependable parameter by considering UCI depository. Here they were consider13000 fuzzification rules to get best decision making. The model gave 94 per cent of prediction disease's accuracy.

Swapna et al. [18], used convolutional neural networks (CNNs) and CNN-LSTM combinations to automatically detect abnormalities. Unlike traditional analytical methods, DLMs do not require feature extraction, and initial classifications are achieved by forming training and test data. Using CNN-LSTM, the study's greatest accuracy for the test data was 90.9%. However, this model suffers from poor quality, bias, and interpretability.

Ghasemieh et al. [19], employed supervised machine learning algorithms to predict diabetes and CHDs independently. Consequently, we may uncover feature similarities across illnesses that affect their prognosis. Prediction of prediabetes and undiagnosed diabetes was also considered. The NHANES (National Health and Nutrition Examination Survey) dataset was used to train and evaluate several algorithms for illness prediction. In addition, this study investigates a weighted ensemble model that incorporates the outcomes of numerous supervised learning models to improve the prediction ability. As part of our ongoing efforts, we intend to investigate the usefulness of factors in electronic health records in order to construct more accurate models.

Devi and Khemchandani [20], presented promising approach to predict diabetes and diagnosis. the proposed model follows fuzzy verdict mechanism. The rules used in fuzzy makes the decision on possibility of an individual is suffering from diabetes or not. Here the main parameter was urine for giving proper diagnosis. The accuracy of this mechanism was improved.

III. PROPOSED METHODOLOGY

In the process of prediction and prevention of CHD disease can be divided two subpart as showed in Fig 2, in the first part represent the various steps involved. For example, the initial stage is data collection, followed by data preprocessing and computation. During preprocessing, the obtained data were evaluated and checked for incomplete data. After preprocessing, the data are transmitted to the server for analysis, in this stage, the attribute selection take place for suitable splitting of given data as group wise by using heuristic approach. The data validation is use to fix the quality data to choose best algorithm than, an algorithm is designed to integrate the odds ratios into a CHD risk score and detect the O-SBGC-LSTM stage to compute and assess the data, the working principle of O-SBGC-LSTM will be described following section. Here, we separated our data into 80:20 training and testing datasets to deploy the learning models. The other side of Fig 2. mentioned process of preventing the disease with help of Fuzzy Inference System. Here the first phase consists decision manager. The Decision management is the process of selecting the best option from a range of alternatives to make informed decisions. There are two ways to manage decisions. The first is through a temporal manager, which uses a knowledge-based database to provide operators based on related actions. Knowledge-based systems have a set of rules that can be used to achieve predicted results in fuzzy inference systems. The Rule base fuzzy logic in rule manager are just expressions that may be generated using "IF X THAN Y" rules. In this scenario, x and y are fuzzy sets that will be represented with linguistic values for the majority of cases. The data were available from different databases and were not similar, but fuzzy logic handled the data. Fuzzy logic introduces the term linguistic for making decisions for these records. linguistic follows between 0 and 1 values. This work uses trapezoidal fuzzy membership, and a certain degree is considered for all the fuzzy rules that are accessible. Here, corresponding vague rules for disease control were generated. For instance, this work considers three symptoms for determining the disease using two linguistic words and makes eight other combinations. while generating a crisp value by defuzzification to handle the risk level [21].

In the second phase of the prevention i.e Fuzzy Logic-based CHD Control System (FLCHDCS), were discussed with Fig 8. in the following section. This work proposes a distinctive method for evaluating the risks of CHDs that could be applied as a risk assessment tool and could be updated when new information becomes available with a realistic aim for CHD prevention. First, the CHD risk and preventative factors were identified using a systematic search approach. Age, sex, education, BMI, diabetes, depression, serum cholesterol, traumatic brain injury, use of alcohol, smoking, participation in social activities, physical activity, cognitive activity, consumption of fish, and pesticide exposure were identified as risk factors and protective factors for CHDs, for which odds ratios were published or could be calculated. Odds ratios were included in an algorithm that determined the CHD risk scores. This technique allows for interactions among risk factors, since recent research indicates that midlife is a critical age for various risk factors, which allows for their varied influence across the life course [22]. Intensive lifestyle interventions are intended to help people lose weight by reducing calorie consumption and increasing physical activity. This program was compared to a control condition in which diabetes assistance and education were provided. Finally, as shown in Fig 2, In prevention model follows the fuzzy based rule techniques. The process can be involved by applying fuzzy rule on diabetes complication like heart disease datasets, and by considering most required attributes to control or preventing the complication of diseases like CHD dataset. For example, patient's sugar level, cholesterol status, Body Mass Index (BMI), day to day activities and food habits. When these values are abnormal, the prevention model gives appropriate suggestions to the patient attendees as well as doctors. The model basically consists Fuzzy Inference System (FIS). The fuzzy rules are to be fine-tuned by using the fuzzification process on variables of inputs. The triggered fuzzy rules are useful for determining the fuzzy set of output [23]. A degree is taken considered for all the available fuzzy rules. Here, it generates the related fuzzy rules for performing the disease control [24].

A. DATA PRE-PROCESSING AND PREVENTION USING FUZZY-RULE BASED TECHNIQUES

With the help of CHD and diabetes data, the model must predict and diagnose the disease. Collected data were obtained from the National Institute of Diabetes. Based on the sugar level, CHD diagnostic measurements are dependent. There are many limitations in choosing particular instances from bulk storage.

Data pre-processing enhances the quality of outcomes for the mining process and assists in their efficacy. Hence, data pre-processing is crucial for the successful mining of data. Examination of the Pima Indians Diabetes dataset concluded that two rounds of pre-processing were necessary for the data used. The below Fig 3 shows preprocessing stage in the prediction framework. Here, normally the value of the missing data was zero [25]. Because of the impossibility of having a value of zero, all instances of zero for a particular field in this section were deleted. As a result, instances with missing data were removed. The data discretization process was then completed. Data discretization involves turning continuous sets of attribute values into finite collections of intervals and providing intervals with different data values. With exceptions, they impose ordering on discretized attributes, and discrete values are associated with a certain unconstrained attribute. data periods. Discretization expedites many data-mining activities, such as the generation of association rules, classifications, and predictions, while also enhancing the accuracy of executions.

B. DISEASE DETECTION PROCESS USING O-SBGC-LSTM

Prevention of CHDs is mostly based on examinations of BMI and glucose levels for corresponding ages. To add more data for feature creation, the data may be taught and evaluated. Clinical data analysis has a significant problem when predicting heart illness. Analysis and handling of medical data become more challenging as its volume rises. The detection findings produced by present approaches are erroneous, necessitating the development of a deep learning model for illness detection. This study creates an EOA-based SBGC-LSTM for preventing and diagnosing heart disease using medical data.

