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Cardiovascular Disorder Detection with a PSO-Optimized Bi-LSTM Recurrent Neural Network Model

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Abstract: The medical community is facing ever-increasing difficulties in identifying and treating cardiovascular diseases. The World Health Organization (WHO) reports that despite the availability of numerous high-priced medical remedies for persons with heart problems, CVDs continue to be the main cause of mortality globally, accounting for over 21 million deaths annually. When cardiovascular diseases are identified and treated early on, they cause far fewer deaths. Deep learning models have facilitated automated diagnostic methods for early detection of these diseases. Cardiovascular diseases often present insidious symptoms that are difficult to identify in a timely manner. Prompt diagnosis of individuals with CVD and related conditions, such as high blood pressure or high cholesterol, is crucial to initiate appropriate treatment. Recurrent neural networks (RNNs) with gated recurrent units (GRUs) have recently emerged as a more advanced variant, capable of surpassing Long Short-Term Memory (LSTM) models in several applications. When compared to LSTMs, GRUs have the advantages of faster calculation and less memory usage. When it comes to CVD prediction, the bio-inspired Particle Swarm Optimization (PSO) algorithm provides a straightforward method of getting the best possible outcomes with minimal effort. This stochastic optimization method requires neither the gradient nor any differentiated form of the objective function and emulates the behaviour and intelligence of swarms. PSO employs a swarm of agents, called particles, that navigate the search space to find the best prediction type.This study primarily focuses on predicting cardiovascular diseases using effective feature selection and classification methods. For CVD forecasting, we offer a GRU model built on recurrent neural networks and optimized with particle swarms (RNN-GRU-PSO). We find that the proposed model significantly outperforms the state-of-the-art models (98.2% accuracy in predicting cardiovascular diseases) in a head-to-head comparison.

Keywords: Cardiovascular Disorders, Recurrent Neural Network, Gated Recurrent Unit, Particle Swarm Optimization, Feature Processing, Classification.

I. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular disease is the leading cause of death worldwide. The wide variety of predisposing conditions makes it difficult to spot cardiovascular diseases (CVD) [1]. Conditions such as hypertension, dyslipidemia, diabetes, and an irregular heart rhythm are risk factors. Symptoms of CVD may vary between genders [2]. While women are more prone to experience other symptoms including nausea, extreme tiredness, and shortness of breath, men are more likely to suffer chest pain. Many different strategies have been explored by researchers looking to foretell heart diseases [3]. However, there are a number of reasons why disease prognoses made too early are ineffective. The approach's intricacy, execution time, and accuracy are all factors in these drawbacks. This is why prompt medical attention after an accurate diagnosis is so crucial [4].

In order to reduce mortality rates and enhance treatment and preventative decisions, it is advised that high-risk patients and those with advanced stages of heart disease be identified early using a prediction model. In automatic detection systems (ADS) [5], a prediction model is used to aid doctors in determining a patient's risk for cardiovascular disease, and then the patient is given the necessary care to reduce that risk [6]. It has been shown in a number of studies that using a ADS can enhance the quality of decisions made, the efficiency of clinical decision making, and the efficacy of preventative care [7]. For people over the age of 35, coronary artery disease (CAD), also known as ischemic heart disease (IHD), is the primary cause of mortality [8]. During the same period, it

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surpassed all others as China's leading cause of death. IHD develops when coronary artery stenosis reduces blood flow to the heart. Serious complications might arise from myocardial injury, such as ventricular arrhythmia or even abrupt cardiac death [9].

Coronary artery disease, which can result in a heart attack, is the most prevalent form. Heart health is influenced by a number of lifestyle choices, including cholesterol, pulse rate, and glucose management [10]. Heart disease can be caused by many things, but heredity, hypertension, cholesterol, age, gender, type of diet, calcium intake, the condition of the blood vessels, and how much they have been stretched all rank high on the list [11]. Death from heart disease has surpassed death from any other cause in many parts of the world. The purpose of this research is to improve upon the current RNN deep learning model used to identify cardiac issues. The healthcare business is only one of many that has benefited from the proliferation of AI [12], machine learning, and deep learning from the early to mid-2000s. As a result of deep learning, the healthcare industry can analyze data at lightning speed without sacrificing precision [13]. While the human brain utilizes a mathematical model to interpret statistical data, deep learning takes a more analogous approach [14].

For a desired predicted outcome, deep learning uses micro-analytics on the data and a neural network's many neurons and layers [15]. Prediction models for heart disease that are accurate and thorough enough to help doctors catch problems early on can only be created with the help of deep learning. When attributes are missing from datasets, prediction quality decreases. Although algorithms for machine learning and methodologies have shown highly successful in predicting cardiovascular disorders, there is still a need to direct future research efforts on solving pressing issues like dealing with high-dimensional data [16] and the overfitting phenomenon.

Many studies have shown that RNN, and especially LSTM, are well-suited for processing long series data, and more and more research is being done on the topic of using LSTM to anticipate hospital outpatient volume. The issue typically arises with standard RNN [17] while trying to make a connection between old and new data [18]. Long-term reliance describes this issue. When compared to a regular LSTM, a Bi-LSTM is unique since it takes in information in both directions [19]. The input in a regular LSTM can only go in one of two directions—either forward or backward [20]. However, with bi-directional input, both new and old information can be preserved without loss.Figure 1 depicts the Bi-LSTM design.