1) GRAPH CONVOLUTION NEURAL NETWORK

GCNN is a broad and successful approach for learning graph-structured data representation [26]. On a variety of tasks, many GCNN variations have obtained state-of-art outcomes. For action recognition based on skeletons, let $\mathbb{G}_t = \mathbb{V}_t, E_t$ represents a graph G of input data at time t, where $\mathbb{V}_t$ stands for N joint nodes and E_t implies skeleton edge sets. The neighboring set of nodes $\mathbb{V}_{ti}$ can be defined as.

$$N(\mathbb{V}_{ti}) = \mathbb{V}_{ti} | d(\mathbb{V}_{ti}, \mathbb{V}_{tj}) \leqslant D \tag{1}$$

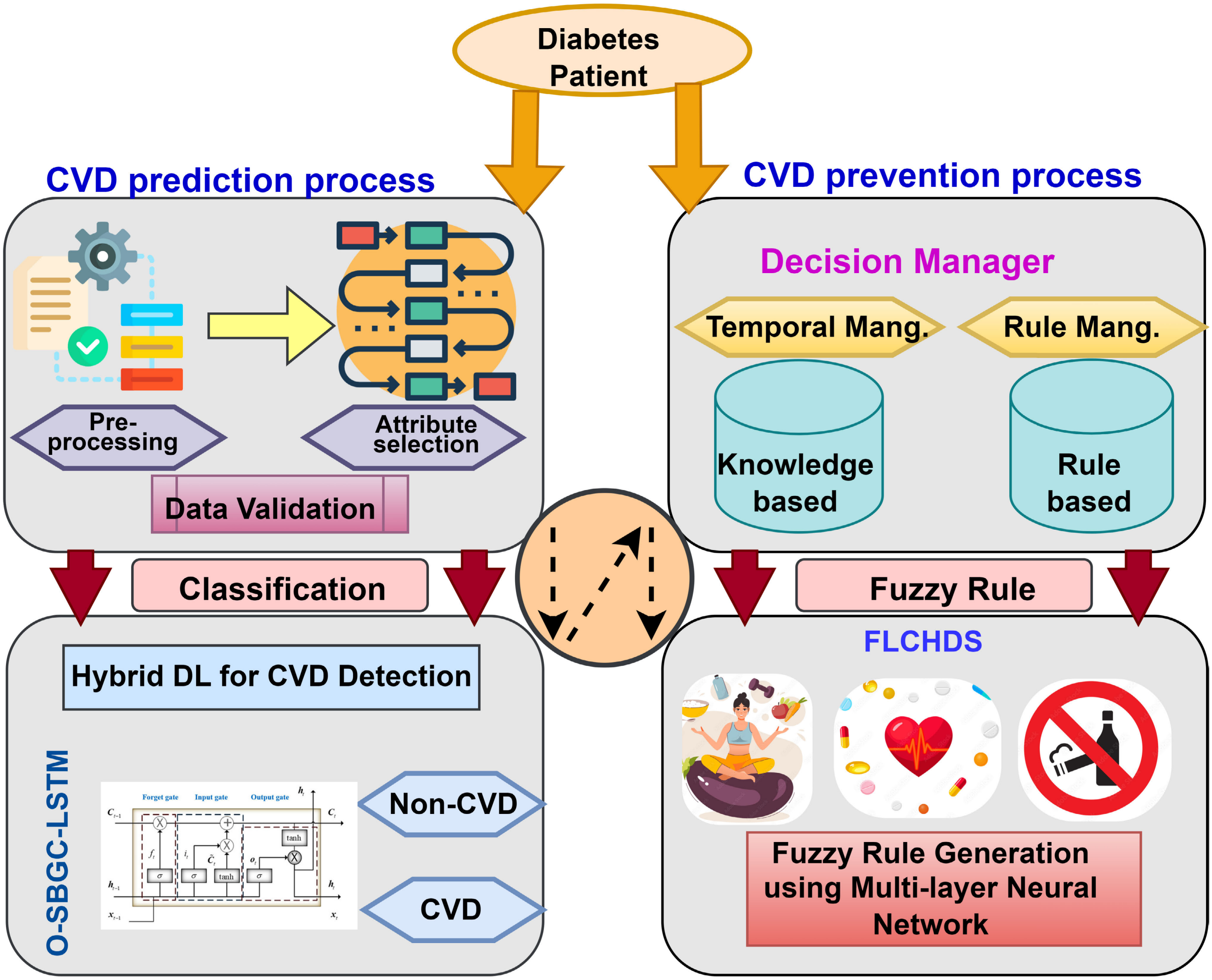

FIGURE 2. **The architecture of proposed work: prediction and prevention of CHD Disease.**

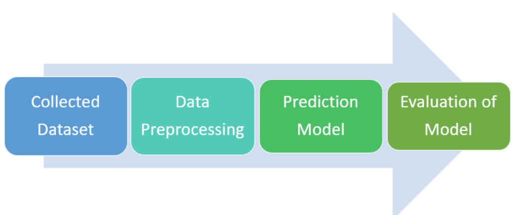

FIGURE 3. **Data Pre-processing stage.**

In Eq (1), where $d(\mathbb{V}_{ti}, \mathbb{V}_{tj})$ $\mathbb{V}_{tj}$ to $\mathbb{V}_{ti}$. The graph labeling function lab: $\mathbb{V}_t 1, 2, \ldots, K$ represents the assigned labels $1, 2, \ldots, K$ for graph nodes $\mathbb{V}_{tj} \epsilon \mathbb{V}_{ti}$., which partition neighboring set $N(\mathbb{V}_{ti})$ of nodes $\mathbb{V}_{ti}$ into a fixed number of K subsets. Graph convolutions can be computed using.

$$Y_{output}(\mathbb{V}_{ti}) = \sum_{\mathbb{V}_{ti} \epsilon N(\mathbb{V}_{ti})} \left(\frac{1}{Z_{ti}(V_{ti})} \right) X(V_{ti}) \mathbb{W}(\ell ab(\mathbb{V}_{ti}) \quad (2)$$

In Eq (2), $X(\mathbb{V}_{tj})$ represents the features of nodes $(\mathbb{V}_{tj}) \cdot \mathbb{W}(\cdot)$ implies weight function that allocates weights and indexed by labels lab$(\mathbb{V}_{tj})$ from K weights. $Z_{ti}(\mathbb{V}_{tj})$ represents the corresponding subset that normalizes features. $Y_{output}(\mathbb{V}_{ti})$ represents the outputs of the graph convolutions at node $\mathbb{V}_{tj}$. More specifically, with adjacent matrices, Eq. (2) can be represented as

$$Y_{output} = \sum_{(k=1)}^{k} \bigvee_{k}^{(-1/2)} AMK \bigvee_{k}^{(-1/2)} X\mathbb{W}_k \quad (3)$$

where in Eq (3), $(AM)_k$ is the adjacency matrix in spatial configuration of the label $k \epsilon 1, 2, \ldots, K$. $\bigwedge_k^{ii} = \sum_j AM_k^{ij}$ is a degree matrix.

2) SCRUTINY BOOSTED GRAPH CONVOLUTIONAL LSTM

Many studies have shown that LSTM as a type of recurrent neural network (RNN), is adept at handling long-term temporal connections for sequence modeling. Various LSTM-based

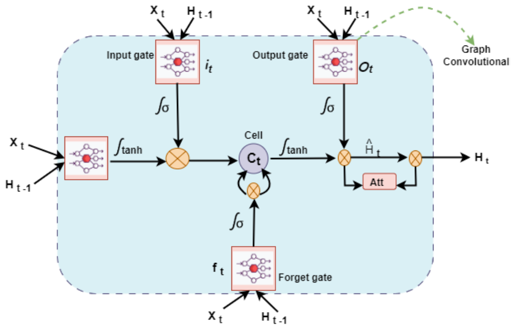

FIGURE 4. The structures of SBGC-LSTM unit.

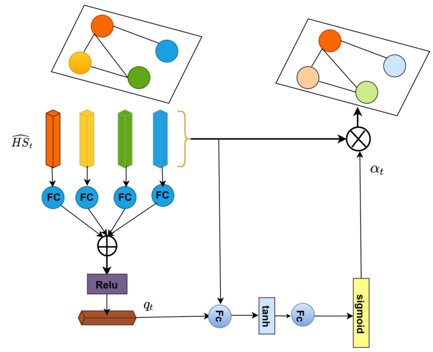

FIGURE 5. Illustration of the spatial attention network.

models have been used to understand the temporal dynamics of skeletal sequences. However, the completely connected operator in LSTM places restrictions on the ability to ignore spatial correlation for skeleton-based action detection. When compared to LSTM, SBGC-LSTM is better able to capture discriminative characteristics in spatial configuration and temporal dynamics, as well as evaluate the link between the co-occurrence of the spatial and temporal domains. Similar to LSTM, SBGC-LSTM has three gates: an input i_{gt}, forget f_{gt}, and output O_{gt} gate. However, these gates are constructed using a graph convolution operator. The SBGC-LSTM's input X_t, hidden state HS_t, and cell memory. CM_t is the graph-structured data. Fig 4 depicts the structure of the SBGC-LSTM unit. In SBGC-LSTM, the graph convolution operator enables the spatial and temporal dynamics of the hidden state HS_t and the cell memory CM_t. Unlike LSTM, the inner operator of SBGC-LSTM graph convolution calculations. This scrutiny technique is used to improve the properties of critical nodes to showcase more discriminative information. The functions of the SBGC-LSTM units are as follows:

$$ig_t = \sigma(\mathbb{W}_{xi} \cdot \mathbb{G}X_t + \mathbb{W}_{hig} \cdot \mathbb{G} \times H_{t-1} + big) \quad (4)$$

$$fg_t = \sigma(\mathbb{W}_{xf} \cdot \mathbb{G}X_t + \mathbb{W}_{hfg} \cdot \mathbb{G} \times H_{t-1} + bfg) \quad (5)$$

$$og_t = \sigma(\mathbb{W}_{xo} \cdot \mathbb{G}X_t + \mathbb{W}_{hog} \cdot \mathbb{G} \times H_{t-1} + b0g) \quad (6)$$

$$cm_t = fg_t \odot cm_{t-1} + i_t \odot mi_t \quad (7)$$

$$cm_t = fg_t \odot cm_{t-1} + i_t \odot mi_t \widehat{HS}_t = og_t \odot \tanh(Cm_t) \quad (8)$$

$$\widehat{HS}_t = og_t \odot \tanh(Cm_t) \quad (9)$$

$$HS_t = f_{att}(\widehat{HS})_t + (\widehat{HS})_t \quad (10)$$

From above Eq (4) − (10) where $\cdot$G represents the graph convolution operators and $\odot$ stands for Hadamard products. $\sigma(\cdot)$ denotes a sigmoid activation function. mi_t represents modulated inputs. H_t represents the intermediate hidden states. $\mathbb{W}_{xi} * \mathbb{G}X_t$ represents the graph convolutions of $\mathbb{W}_{xi} * \mathbb{G}X_t$ and written as Eq (4) $f_att(\cdot)$ represents the scrutiny networks that represent the discriminative information of key nodes. The sum of $f_{att}(\widehat{HS})_t$ and $(\widehat{HS})_{tas}$ enhances information at important nodes while degrades information at unfocused nodes in an effort to retain the integrity of spatial information. A soft Scrutiny mechanism that can automatically assess the importance of joints is used to enable the scrutiny network to focus adaptively on essential joints. From Eq (4) to Eq (10) shows an example of a spatial Scrutiny network. The intermediate hidden state has substantial temporal dynamics and spatial structural information $(\widehat{HS}_t)$ of the SBGC-LSTM, which facilitates crucial joint selection. Consequently, as a query feature, we first combine all the nodes' data:

$$q_t = ReLU(\sum_{i=1}^{N} \mathbb{W}\widehat{HS_{ti}}) \quad (11)$$

In Eq (11), the W represents learnable parameter matrices, and the scrutiny scores of nodes can be computed using

$$a = sigmoid(V_s \tanh(\mathbb{W}_h \widehat{H}_t + \mathbb{W}_q q_t + b_s) + b_u \quad (12)$$

where in Eq (12), $\delta_t = (\delta_{t1}, \delta_{t2}, \ldots, \delta_{tN})$, and $\mathbb{U}_s$,$\mathbb{W}_{hs}$, $\mathbb{W}_q$ are the learnable parameter matrices. b_s, b_u are biases. Nonlinear Sigmoid functions owing to existing multiple key joints, the hidden state HS_{ti} of nodes $\mathbb{V}_{ti}$ can be described as $(1 + \delta_{ti})$. $\widehat{H}_{ti}$ implies scrutiny enhanced hidden stage, it will be into subsequent SBGC-LSTM layers and finally SBGC-LSTM layer are aggregations of node features which will serve as global features GF_t^g, and weighed sum of focused nodes become local feature LF_t^l:

$$LF_t^g = \Sigma_{i=1}^{N} \alpha_{ti} \cdot \widehat{H}_{ti} \quad (13)$$

In above Eq (13) and (14), the global feature $(GF)_t^g$ and local feature $(LF)_t^l$ respectively were used to predict the class of heart disease through diabetes.

3) SBGC-LSTM NETWORK

This section presents a Scrutiny improved graph convolution LSTM network (SBGC-LSTM) for skeleton-based identification of human activity. The complete workflow of the model is shown in Figure 2 along with the logic of the recommended framework. representations of the joint features. The first linear layers describe the disease dataset features $f_t \epsilon R^{(N256)}$ and $f_t \epsilon R^{(1256)}$, which indicate the sickness of joint i by encoding joint coordinates into 256-dim vectors. Feature f_{ti} is beneficial for learning spatially organized qualities as graphs because the dataset only contains information about illnesses. Frame-difference characteristics called V_{ti} which exist between two succeeding frames, allow

SBGC-LSTM to gather dynamic data. Concatenations of both features as increase the feature information to consider both advantages. When feature f_{ti} and frame difference feature V_{ti} are combined, the scale variations of the feature vectors are combined however, occur. Therefore, to remove the scale variation between the two features, an LSTM layer was applied:

$$E_{ti} = f_{lstm}(concat(f_{ti}, V_{ti})) = f_{lstm}(concat(Af_{ti} - f_{(t-1)})) \tag{14}$$

where in Eq (14), $(Af)_{ti}$ is the expansion characteristic of combination i at time t. The main point here is that the linear portion and LSTM are distributed among several characteristics.

C. TEMPORAL HIERARCHICAL ARCHITECTURE

Following LSTM layers, SBGC-LSTM layers receive series of augmented node features $Af_1, Af_2, \ldots, Af_T$ where $Af_T \in R_N d_e$. Three SBGC-LSTM layers are stacked in the proposed model to learn the temporal dynamics and spatial arrangement. We create a temporal hierarchical design of SBGC-LSTM with average pools in temporal domains and inspired by spatial pooling of CNNs. Due to temporal hierarchical architecture, input temporal receptive fields of top SBGC-LSTM layers become short-term fasteners and are more sensitive to temporal dynamics. Moreover, they drastically reduce computing costs while enhancing performances [27].