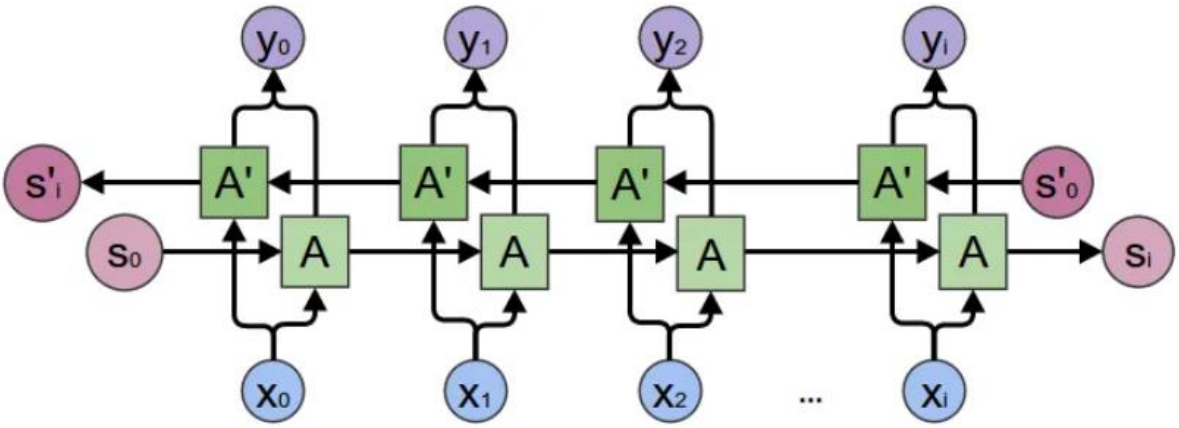

Figure 1: Bi-LSTM Architecture

Bidirectional LSTM networks are trained by presenting each training sequence in both directions to two LSTM networks that share an output layer. The Bi-LSTM, thus, stores information about every possible point before and after a given point in a series. The Figure shows the Bi-LSTM architecture.

In order to use the PSO, a particle-based research space and an optimization [21] objective function must be defined [22]. The algorithm's central idea is to steer the particles in a direction that leads them to the best possible solution. From a point, i.e. its coordinates in the definition set, are carried by each of these particles. An attainable velocity for the particle's forward motion [23]. The particles all move around as the process iterates. The best neighbor, best position, and previous position all have a role in how it progresses [24]. This gradual improvement allows for the discovery of the best possible particle. Particles in close proximity to and interacting with the particle, most notably the particle satisfying the best requirement [25]. At any one time, every particle is aware of its optimal location. The determined criterion value and its associated coordinates are the primary inputs. The goal function's value is determined by comparing the criterion value provided by the current particle to the optimal value at each iteration.In this research, Recurrent Neural Network based GRU Model Using Particle Swarm Optimization for CVD prediction is performed.

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II. LITERATURE SURVEY

One of the most common but potentially fatal cardiovascular disorders, heart failure (HF) affects about 23 million people around the world. Patients with HF who require a bridge to transplanting, recovery, or destination therapy have left ventricular assist devices (LVADs) installed, and these devices are controlled by measuring pulmonary arterial wedges pressure (PAWP) in both physiological and pathological states. Given the lack of commercially accessible, long-term implanted pressure sensors to monitor PAWP, non-invasive, real-time monitoring of abnormal and normal PAWP is of critical importance. Using a set of twenty-four unimodal and bidirectional benchmark functions, the author evaluated HHO+, an improved version of the Harris Hawks optimizer method provided by Fetanat et al. [2].

Clinical studies investigated the role of early diagnosis and treatment in reducing clinical deterioration among ICU patients (ICUs). If clinical risk factors are discovered and developed early, patients' decline can be predicted and prevented. Earlier diagnosis of deterioration in the intensive care unit may also lead to improvements in patient care. Alshwaheen et al. [3] described an innovative model for forecasting the worsening of ICU patients using Long Short-Term Memory-Recurrent Neural Networks. The suggested model is superior to existing alternatives because it can anticipate degradation within the first hour of its initiation. This research uses a cutting-edge GPU virtual machine housed on Google Colaboratory to implement the proposed prediction model. The study also made use of a revolutionary minute-by-minute time-series method.

The alarming death toll and rising prevalence of CVDs around the world emphasise the vital importance of early detection methods. Since phonocardiogram (PCG) signals are low-cost and easy to implement, they have been used for quite some time in this area. Here, CardioXNet was presented by Shuvo et al. [4] as a new lightweight end-to-end CRNN architecture for automatic detection of 5 classes of cardiac auscultation utilizing raw PCG signal: normal, aortic constriction, mitral stenosis, valve disease, and mitral valve prolapse. An important research topic in personalized healthcare is determining the possibility of cardiovascular disease by analyzing data from current EHRs.Modeling a patient's condition over time by identifying temporal patterns from data on repeat visits is a common application of deep neural networks that has emerged in recent years. However, current systems that combine diverse forms of clinical data typically ignore the effects of the patient's age and the unpredictability of the gap between successive medical records. A time-aware multi-type dimension reduction representation learning framework (TAMDUR) for predicting CVD risk was presented by An et al. [5] to address these issues. In this setting, we predict the spread of disease using a time-aware decay model that takes the patient's current health and the intervals between visits into consideration. Finally, a Bi LSTM network and a CNN are created in tandem to learn temporal and non-temporal properties from the various forms of clinical data. In order to synthesize all of these characteristics and their associations into a holistic portrait of the patient, the author developed a self-attention based multi-type data fusion identification layer.