1) LEARNING SBGC-LSTM

At the end, the GF_t^g and $(LF)_t^l$ of time stamp are convert as results o_t^g and $(out)_t^l$ for Cl phases, where $(out)_t = (out)_{t1}, (out)_{t2}, \ldots, (out)_{tCl})$, and finding probabilities being i_{th} phases are obtained in below Eq (15).

$$\widehat{Y}_{ti} = \left(\frac{e^{out_{ti}}}{\sum_{j=1}^{cl} e^{out_{ti}}} \right), i = 1, 2, \ldots cl) \tag{15}$$

Assuming that each attribute step in the top SBGC-LSTM is concealed during training and has short-term dynamics, we supervise the model with the following loss function.

$$\begin{aligned} Loss = &- \sum_{t=1}^{T_s} \sum_{i=1}^{Cl} y_i \log \hat{y}ti^g - \sum t = 1^{T_s} \sum_{i=1}^{Cl} y_i \log \hat{y}ti^l \\ &+ \lambda \sum j = 1^3 \sum_{n=1}^{N} \left(1 \frac{\sum_{t=1}^{T_j} \delta_{tnj}}{T_j} \right)^2 \\ &+ \beta \sum_{j=1}^{3} \frac{1}{t_j} \sum_{t=1}^{T_j} \left(\sum_{n=1}^{N} \delta_{tnj} \right)^2 \end{aligned} \tag{16}$$

where in Eq (16), the ground-truth label is $y = (y_1, \ldots, y_C l)$. T_j indicates the j^{th} SBGC-LSTM layer time-step count. The third term gives every joint equal consideration. The final clause restricts the number of interested nodes. and represent the decaying weight coefficients. It should be emphasized that the probability of only the sum of $\widehat{y}_{T3}^g$ and $\widehat{y}_{T3}^l$ at the latest time step is utilized to determine the illness class.

2) EOA BASED TUNING PROCESS

The EOA was used to optimize the SBGC-LSTM settings. Particle swarm optimization (PSO) and foraging techniques are used in EOA optimizations, which are modelled after eurygasters. Based on the observation that eurygasters use their antennae to scan their surroundings, this is true. The strongest food scents are concentrated in the direction of the antennae; thus, Eurygaster moves in that direction. A meta heuristic optimization technique was developed by Marini and Walczak [28], based on eurygaster behavior. The steps required to optimize SBGC-LSTM using the EOA are shown in Fig 6. The dataset is divided into several categories using a kernel-based clustering approach. Furthermore, the cluster centers were used to initialize the fuzzy rules for SBGC-LSTM. The SBGC-LSTM model was trained using an EOA model. The location of Eurygaster in Q-dimensional space at i was determined using Eq (18).

$$q^{i+1} = q^i + sf(f(q_{ri}) - f(q_{li})) * b * ss^i \tag{17}$$

$$q_{ri} = q^i + \widehat{dist}^i * \widehat{dir} \tag{18}$$

$$q_{li} = q^i - \widehat{dist}^i * \widehat{dir} \tag{19}$$

In the above Eq (19), $\widehat{dir}$ denotes the Eurygaster-seeking direction, which was randomly selected. The lengths of Eurygaster search steps are depicted by ss^i, while $\widehat{dist}^i$ represent distances that antennae encounter in Eq (20). These parameters are initially set to high values, which decrease progressively; as a result, one tries to attain a wide region before reducing to obtain a capacity that is reasonable for Eurygaster. The mark for the correctly detected position is q_{ri}, whereas the left detected position is denoted by q_{li}.

These places include food flavor, which is represented by the fitness function values $f(q_{ri})$ and $f(q_{li})$, which were computed using the recommended method. sf is the function of the symbol. The update of speed and data collected by the antennas has an influence on the position of Eurygaster. Consider the Eurygaster swarm attributes are updated using Eq (21) to Eq (22) such that $E = E_1, \ldots, E_n$. Eurygasteri's location in the D-dimensional searching space is denoted by the expression $E_i = (e_{i1}, e_{i2}, \ldots, e_{iD})^T$. With the optimization solution. The formula for Eurygaster speed is $S_i = (s_i1, s_i2, \ldots, s_{iD})^T$. Each Eurygaster moves at a different speed as they approach the extreme global value. Furthermore, $S_i = (s_i1, s_i2, \ldots, s_{iD})^T$ is used to designate the extremes of each Euryghaster. $E_i = (ex_{i1}, ex_{i2}, \ldots, ex_{iD})^T$. describes global extremes. The EOA algorithm's location and speed updating procedure is as follows:

$$b_{iD}^{j+1} = b_{iD}^j + \alpha s_{iD}^{j+1} + (1 - \alpha)\mu_{id}^j \tag{20}$$

$$s_{id}^{j+1} = \theta s_{id}^j + i_1 rf_1(e_{id}^j + b_{id}^j) + id_2 rf_2(ex_{gD}^j + b_{gD}^j) \tag{21}$$

$$\mu_{id}^j = \lambda^j s_{id}^j sign(f(b_{rfd}^j) - f(b_{id}^j)) \tag{22}$$

$$b_{rd}^{j+1} + s_{id}^{j} \frac{\widehat{h}}{2} \tag{23}$$

$$b_{ld}^{j} = b_{ld}^{j} + s_{id}^{j} \frac{\widehat{h}}{2} \tag{24}$$

$i = 1; 2; \ldots, n, d = 1, 2, \ldots, D$, and j is for each repetition. The value of migration is expressed as μ, which was obtained from the antennae of Eurygaster. The signs α and ϕ in Eq. (23 and 24) are the loosening factor and immobility weight, respectively. This may have modified the limitations of this study. The encounter size is specified by id_1 and id_2, where rf_1 and rf_2 denote the random functions. In the initial stage, we designed the environmental model. The outcome points were chosen as inputs for the given environment. Attributes of the EOA algorithms such as α, ϕ, id_1, and id_2 were assigned. Fast S_i and its status B_i are also assigned randomly in the design. The active function of each Eurygaster was then simplified, and the rate in the extreme individual of Eurygaster was set to E_i. The minimal cost was determined from the E_i extreme individual rate and the extreme global E_g identified. Subsequently, we fixed the Eurygaster swarm attributes using Eq. (21 to 24). The extreme rate h^t and global extreme rate E_g were modified by the fitness function calculation. The cost $\widehat{h}$ was configure with $(V)^t = 0 : 01 + 0 : 95()^{t-1}$, it set high at the start, then decreased with each reputation, mentioned here with $\widehat{h}$. Reputation was then performed for optimization. The global extreme rates E_g obtained by this algorithm are considered the optimal parameters for the SBGC-LSTM model.

3) CHD PREVENTION SYSTEM THROUGH DIABETES DISEASE

To maintain and keep good health, need to control diabetes to avoid complication like CHD, the model having self-report to estimate a probability of disease with outcome variables as a binary estimated in eq (25 and 26). In this model, $P * i$ is a dependent variable, is estimated by

$$p_c^* = \beta^c X_c + err_c \tag{25}$$

$$P_c = \begin{cases} 0 & \textit{if patient not having diabetes} \\ 1 & \textit{if patient with diabetic} \end{cases} \tag{26}$$

4) LINK BETWEEN DIABETES AND HEART DISEASE

CHD most dangerous disease cause of death or disability in people with type 2 diabetes (T2D). um wanted glucose level from diabetes can harm blood vessels and the nerves that control our heart and blood vessels. This damage can lead to heart disease at younger age. Manage our diabetes also helps to lower chances of having heart disease. The other scenario for heart attack is to have habit of smoking. Once it is conformed CHD disease you can control risk of getting heart attack by control glucose level and daily activity of patient along medication, if the person with CHD and Diabetes, need to control four things to avoid complication of heart disease. They need to focus on 1) glucose level in blood 2) bad cholesterol in blood, 3) Body Mass Index of the patient and 4) high blood pressure etc, along these, the patient need

TABLE 1. Different parameter normal/ abnormal values and some effects in abnormal conditions:.

SNo	Parameter	Normal	Abnormal	Complications
1	Glucose	90-110 mg/dl	140-200 mg/dl	Damage normal functionality of organs
2	Cholesterol	140 mg/dl	150 mg/dl	Increase the CHD risk percentage
3	BMI	20-25 kg/m2	30-35 kg/m2	Affects the daily activities
4	Blood Pressure	120/80 mmHg	140/90 mmHg	Fell abnormal condition like dizziness and stroke
5	Smoking	< 1 pac/week	> 2 pac/week	Failure of lugs and its normal functionality

to avoid habit of usage smoking. The proposed method able to control the disease by taking these values and minimise the severity of disease using fuzzy rule-based system. The normal and abnormal values are provided below table 1. The table also shows its consequences.