Predicting who will be at high danger of cardiovascular disease has become increasingly crucial as the number of people leading unhealthy lives rises. Unfortunately, the majority of current prognosis estimation procedures based on pathology are either extremely costly or fraught with diagnostic error. Many automated algorithms based on machine learning have been developed to analyze premorbid data about patients obtained from EHRs in order to forecast the onset of cardiovascular disease. Obtaining accurate and robust depictions of patients is far more difficult than selecting acceptable features from continuous and heterogeneous EHRs. High-quality characteristics can be learned from EHRs instantly, disparate medical data can be integrated in real time, and the risk of cardiovascular disease in patients may be predicted,An et al. [6] proposedDeepRisk, a fully-integrated design that uses learning algorithm and deep neural networks.

Diabetics, to avoid complications, must have ready access to medical care at all times. Their strategies for disease management yield vast reams of data useful in a range of contexts, from the clinical to the managerial. The prognosis of cardiovascular disease, the leading cause of excess mortality in diabetes, is one example of how secondary use of these data by institutions is impeded by access and processing constraints. To predict major adverse cardiovascular events (MACE), Longato et al. [7] proposed a deep learning algorithm using administrative claims data from 214,676 people with diabetes in the Veneto region of North East Italy for training and testing. Predicting the incidence of the 4P-MACE composite endpoint requires analyzing a year's worth of pharmacy and hospitalization claims in addition to basic patient's information. Common forecast horizons range from one to five years into the future. Due to the temporal structure of the data, the author reframed the problem as a multi-outcome, multi-label multiclass classification with a custom loss to handle censoring.

Chronic vascular diseases have become an international epidemic. Early diagnosis of cardiovascular diseases and their potential prevention or treatment has the potential to reduce mortality rates. Machine learning algorithms provide some hope for improving our ability to identify and avoid possible threats. Several methods were incorporated into the model created by Ghosh et al. [9] to improve CVD forecasting. The

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author trained a strong model with the help of fast data collection, preprocessing, and transformation techniques. The author did this by utilising a mashup dataset. Relief and LASSO were employed by the author to choose the most promising features for further analysis.

III. PROPOSED MODEL

Blood vessels known as coronary arteries transport oxygenated blood to the heart muscle. A recent study reveals that the United States has the highest per capita rate of individuals with heart disease. Symptoms of heart disease include general weakness, difficulty breathing, swollen feet, fatigue, and other signs of exhaustion. Lifestyle factors, such as smoking, unhealthy diet, high cholesterol levels, hypertension, and lack of physical activity, can contribute to a person's increased risk of CVD.

Due to the narrowing of arteries that feed blood to the heart and brain, coronary artery disease (CAD) can produce symptoms like chest pain, angina, and heart attacks.Cardiovascular disease, heart failure, congenital heart problems, and cardiac rhythm disorders are all other types of heart illness. Traditional diagnostic methods for heart diseases were time-consuming and often inaccurate. The scarcity of diagnostic resources and trained medical professionals, especially in developing countries, adds to the difficulty in diagnosing and treating heart diseases. Nevertheless, accurate identification of heart diseases is crucial to prevent further complications for patients.

The death toll from heart disease continues to rise throughout all regions of the world, not just the developing ones. The proposed model framework, as illustrated in Figure 2, aims to address these challenges and improve the diagnosis and treatment of heart diseases.

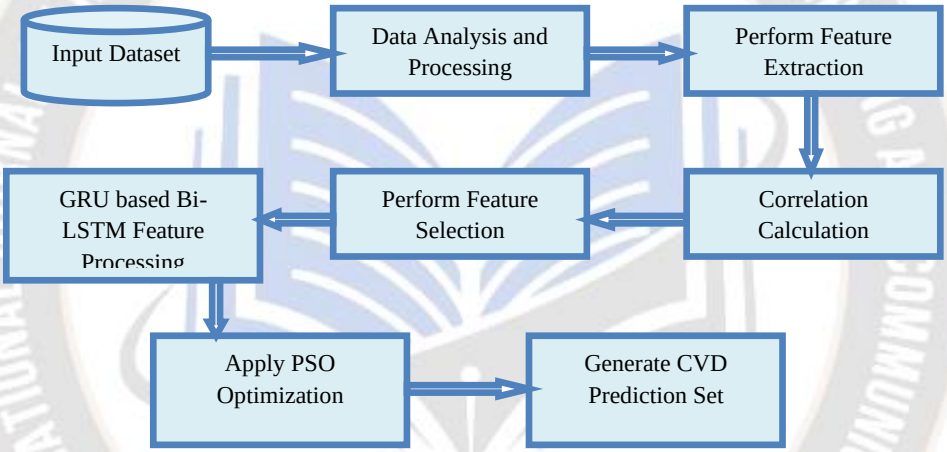

Figure 2: Proposed Model Framework

The Bi-LSTM model employed in this study, a deep learning instance, utilizes forward and backward data processing to enhance classification accuracy. The forward layer in the Bi-LSTM processes data from left to right for data analysis, while the backward layer, responsible for token analysis, operates in the reverse direction. RNNs with long short-term memories (LSTM) are particularly good at remembering key pieces of data. The forward hidden layer is composed of a hidden unit function h at each time step t, as changed by the current state ht+1 and the input data. The backward layer applies the same function, learned from the hidden layers in the future, ht+1, using the available information.

In the particle swarm optimization approach used here, both the current global best g and each individual's best x at iteration t are considered. While the individual best likely introduces diversity to high-quality solutions, this can also be achieved through randomization. Therefore, choosing the individual best may not be necessary unless the optimization problem is highly nonlinear and multimodal. PSO is a population-based optimization method that takes cues from the collective intelligence of natural systems like bird flocks and fish schools. Sharing similarities with other evolutionary computation techniques, PSO refines the search for the optimal solution with iterative generational updates, starting from a seed population.

Unlike genetic algorithms, PSO does not employ evolutionary operators such as crossover or mutation. Particles in PSO navigate the problem space, guided by the currently ideal particles. PSO serves as a space- and time-efficient data-processing algorithm that accurately predicts CVD in the proposed research. This research uses a GRU model trained with particle swarm optimization (RNN-GRU-PSO) for CVD forecasting. The general model of PSO is illustrated in Figure 3.

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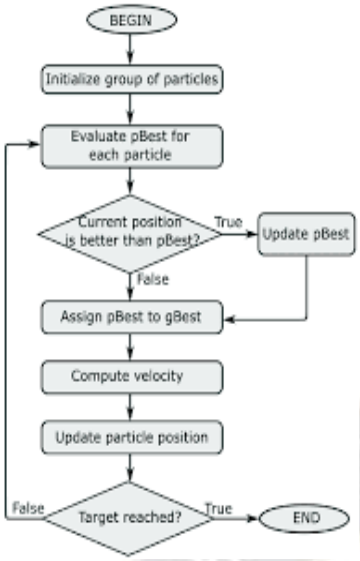

Figure 3: The general model of PSO

Output: Prediction Set {Pset}

Step-1: The cardiovascular dataset is first taken into account, and its records are then evaluated and processed in preparation for feature extraction. The records in the CDset is considered and analyzed for attribute range analysis that is performed as

$$CVDset[N] = \sum_{i=1} \text{getattrib}(\text{CDset(i)}) + \text{avg}\left(\frac{\text{getmaxVal(i)}}{\text{size(CDset)}}\right) + \text{mean}(\max(\text{i}, \text{i}+1))$$

The model Avg is used to determine the average of the dataset's attributes, whereas the model mean determines the average value of every pair of records in the dataset.

Step-2: The records in the dataset after analysis, perform the extraction of features from the dataset. These features represent the properties of CVD diseases. The feature extraction is performed that extracts all the features from the dataset that is performed as

$$FExtrset[N] = \sum_{i=1}^{N} maxrange(getattrib(i)) + minrange(getattrib(i)) + \frac{diff(CVDset(i, i+1))}{size(CVDset)}$$

Step-3: The extracted characteristics' correlation is then determined. In feature selection, correlation analyses are employed to determine which features will be most useful in making a prediction. The correlation calculation and weights allocation to the features are performed as

$$CorrSet[N] = \prod_{i=1}^{N} \max_{1 \le r \le N} (FExtrset(i) + \prod_{i=1}^{N} \frac{simm(FExtrset(i, i+1)}{size(FExtrset)} + \text{maxattrb}(\tau(\text{i}, \text{i}+1))$$

$\tau$is the model for dependency checking of every 2 features in the feature extracted set. Features are given relative importance according on their correlation coefficient. These weights are assigned according to

$$Walloc(CorrSet[N]) = \sum_{i=1}^{N} \frac{\max(CorrSet(i, i+1)) + \sum_{i=1}^{N} \max(\text{diff}(CorrSet(i+1, i)))}{\tau}$$

Step-4: The selection of features is carried out in accordance with the feature weights and the feature correlation. The training process can be carried out based on the chosen characteristics. The steps involved in selecting relevant features and feature subset generation is performed as

$$FselSet[N] = \sum_{i=1}^{N} \text{Max}(\text{Walloca(i}, \text{i}+1) + \frac{CorrSet(FExtrset(i)) + \min(\tau(\text{i}, \text{i}+1))}{\text{size(Walloc)}}$$

Step-5: In order to update the hidden network situation selectively at each time step, GRU relies on gating methods. Information entering and leaving the network can be managed with the use of gating mechanisms. The GRU has a reset gate as well as an update gate. Training the BiLSTM model entails setting its initial parameters and variables based on the GRU gates processing of the chosen features, and then activating the hidden layer processing to begin attribute processing and analysis. Attribute processing for the GRU-based BiLSTM hidden layer is carried out as