D. FUZZY LOGIC AND FUZZY RULES

In this phase, we discuss the use of fuzzy rules and the proposed multi-neural network in the classification process in detail. First, it explores fuzzy rules and justifications. Fuzzy logic, which contains a variety of data types, is used to handle the ambiguity of healthcare records. In fuzzy logic, language terms are utilized to help decide between the various types of records. The fuzzy rules are created by using the language words and distances from 0 to 1 for each term. In this study, trapezoidal fuzzy membership was used. The male patient described the severity of his symptoms using the language terms in Table 1. Here, the pain level of the supra-public is thought of as "Action-1," "Action-2," and "Action-3" because the seriousness of the experience is not known. In this study, five different methods of identifying a condition based on the amount of pain were examined [29]. Furthermore, the results for each object are not the same as the results for any other object. The fuzzy rules are fine-tuned by using fuzzification on the input factors. The prompted fuzzy rules can be used to determine the fuzzy set of the output.

E. FUZZY INFERENCE SYSTEM (FIS)

The FIS combines the input and output spaces. It can be involved in decision making. The aim of FIS is gives conclusion while considering on IF-THAN rules, and also, FIS were used "AND/OR" links for conforming required actions. FIS is a major part of fuzzy-logic rule-based systems. The system accepts input as fuzzy, sometimes unequal, but the output consists of a fuzzy set from the FIS. FIS is triggered

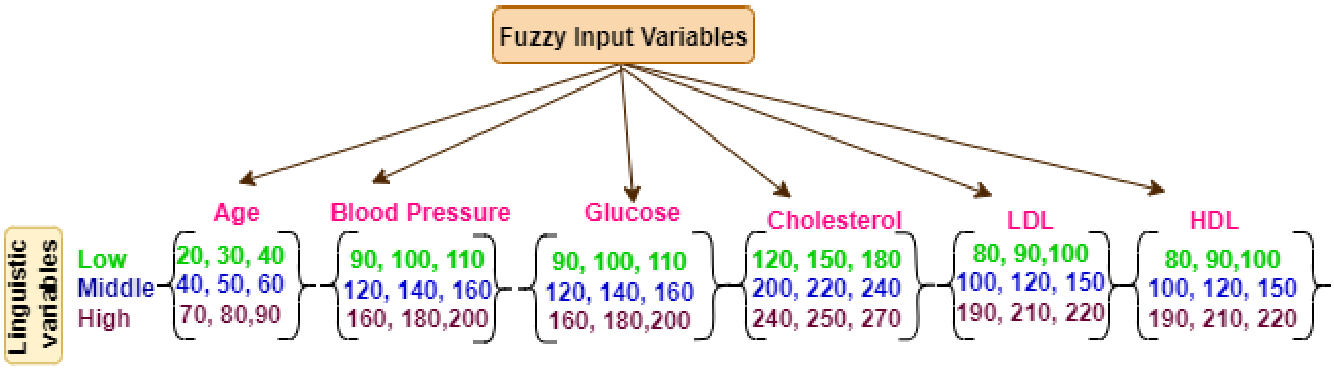

FIGURE 6. Different linguistic variables.

TABLE 2. Fuzzy rules, conditions and required actions to avoid seriousness of CHD:.

Sno.	Rule No.	Conditions	Action Required
1	Rule 1	CVD is under control	Continue with normal day-to-day activities
2	Rule 2	CVD is moderate	Need CHD treatment with regular check up
3	Rule 3	CVD is at risk	Take proper insulin & CHD medicine, do exercise and avoid smoking usage
4	Rule 4	CVD is high risk	Take proper CDH medicine & dosage of insulin, change habit of food and avoid smoking & drinking usage
5	Rule 5	CVD is very high risk	Follow the patient history and medical summary, change habit of food, concentrate on day-to-day activities and avoid smoking & drinking usage

by fuzzification and defuzzification for decision-making. FIS also named as Fuzzy expert system. The various applications were maintained by fuzzy logic rules set, such as manufacture field, natural language processing and artificial intelligent systems etc. It has several functional units showned in the below Fig 7, such as fuzzification, rule base, database, decision making and defuzzification. initially fuzzification can converts the crisp form into fuzzy form, next the rule base can be used to form IF-THAN rules, the unit is Knowledge base which consists the different membership functions, next one is the decision making can be used to process the needful operations on the rule, finally the defuzzification can be convert the fuzzy set into crisp set as output. There are two types such: Mamdani FIS and Sugeno FIS. Mamdani introduced mamdani in 1975. This method sets the process of aggregating multiple output membership functions to generate a single output membership function. Sugeno was introduced by Takagi-Sugeno-kang in 1985. This method was similar to the Mamdani method. In this method, the first two units are the same in the FIS process, but the output of Sugeno is either linear or constant, and the advantages of Sugeno are flexible compared to the Mamdani model. Here, our research work follows mamdani model because one fuzzy output (IF-THEN statements and AND/OR connectives) distribute is carried out by forming all the fuzzy rules.

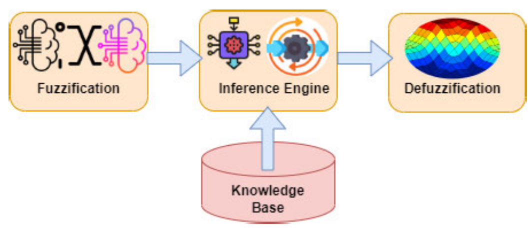

FIGURE 7. Smart Art of the prevention methodology.

1) ARCHITECTURE OF FUZZY LOGIC-BASED CHD CONTROL SYSTEM (FLCHDCS)

In the above Fig 8 shows, the architecture of prevention CHD using fuzzy expert system (FLCHDCS), which collects data from the patient based on the most common attributes of CHD with Diabetes such as age, blood pressure, cholesterol, blood sugar, low-density lipoproteins, and high-density lipoproteins can be stored in the database. In the next step, the model can analyze and normalize the given parameters and select the required parameter that plays the main role in the prevention mechanism based on expert knowledge by applying the fuzzy logic approach [30]. The final step can be reported as a suggestion to the patient by their attendees or physicians. The variables used in this study for the FIS are shown in Fig 6.

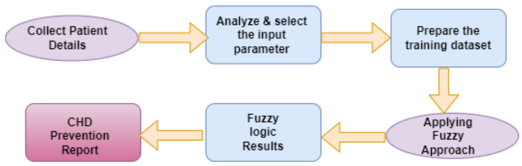

FIGURE 8. Architecture of FLCHDCS.

The Fuzzy variable age can be forms three fuzzy numbers like Age*(Low, Medium, High)*. Another fuzzy variable, blood pressure, can have three fuzzy numbers, such as Blood Pressure*(Low, Medium, High)*. cholesterol fuzzy variable also has three fuzzy numbers; for example, Cholesterol*(Low, Medium, High)*. next variable blood sugar can divide three fuzzy numbers, such as Blood sugar*(Low, Medium, High)*. LDL value fuzzy variable consisting of LDL value *(Low, Medium, High)*, and HDL value fuzzy variable consisting of HDL value *(Low, Medium, High)* fuzzy variables were used. Output variable with five fuzzy numbers CHD*(Low, Moderate, Risk, High Risk, Very High Risk)*. Fig 6 shows the linguistic values of different attributes of the CHD dataset.

The abnormal values showed in the table 1 are used in step 4.1 and 4.2 for finding severity of disease

Prediction Steps using FIS:

basic required data:

Fuzzy set of Age, Glucose, BMI, Cholesterol, and Insulin units are the input to the system.