Reset Gate: RT = sigmoid(Wr * [h{t-1}, xt])
Update Gate: ZT = sigmoid(Wz * [h{t-1}, xt])
Candidate hidden state: HT = tanh(Wh * [RT * h{t-1}, xt])
Hidden state: HT= (1 – ZT) * h{t-1} + ZT * HT'

Here, Wr, Wz, and Whrepresents learnable weight matrices, xt is represented as input considered at time t, h{t-1} is indicated as the previous hidden state, and ht is considered as the current hidden state.

$$i_t = sigmoid(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$$
$$f_t = sigmoid(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$$
$$g_t = tanh(W_{ig}x_t + b_{ig} + W_{hc}h_{t-1} + b_{hg})$$
$$o_t = sigmoid(W_{io}x_t + b_{i0} + W_{ho}h_{t-1} + b_{ho})$$
$$c_t = f_t * c_{t-1} + i_t * g_t$$

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$h_t = o_t * \tanh(c_t)$

$p(R_{ij}|U_i, V_j, \sigma^2) = \prod(R_{ij}|U_i^T V_j, \sigma^2).$

$i'_t = sigmoid(W'_{ii}x'_t + b'_{ii} + W'_{hi}h'_{t-1} + b'_{hi})$
$f'_t = sigmoid(W'_{if}x'_t + b_{rif} + W'_{hf}h'_{t-1} + b'_{hf})$
$g'_t = tanh(W'_{ig}x_t + b'_{ig} + W'_{hc}h'_{t-1} + b'_{hg})$
$o'_t = sigmoid(W'_{io}x_t + b'_{i0} + W_{rho}h'_{t-1} + b'_{ho})$
$c_{rt} = f'_t * c'_{t-1} + i'_t * g'_t$
$h'_t = o'_t * \tanh(c'_t)$

$p'(R'_{ij}|U'_i, V'_j, \sigma^2) = \prod(R'_{ij}|U'^T_i V'_j, \sigma^2).$

$$Hlayer(i,o,G) = \sum_{i=1}^{N} Walloc(ZT(i,o)) + \max(CorrSet(h(t), h(t+1)) + \lim_{i \to N}\left(o'_t + \frac{c_t + i'_t}{n}\right)^2 + \frac{\max(p'(R'_{ij}|U'_i, V'_j, \sigma^2))}{\min(p(R_{ij}|U_i, V_j, \sigma^2))}$$

An activation vector (i), an activation gate (f), an activation input (g), an activation output (o), an activation input (c), and an activation hidden state (h) are all shown here.

Step-6: Based on the GRU based Bi-LSTM feature set, PSO optimization is applied for generating accurate prediction set. Based on the behavior and intelligence of swarms, PSO is a stochastic optimization method. In PSO, problem-solving is approached through the lens of social interaction. The search space is traversed by a swarm of particlesthat are all actively trying to find the optimal answer. The procedure is carried out by

for each particle (record) in the CDset[N] do
for i in range(swarm_size):
if swarm[i].fitness <best_swarm_fitness:
best_swarm_fitness = swarm[i].fitness
best_swarm_value = swarm[i].value
Initialize the particle'sbest comparison parameter $R_i \leftarrow R_{new}$
if fit(R_i) < fit(R_{new}) then
update the prediction set: PDset ← R_{new}
else
Change the swarm position: $R_{new} \leftarrow R_{new+i}$
for each particle G = 1,2 ..., M do
for each dimension D = 1, 2..., N do
Update the particle's as: $R_{new} \leftarrow R_{new} + R_{new+i}$
FitnessV←max(R_{new},R_{new+i})
if fit(R_{new}) < fit($R_{new} + R_{new+i}$) then
Update the particle's
Generate the prediction set

Step-7: CVD affects the heart and vascular system, making it a potentially fatal condition for humans. The PSO optimization based on repetitive processing of feature set, final disease prediction set will be generated. The process of CVD prediction set generation is performed as

$$Pset = \sum_{i=1}^{N} \max(\text{FitnessV(i, i + 1)}) + \max\left(\left(o'_t + \frac{c_t + i'_t}{n}\right)\right) + \max(Hlayer(i,o,G)) - \prod\prod(R_{ij}|U_i^T V_j, \sigma^2).$$

IV. RESULTS

Heart disease and other circulatory disorders account for a disproportionate share of global mortality and disability. Therefore, early and automatic CVD detection can greatly improve survival rates. Despite the large number of research aimed at this end, there is always potential for development in terms of efficiency and dependability. The use of big data and analytics has shown to be extremely helpful in the healthcare sector. The high mortality rate from heart attacks makes it crucial to extract medical data in order to forecast and treat these conditions. High-quality services are required to prevent clinical errors with dire consequences. Proper decision support systems can help hospitals reduce the cost of clinical tests. Consequently, hospitals currently utilize hospital information systems to manage patient records. Despite the massive amount of data generated in the healthcare sector, only a small fraction is utilized. A new approach is needed to reduce costs and simplify heart disease prediction.

Cardiovascular disease is a major killer both in India and around the world. Rural areas in India face a severe shortage of cardiologists and other medical professionals. Therefore, developing a reliable, automated system to analyze phonocardiograms and diagnose heart diseases is crucial. Cardiovascular disease may only impact a specific region of the heart, meaning the patch area could be healthy despite originating from a heart with diseases. As a result, even at a higher computational cost, multiple large sections should be utilized. The final diagnosis of heart health or CVD would depend on the classification of most portions from that heart. Traditional risk assessment models assume linearity between risk factors and CVD outcomes. However, several risk factors have non-linear interactions, complicating their integration into such models. Properly incorporating multiple risk factors requires understanding more nuanced relationships between risk factors and outcomes.

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This research uses a GRU model trained with particle swarm optimization (RNN-GRU-PSO) for CVD forecasting. To gauge its efficacy, the suggested model is compared to Group Bi-LSTM (GBi-LSTM). Feature extraction helps minimize data redundancy, ultimately facilitating model construction with reduced computational effort and accelerating learning and generalization phases. All of the features needed for CVD prediction are successfully extracted by the suggested model. Feature Extraction, In Brief Levels of Time in the Existing Model and the Proposed Model, as Displayed in Table 1 and Figure 4.

TABLE I: FEATURE EXTRACTION TIME LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	12	21
20000	14	22
30000	15	22.1
40000	16	22.2
50000	16.5	22.3
60000	17	22.4

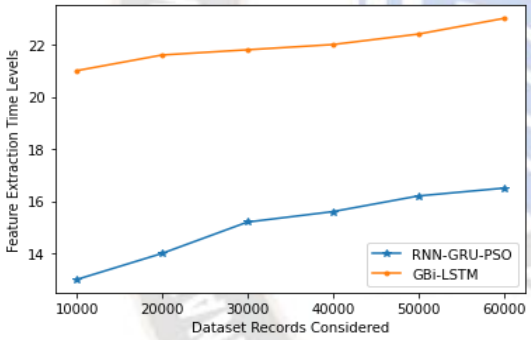

Figure 4: Feature Extraction Time Levels

The strength of the bond between two characteristics is measured by the correlation coefficient. A perfect positive correlation, represented by a value of 1, indicates that both variables change in the same way. The perfect inverse correlation is -1, while the absence of any linear relationship between the variables is indicated by a value of 0. Correlation analysis is computed by dividing the covariance of the two variables by the sum of their standard deviations. Table 2 and Figure 5 show the existing and suggested models' Correlation Calculation Accuracy Levels, respectively.

TABLE II: CORRELATION CALCULATION ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	96.4	88.5
20000	96.8	88.7
30000	97.4	89
40000	97.6	91
50000	98	91.3
60000	98.2	91.6

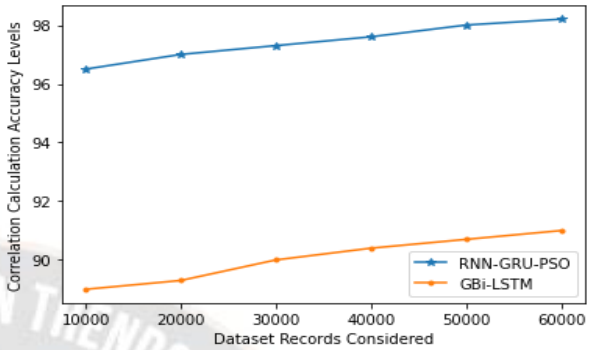

Figure 5: Correlation Calculation Accuracy Levels

Feature selection is a crucial process for creating a more accurate prediction model. Reducing the quantity of input features can improve model performance and lower the computational cost of modeling. Both the current and proposed models' Feature Selection Accuracy Levels are shown in Table 3 and Figure 6.

TABLE III: FEATURE SELECTION ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	95.4	88.2
20000	95.7	88.7
30000	96	90.3
40000	97	91.4
50000	97.6	92
60000	98	93.3

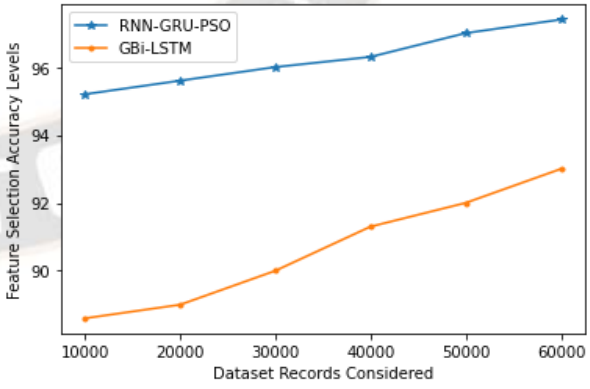

Figure 6: Feature Selection Accuracy Levels

A neural network's hidden layers are crucial to its ability to process inputs and generate an accurate prediction or other target value. These layers allow the algorithm to assign weights to the inputs and route them through an activation function. Similar to the Recurrent Neural Network (RNN), but with its own built-in gating mechanisms, is the Gated Recurrent Unit (GRU). At each time step, the GRU cell

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processes sequential input data and the memory, also known as the hidden state. The RNN cell's hidden state is then fed back into the cell along with the subsequent input data. Table 4 and Figure 7 display the Hidden Layer Processing Accuracy Levels of the proposed and existing models, respectively.