Outcomes:

Fuzzy set CHD status.

Step 1: Input scrip values of Age, Glucose, BMI, Cholesterol, and Insulin units.

Step 2: Set the triangle membership function for the fuzzy numbers.

Step 3: Built the fuzzy numbers for Age, Glucose, BMI, Cholesterol, and Insulin units.

Step 4: Execute mamdani's fuzzy inference method

Step 4.1: input the rules and calculate the matching degree of rule with 'OR' disjunction for fuzzy input set $(Age_{(young,youth,old)})$, $(BMI_{(low,medium,high)})$, $(Glucose_{(low,medium,high)})$, $(INS_{(low,medium,high)})$, $(Cholesterol_{(low,medium,high)})$.

Step 4.2: Calculate the aggregation of the fired rules for output set CHD*(Low, Normal, Modurate, Risk, High Risk)*.

Step 5: Defuzzification into crisp values by

$$Z * \left(\frac{\int \mu A(Z) z dz}{\int \mu A(z) dz} \right) \tag{27}$$

In the above Eq (27), Where denotes algebraic integration, μA(z) means of fuzzy number of the output fuzzy variables CHD and z represents the weight for μA(z).

Step 6: Present the knowledge in the form of the human nature language.

End

2) RULES FOR FUZZY SYSTEM

The following five rules were used in this experiment using OR and AND connectives for CHD Control and prevention. Prevention methods use fuzzy rules and fuzzy inference mechanisms on the prediction dataset. These methods follow a set of IF-THEN statements [29]. In the above table 2 represent different rules formed by union operation, each rule gives appropriate risk factor and suggestion that can be followed by patient as per severity of disease.

- Rule 1) IF ((Cholesterol is normal) OR (Glucose level is normal) OR (BMI is Normal AND age is young)) THEN (CHD is under control)
- Rule 2) IF ((Cholesterol is abnormal) OR (Glucose level is normal) OR (BMI is Normal) OR (age is middle)) THEN (CHD is moderate) (CHD is at risk)
- Rule 3) IF ((Cholesterol is abnormal) OR (Glucose level is abnormal AND insulin is not enough) OR (BMI is abnormal) OR (age is middle)) THEN (CHD is at risk)
- Rule 4) IF ((heart disease is abnormal) OR (Glucose level is abnormal AND insulin is not enough) OR (BMI is normal) OR (age is middle)) THEN (CHD is high risk)
- Rule 5) IF ((heart disease is high) OR (Glucose level is high AND insulin is not enough) OR (BMI is abnormal) OR (age is old)) THEN (CHD is very high Risk)

The above rules were used to identify diseases that harm patients, such as heart disease and diabetes. These rules can help make good decisions about medical reports and benchmark datasets with one input layer, one output layer, and two hidden layers as processing layers. The softmax function was chosen as the activation function for the input value. This changes the output layer of the neural network used for classification, which improves classification accuracy.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The suggested work, O-SBGC-LSTM, categorizes the gathered kaggle into two groups: normal and impacted. Following dataset initialization, values are passed via a representation operation in which data are converted into numerical values, which take the matrix form as the first phase of the job and then will be the supplied input of the suggested O-SBGC-LSTM for CHD classification [31]. In this study, we computed a confusion matrix, which summed the classifier's classification performance on the test dataset. It is commonly used to compute performance measurements (e.g., accuracy, sensitivity, specificity, precision, and F1 score). Subsequently, the top three characteristics (Age, BMI, and glucose level) were chosen, and they provided 30% of all features, and each of the remaining features can only provide a small (less than 2.3%) impact on distinguishing CHDs from non-CHDs in T2DM patients. The performance of the proposed method is compared with that of known approaches such as SVM and CNN. The confusion matrix was used to calculate the MADNN and O-SBGC-LSTM measures, which were based on the following formulas:

$$Accuracy = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) * 100 \quad (28)$$

$$Precision = \left(\frac{TP}{TP + FP}\right) * 100 \quad (29)$$

$$F1score = \left(\frac{2 * precision * Recall}{Precision + Recall}\right) * 100 \quad (30)$$

$$Recall = \left(\frac{TP}{TP + FN}\right) * 100 \quad (31)$$

where TP denotes the total amount of illness data that are currently CHD-positive and are categorized as CHD-positive. The term FN refers to the total amount of illness data that are now CHD-positive but are categorized as CHD-negative. True Negative (TN) refers to the entire amount of illness data that are currently CHD-negative and categorized as such. FP stands for False Positive, and it refers to the total amount of illness data that are now CHD-negative but are categorized as CHD-positive. Fig 9 shows the prediction results. In table 1 consists different clinical's numerical values that were used in existing and proposed models.

The accuracies of the proposed and current models for the counts of features in a particular database are shown in Fig 9. O-SBGC-LSTM improves accuracy while shortening the processing time. Because it does not require a large number of derived variables during reduction, MADNN and O-SBGC-LSTM achieved accuracies of 98.1% and 98.61%, respectively, it follows the above Eq (27). When compared to all other models; consequently, the proposed approach outperforms current algorithms in terms of good validation findings for predicting CHDs. The prediction model is available online for people to self-check, and if the chance is high enough, it may be used as an early warning for developing CHDs. Furthermore, doctors can utilize the online web server as an additional tool to assess the possible risks of CHDs to patients. Furthermore, doctors can use the online web server as an additional tool to assess the risk of CHDs in T2DM patients. Doctors can also utilize risk-contribution data to create personalized treatment plans for individual patients.

The accuracies of the proposed and current models for the counts of features in a particular database are shown in Fig 9. Precision increased as the number of characteristics increased.In [32] comparison to SVM and CNN, MADNN and O-SBGC-LSTM achieved recalls of 99% and 99.2%, respectively. It is calculated by using Eq (28). This is due to the fact that the O-SBGC-LSTM reduces the calculation time of the derived factors, allowing for the simplest fine-tuning of the O-SBGC-LSTM and so increasing the accuracy rate. First, the characteristics of this study were restricted. As a result, the model may be enhanced in the future if more important information from other aspects (such as medication history and cardiac imaging data) are incorporated. Second, known characteristics (such as age, BMI, and glucose) may have nonlinear relationships. Despite its capabilities,

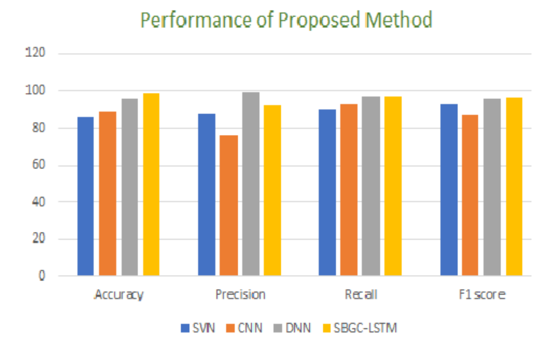

FIGURE 9. Performance of proposed work by mentioning its percentage of accuracy, precision, recall, and F1-score.

the O-SBGC-LSTM model could not detect and explain all types of compositions. As a result, when the number of nonlinear compositions rises in real-world circumstances for CHD prevention and detection, inaccuracy accumulates.

The F1-score of the proposed and current models for counts of features in the supplied datasets is shown in 9 and it was calculated by Eq (29). The f-measure is maximized, while the count of features is maximized. For example, MADNN and O-SBGC-LSTM produce an f-measure of 96% and 96.5%, respectively, when compared to all other models such as SVM and CNN. The O-SBGC-LSTM surpassed the other five approaches in terms of accuracy and the F1 scale, as shown above. These enhancements are mostly the result of addressing lengthy dependencies in text using bidirectional LSTM layers, thereby attaining a high F1-score.

Fig 9 shows the recall of the proposed and existing models for the characteristic counts in a given database. The recall increases with the number of attributes. MADNN and OSBGC-LSTM obtained recall of 97% and 97.5%. respectively, it can be calculated by above Eq (30). In contrast to SVM and CNN. Existing techniques under fit because they are simplistic models that are inadequate for high-dimensional datasets. The suggested technique employs local features of variable lengths by utilizing SBGC-LSTM layers of varying sizes, which improves the specificity of the proposed method. Its hyper parameters are optimized by the EOA, which improves detection efficiency; consequently, the proposed approach outperforms current algorithms in terms of good validation findings for predicting DR illness. The fact that the training and independent validation datasets come from the same hospital and that there are no tracking data for patients with non-CHD clinical diagnoses but with high risks from the prediction model, which may be a source of bias, is another key shortcoming of the present techniques. The O-SBGC-LSTM model will be stronger and more persuasive if multi-source training and cohort monitoring data are provided.

A. PREVENTION EXPERIMENTAL DETAILS

The output of prevention involves considering sentence analysis and decision sentences. In the below table 3 represent

TABLE 3. Sample input for FIS and suggestion actions.

Clinical Data	Cholesterol	Glucose	Insulin	Body mass index	Age
	120	140	2.5 units	37.01	30
Sentence Analysis	IF ((Cholesterol is abnormal) OR (Glucose level is normal) OR (BMI is Normal) OR (age is middle)) THEN (CHD is moderate)				
Decision Sentence	The decision sentence justifies that the possibility of suffering from CHD for the person is medium (0.293)				
Medical Actions	The medical practitioner justification is that person is non-CHD, and suggested him/her to continue CHD treatment with proper check-ups.				

prevention by giving suggestion as per rule based outcomes data.

1) Sentence Analysis: Sentence Analysis represents the physical data of the person as glucose level of person fuzzy numbers like Glucose*(low, medium or high)*. another fuzzy variable Insulin can be three fuzzy numbers such as INS(low, medium, high). BMI fuzzy variable also having three fuzzy numbers for examples BMI*(low, medium, high)*. For the fuzzy variable, cholesterol can be divided into three fuzzy numbers such as cholesterol *(low, medium, high)*. age fuzzy variable consisting of age *(young, youth, old)* is used.
2) Decision sentence: Decision sentence is used to express the possibility or the chances of a person suffering from CHD as represented. [CHD*(Low, Moderate, Risk, High Risk, Very High Risk)*].
possibility: [0, 1].

Where 0 indicates that the person is free from CHD disease and 1 indicates that the person is suffering from CHD. The above rules were applied for predicting the dead diseases including diabetic and heart disease. These rules are useful for making effective decision on medical reports and bench mark datasets one input layer, one output layer and two hidden layers as processing layers. The input value selects the soft-max function as an activation function, and it transforms the output layer in the neural network that is used to perform classification and increased the classification accuracy.

V. CONCLUSION AND FUTURE SCOPE

In this study, we provide a novel neural network method to estimate the status of CHD. By applying a scrutiny mechanism with EOA to obtain an adaptive weight for the hybrid method, the model extracts unique and common embedding from topology, node attributes, and their collaborations with our experimental testing on the dataset. The O-SBGC LSTM acquires the most essential information from the node and improves model accuracy by a large margin. The experiment also proves that the proposed method exhibits better results in various performance metrics than several existing baselines. To improve the prediction performance, the excellent prediction ability will optimize its application in the diagnosis and treatment of postoperative recurrence while simplifying the diagnosis process with an accuracy of 98%. The proposed work also manages to prevent CHD by providing suggestions according to the CHD disease level. Fuzzy inference systems take different clinical data and generate decisions for doctors for effective treatment, so that the risk to the patient can be avoided. In the future, the model can use more computational techniques to improve the model performance to accurately and effectively prevent the CHD status level.

ABBREVIATIONS

The following abbreviations shown in Table. 4 are used in this manuscript

TABLE 4. Abbreviation.

Abbreviation	Meaning
BMI	Bady Mass Index
CHD	Coronary Heart Disease
CNN	Convolutional Neural Network
DLM	Deep Learning Methods
EOA	Eurygaster Optimization Algorithm
GCNN	Graph Convolutional Neural Network
LSTM	Long Short Term Memory
MADNN	Multi-head Deep Neural Network
MLT	Machine Learning Techniques
NFIS	Neural Fuzzy Inference System
O-SBGCLSTM	Optimal Scrutiny Boosted Graph Convolution LSTM
RNN	Recurrent Neural Network
SVM	Support Vector Machine
T2DM	Type 2 Diabetes Mellitus

ACKNOWLEDGMENT

The authors would like to thank the management of Vellore Institute of Technology, Vellore, India for funding the Open Access Article Processing Charges.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] P. Saeedi, I. Petersohn, P. Salpea, B. Malanda, S. Karuranga, N. Unwin, S. Colagiuri, L. Guariguata, A. A. Motala, K. Ogurtsova, J. E. Shaw, D. Bright, and R. Williams, "Global and regional diabetes prevalence estimates for 2019 and projections for 2030 and 2045: Results from the international diabetes federation diabetes atlas, 9th edition," *Diabetes Res. Clin. Pract.*, vol. 157, Nov. 2019, Art. no. 107843.

[2] M. Sachdev and A. Misra, "Heterogeneity of dietary practices in India: Current status and implications for the prevention and control of type 2 diabetes," *Eur. J. Clin. Nutrition*, vol. 77, no. 2, pp. 145–155, 2023.

[3] *Ministry of Health and Family Welfare*, VIKAS SHEEL, New Delhi, India, 2016.

[4] B. J. Gersh, "Incidence of cardiovascular risk factors in an Indian urban cohort: Results from the New Delhi Birth Cohort," *Yearbook Cardiol.*, vol. 2012, pp. 249–252, Jan. 2012.

[5] F. B. Hu, "Globalization of diabetes: The role of diet, lifestyle, and genes," *Diabetes care*, vol. 34, no. 6, pp. 1249–1257, 2011.

[6] K. Dhana, J. Nano, S. Ligthart, A. Peeters, A. Hofman, W. Nusselder, A. Dehghan, and O. H. Franco, "Obesity and life expectancy with and without diabetes in adults aged 55 years and older in The Netherlands: A prospective cohort study," *PLOS Med.*, vol. 13, no. 7, Jul. 2016, Art. no. e1002086.

[7] H. Y. Yong, Z. M. Shariff, B. N. M. Yusof, Z. Rejali, Y. Y. S. Tee, J. Bindels, and E. M. van der Beek, "Independent and combined effects of age, body mass index and gestational weight gain on the risk of gestational diabetes mellitus," *Sci. Rep.*, vol. 10, no. 1, p. 8486, May 2020.