TABLE IV: HIDDEN LAYER PROCESSING ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	96	88.6
20000	96.3	90
30000	96.8	90.4
40000	97	90.8
50000	97.5	91
60000	98	91.7

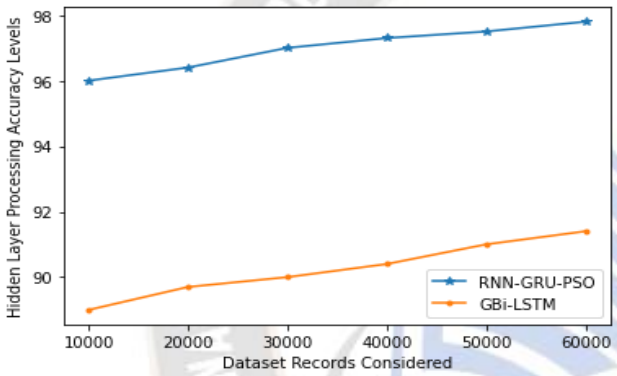

Figure 7: Hidden Layer Processing Accuracy Levels

The Gated Recurrent Unit (GRU) can be thought of as a simplified version of the Long Short-Term Memory (LSTM) with a forget gate, despite lacking an output gate and having fewer parameters. GRUs avoid revealing their cell state during communications and instead employ the covert state. There are only two gates needed for a GRU: the reset gate and the update gate. Table 5 and Figure 8 display the GRU Processing Time Levels of the new and existing models, respectively.

TABLE V: GRU PROCESSING TIME LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	13.5	19
20000	14.4	20
30000	15.6	20.4
40000	15.8	21
50000	16	22
60000	17	22.6

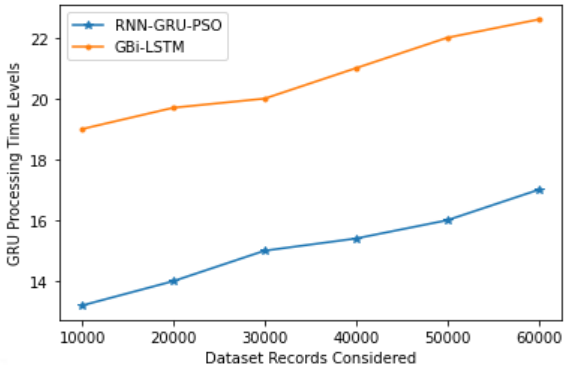

Figure 8: GRU Processing Time Levels

A Bidirectional Long Short-Term Memory (BiLSTM) layer can be trained on medical data to discover long-term dependencies both forward and backward between time intervals. These capabilities are beneficial when users want the system to capture information from the entire time sequence at each step. In classification problems, bidirectional LSTMs enhance the performance of regular LSTMs by training two separate LSTMs on the input data and its reverse sequence. This approach increases the network's understanding and enables faster outcomes. Accuracy in Bi-LSTM processing is displayed in Table 6 and Figure 9 for both the proposed and current models.

TABLE VI: BI-LSTM PROCESSING ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	93	87.7
20000	94.3	88.2
30000	95	89
40000	96	91
50000	96.3	91.2
60000	97.5	92

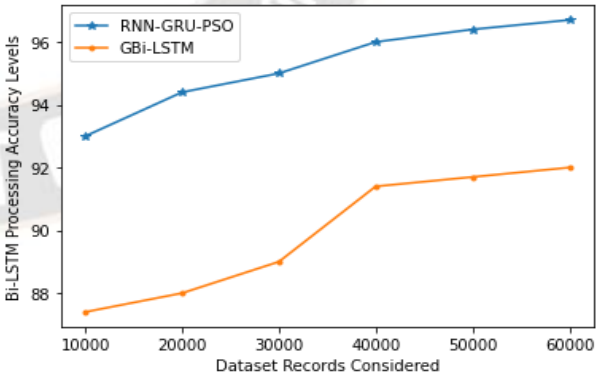

Figure 9: Bi-LSTM Processing Accuracy Levels

Using a population-based strategy, Particle Swarm Optimization (PSO) is a stochastic way to addressing optimization issues. The flocking and schooling behaviors of birds and fish in the wild served as inspiration for this concept, PSO has proven its effectiveness as an optimization algorithm by thoroughly exploring high-dimensional problem spaces.

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This powerful stochastic optimization method is founded on swarm intelligence and collective motion principles. The PSO Optimization Accuracy Levels of the New and Old Models are Shown in Table 7 and Figure 10.