[8] V. Mohan, G. Radhika, P. Vijayalakshmi, and V. Sudha, ‘‘Can the diabetes/cardiovascular disease epidemic in India be explained, at least in part, by excess refined grain (rice) intake?’’ *Indian J. Med. Res.*, vol. 131, no. 3, pp. 369–372, 2010.
[9] L. A. Zilliox, K. Chadrasekaran, J. Y. Kwan, and J. W. Russell, ‘‘Diabetes and cognitive impairment,’’ *Current Diabetes Rep.*, vol. 16, no. 2, pp. 1–11, 2016.
[10] A. H. Gonsalves, F. Thabtah, R. M. A. Mohammad, and G. Singh, ‘‘Prediction of coronary heart disease using machine learning: An experimental analysis,’’ in *Proc. 3rd Int. Conf. Deep Learn. Technol.*, Jul. 2019, pp. 51–56.
[11] T. Nazir, A. Irtaza, A. Javed, H. Malik, D. Hussain, and R. A. Naqvi, ‘‘Retinal image analysis for diabetes-based eye disease detection using deep learning,’’ *Appl. Sci.*, vol. 10, no. 18, p. 6185, Sep. 2020.
[12] J. Nahar, T. Imam, K. S. Tickle, and Y.-P.-P. Chen, ‘‘Association rule mining to detect factors which contribute to heart disease in males and females,’’ *Expert Syst. Appl.*, vol. 40, no. 4, pp. 1086–1093, Mar. 2013.
[13] U. Pradip Ravaji and A. A. Moghe, ‘‘CSChO-deep MaxNet: Cat swam chimp optimization integrated deep maxout network for heart disease detection,’’ *Biomed. Signal Process. Control*, vol. 85, Aug. 2023, Art. no. 104706.
[14] M. A. Karaolis, J. A. Moutiris, D. Hadjipanayi, and C. S. Pattichis, ‘‘Assessment of the risk factors of coronary heart events based on data mining with decision trees,’’ *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 3, pp. 559–566, May 2010.
[15] E. Longato, G. P. Fadini, G. Sparacino, A. Avogaro, L. Tramontan, and B. Di Camillo, ‘‘A deep learning approach to predict diabetes’ cardiovascular complications from administrative claims,’’ *IEEE J. Biomed. Health Informat.*, vol. 25, no. 9, pp. 3608–3617, Sep. 2021.
[16] S. S. Sarmah, ‘‘An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network,’’ *IEEE Access*, vol. 8, pp. 135784–135797, 2020.
[17] B. S. Ilango and N. Ramaraj, ‘‘A hybrid prediction model with F-score feature selection for type II diabetes databases,’’ in *Proc. 1st Amrita ACM-W Celebration Women Comput. India*, Sep. 2010, pp. 1–4.
[18] G. Swapna, S. Kp, and R. Vinayakumar, ‘‘Automated detection of diabetes using CNN and CNN-LSTM network and heart rate signals,’’ *Proc. Comput. Sci.*, vol. 132, pp. 1253–1262, Jan. 2018.
[19] A. Ghasemieh, A. Lloyed, P. Bahrami, P. Vajar, and R. Kashef, ‘‘A novel machine learning model with stacking ensemble learner for predicting emergency readmission of heart-disease patients,’’ *Decis. Anal. J.*, vol. 7, Jun. 2023, Art. no. 100242.
[20] R. Deviand and V. Khemchandani, ‘‘Application of data mining techniques for diabetic dataset,’’ in *Proc. 4th Nat. Conf., Comput. Nation Develop.*, 2010, pp. 1–12.
[21] P. Nagaraj and P. Deepalakshmi, ‘‘An intelligent fuzzy inference rule-based expert recommendation system for predictive diabetes diagnosis,’’ *Int. J. Imag. Syst. Technol.*, vol. 32, no. 4, pp. 1373–1396, Jul. 2022.
[22] J. J. Joseph, P. Deedwania, T. Acharya, D. Aguilar, D. L. Bhatt, D. A. Chyun, K. E. Di Palo, S. H. Golden, and L. S. Sperling, ‘‘Comprehensive management of cardiovascular risk factors for adults with type 2 diabetes: A scientific statement from the American Heart Association,’’ *Circulation*, vol. 145, no. 9, pp. e722–e759, Mar. 2022.
[23] C. A. Reyes-García and A. A. Torres-Garcia, ‘‘Fuzzy logic and fuzzy systems,’’ in *Biosignal Processing and Classification Using Computational Learning and Intelligence*. Amsterdam, The Netherlands: Elsevier, 2022, pp. 153–176.
[24] K. M. Aamir, L. Sarfraz, M. Ramzan, M. Bilal, J. Shafi, and M. Attique, ‘‘A fuzzy rule-based system for classification of diabetes,’’ *Sensors*, vol. 21, no. 23, p. 8095, Dec. 2021.
[25] Y. Jin, R. Wang, X. Zhuang, K. Wang, H. Wang, C. Wang, and X. Wang, ‘‘Prediction of COVID-19 data using an ARIMA-LSTM hybrid forecast model,’’ *Mathematics*, vol. 10, no. 21, p. 4001, Oct. 2022.
[26] S. Zhang, H. Tong, J. Xu, and R. Maciejewski, ‘‘Graph convolutional networks: A comprehensive review,’’ *Comput. Social Netw.*, vol. 6, no. 1, pp. 1–23, Dec. 2019.
[27] X. Chen, Y. Zhang, L. Du, Z. Fang, Y. Ren, K. Bian, and K. Xie, ‘‘TSSRGCN: Temporal spectral spatial retrieval graph convolutional network for traffic flow forecasting,’’ in *Proc. IEEE Int. Conf. Data Mining (ICDM)*, Nov. 2020, pp. 954–959.
[28] F. Marini and B. Walczak, ‘‘Particle swarm optimization (PSO). A tutorial,’’ *Chemometric Intell. Lab. Syst.*, vol. 149, pp. 153–165, Dec. 2015.
[29] R. K. Jha, S. K. Henge, S. K. Mandal, A. Sharma, S. Sharma, A. Sharma, and A. A. Berhanu, ‘‘Neural fuzzy hybrid rule-based inference system with test cases for prediction of heart attack probability,’’ *Math. Problems Eng.*, vol. 2022, pp. 1–18, Sep. 2022.
[30] U. Hanif, M. Talha, and N. Abbas, ‘‘An intelligent system for diagnosis of cardiovascular disease empowered with fuzzy inference system: Diagnosis of cardiovascular disease empowered with fuzzy inference system,’’ *Int. J. Comput. Innov. Sci.*, vol. 1, no. 4, pp. 21–33, 2022.
[31] R. Alizadehsani, A. Khosravi, M. Roshanzamir, M. Abdar, N. Sarrafzadegan, D. Shafie, F. Khozeimeh, A. Shoeibi, S. Nahavandi, M. Panahiazar, A. Bishara, R. E. Beygui, R. Puri, S. Kapadia, R.-S. Tan, and U. R. Acharya, ‘‘Coronary artery disease detection using artificial intelligence techniques: A survey of trends, geographical differences and diagnostic features 1991–2020,’’ *Comput. Biol. Med.*, vol. 128, Jan. 2021, Art. no. 104095.
[32] M. Swathy and K. Saruladha, ‘‘A comparative study of classification and prediction of cardio-vascular diseases (CVD) using machine learning and deep learning techniques,’’ *ICT Exp.*, vol. 8, no. 1, pp. 109–116, Mar. 2022.

B. RAMESH received the M.Tech. degree in computer science and engineering from the National Institute of Technology, Tiruchirappalli, India, in 2009. He is currently pursuing the Ph.D. degree with the School of Computer Engineering and Information Systems, Vellore Institute of Technology, Vellore, India. His research interests include machine learning and deep learning.

KURUVA LAKSHMANNA received the B.Tech. degree in computer science and engineering from the Sri Venkateshwara University College of Engineering, Tirupati, India, in 2006, the M.Tech. degree in computer science and engineering (information security) from the National Institute of Technology Calicut, Kerala, India, in 2009, and the Ph.D. degree from VIT, India, in 2017. He is currently an Associate Professor with VIT. He has published research articles in IEEE, Elsevier, and Springer, most of which are indexed in the SCOPUS database. His research interests include machine learning, data mining in DNA sequences, the IoT, and data science and security.