TABLE VII: PSO OPTIMIZATION ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	92.3	88
20000	93	89
30000	94	90.4
40000	94.6	91
50000	96	92
60000	97.6	92.7

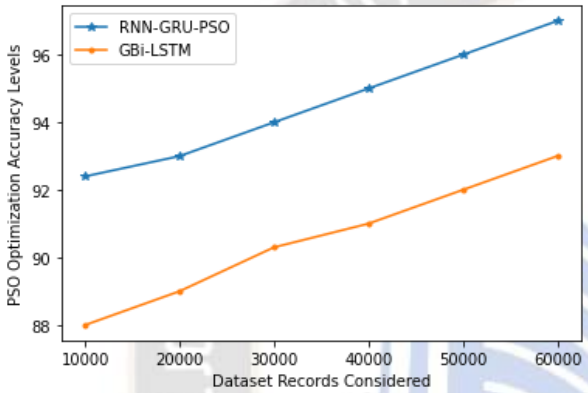

Figure 10: PSO Optimization Accuracy Levels

The development of this method began with a search of medical records for information that could be used to determine an individual's cardiovascular disease characteristics and the severity of their risk factors for developing cardiovascular disease. The rise in CVD-related deaths worldwide can be attributed to a delay in treating long-term patients, particularly those with CVD. Continuous monitoring of blood pressure is crucial for preventing cardiovascular diseases, as blood pressure can be effectively controlled and diagnosed with diligent care. The CVD Detection Accuracy Levels of the Proposed and Conventional Models are shown in Table 8 and Figure 11.

TABLE VIII: CVD DETECTION ACCURACY LEVELS

Dataset Records Considered	Models Considered	
	RNN-GRU-PSO Model	GBi-LSTM Model
10000	95.3	91
20000	96	92
30000	96.3	93
40000	96.7	93.4
50000	97	93.6
60000	98	93.8

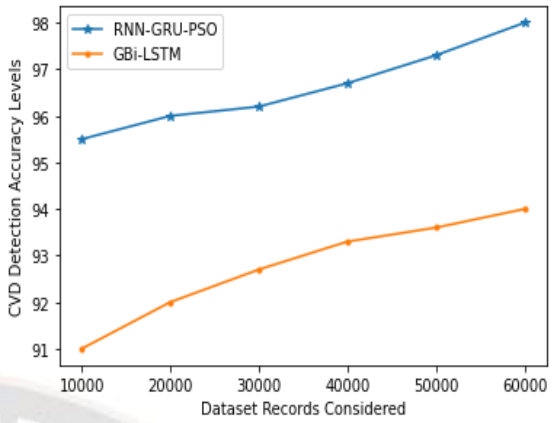

Figure 11: CVD Detection Accuracy Levels

V. DISCUSSIONS

Before we conclude this discussion on the research paper focused on detecting cardiovascular disorders using a PSO-optimized Bi-LSTM RNN model, let's delve into some of the key points and their implications:

Challenges in detecting CVD: Traditional methods of detecting CVD can be time-consuming, less accurate, and resource-intensive. This emphasizes the requirement for a fully automated, efficient, and accurate detection system to enhance patient outcomes while decreasing healthcare costs.

Advantages of the proposed model: The RNN-GRU-PSO model integrates the best features of recurrent neural networks, long short-term memory, and particle swarm optimization to produce a powerful and precise method of forecasting. By processing data in both forward and backward directions, the Bi-LSTM RNN model is better equipped to learn and extract relevant features from the dataset. Furthermore, PSO aids in the optimization of the model, leading to improved performance.

Feature extraction and selection: In order to construct a reliable model, it is necessary to extract and choose relevant features. By focusing on the most relevant features and reducing data redundancy, the model can learn more efficiently and deliver better predictions.

Comparative analysis: When compared to conventional GBi-LSTM models, the suggested RNN-GRU-PSO model shows that the unique technique is superior. The outcomes highlight the potential of the suggested model in practical settings, suggesting it beats the conventional models in terms of accuracy and efficiency.

Potential applications: The suggested approach has broad healthcare applications, especially in the prevention and early diagnosis of cardiovascular illnesses. By improving accuracy and reducing diagnostic times, this model could play a critical role in enhancing patient care, enabling more effective treatments and interventions, and ultimately saving lives.

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Future research directions: Further research could explore ways to refine and enhance the proposed model, investigate its applicability to other medical conditions, and assess its performance in real-world clinical settings. Additionally, it could be interesting to examine the integration of this model with other advanced machine learning techniques or data sources to further improve its predictive capabilities.

VI. CONCLUSION

In conclusion, the research paper presents a novel approach to detecting cardiovascular disorders using a PSO-optimized Bi-LSTM RNN model. The suggested model outperforms baseline approaches in terms of accuracy and efficiency because it combines the benefits of recurrent neural networks, long short-term memory, and particle swarm optimization. The importance of feature extraction and selection in building an effective model has also been emphasized.

The potential applications of this model in healthcare, particularly for early detection and diagnosis of cardiovascular diseases, are significant. By providing more accurate and timely diagnoses, this model can improve patient outcomes, reduce the burden on healthcare systems, and ultimately save lives.

The use of a Recurrent Neural Network-based GRU Model with Particle Swarm Optimization for CVD prediction in this research shows promising results, achieving 98.2% accuracy levels. By considering the most relevant features for CVD prediction, the proposed model demonstrates its potential as a reliable tool for medical professionals.

Future research directions include refining and enhancing the proposed model, exploring its applicability to other medical conditions, and evaluating its performance in real-world clinical settings. Additionally, investigating the integration of this model with other advanced machine learning techniques or data sources could lead to further improvements in its predictive capabilities, making it an even more valuable tool for healthcare professionals and researchers.

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