Cardiovascular Disorder Detection in Diabetes Mellitus Patients: An Integrated VGG and Bi-LSTM Model Optimized Using the ABC Algorithm

Bhagyalaxmi
Research Scholar,Department of Computer Science,GITAM School of Science,GITAM University
Visakhapatnam,India
bhagyalaxmigit@gmail.com

Dr.Muktevi Srivenkatesh
Associate Professor,Department of Computer Science, GITAM School of Science,GITAM Deemed to be University
Visakhapatnam, India
smuktevi@gitam.edu

Abstract-There is a major public health concern at the intersection of Diabetes Mellitus (DM) and Cardiovascular Diseases (CVDs). Patients with a diabetes diagnosis are more likely to experience a variety of cardiovascular problems. Better patient outcomes and lower healthcare costs can result from early diagnosis of these problems. This study presents a fresh computational model to tackle this problem. This research presents an integrated method that optimizes the VGG and Bidirectional Long Short Tem Memory (Bi LSTM) models together with the help of the Artificial Bee Colony (ABC) algorithm, which is based on the swarm intelligence of artificial bees. Cardiac images are processed using the VGG network, which has been shown to be highly effective in image classification, while the Bi LSTM is optimized for processing time series data from medical sensors, such as heart rates and blood sugar levels. The selected characteristics are then used in the proposed VGG 16 model before being sent to Bi-LSTM for further processing and abnormality detection. The VGG consists of 16 layers, all of which are blocks of 2D Convolution and Max Pooling layers. The ABC method was created as a result of research into intelligent behavior and is now widely used in areas such as problem solving, categorization, and optimization. The ABC algorithm is used to the unified model, which results in improved adaptability, speed of convergence, and robustness. To better forecast cardiovascular diseases, this research presents an Integrated VGG16 model with Bi-LSTM model with ABC optimization (VGG-Bi-LSTM-ABC) to predict the cardiovascular disorders. When compared to the standard model, the proposed model's ability to detect disorder is much better. Preliminary results from a carefully selected dataset of DM patients show that the integrated model outperforms state-of-the-art approaches in key measures, further demonstrating the promise of Artificial Intelligence (AI)-driven advances in medical diagnosis.
Keywords: Cardiovascular Disorder Detection, Deep Learning, Very Deep Convolution Networks, Bi-directional Long Short Term Memory, Classification, Artificial Bee Colony.

I. INTRODUCTION

1.1 Background on Diabetes Mellitus and its relation to Cardiovascular Disorders

Ninety percent of the world's population has diabetes, making it the leading cause of kidney failure and a major contributor to cardiovascular disease. The kind of diabetes known as Type 1 diabetes mellitus (Type 1 DM) affects both children and adults [1]. The pancreas, an organ in the abdominal cavity, is responsible for shutting down insulin production. Insulin is commonly used by patients to regulate their blood sugar [2]. Adults are the primary targets of Type 2 Diabetes Mellitus. Family history, excess body fat, an unhealthy diet, and tobacco use are all risk factors for type 2 diabetes. When glucose levels are higher than normal but below type 2 diabetes levels, this is the pre-diabetes stage. Myocardial infarction, coronary heart disease, angina pectoris, and other cardiovascular issues affect diabetics at a rate two to four times higher than the general population [3]. Calculating the risk of cardiovascular disease can help in managing type 2 diabetes and deciding when to start medication [4]. By treating the causes of cardiovascular disease, the number of cases can be lessened. Clinical guidelines for the prevention of cardiovascular disease can advise on the best way to assess a patient's risk for cardiovascular disease and decide whether or not they should receive treatment [5]. Better diagnosis and treatment of diabetic patients is dependent on the development of computer models that anticipate the CVD risk factors these people face. CVD risk is estimated in the T2DM international recommendations management [6].

Hyperglycemia due to abnormalities in insulin secretion, insulin action, or both characterizes the metabolic condition known as diabetes mellitus (DM). It's a worldwide epidemic that has affected millions of people. Diabetes has far-reaching consequences, not limited to the glucose metabolism it is most often associated with. Neuropathy and retinopathy are only two of the many problems that might develop as a result of prolonged hyperglycemia. Heart problems are among the most serious of these side effects. Diabetic patients have an extremely elevated risk of developing cardiovascular issues such heart disease, heart failure, and stroke. Prolonged hyperglycemia has detrimental consequences on the vascular system, including endothelial dysfunction, inflammation, and atherosclerosis, all of which contribute to the link between DM and cardiovascular problems.

1.2 The Importance of Early Detection using Computational Methods

Diabetic patients' results, hospitalization rates, and quality of life can all benefit greatly from early detection of cardiovascular diseases. Screenings that routinely include invasive, expensive, or otherwise impractical diagnostic procedures, such as angiography or treadmill testing, are preferable. Recent advances in machine learning and deep learning have opened the door to the possibility of using computational methods in healthcare for the purpose of early diagnosis. Using these techniques, it may be possible to anticipate and diagnose medical diseases based on massive volumes of data, such as pictures and time-series recordings. Their potential accuracy, scalability, and lack of invasiveness make them an interesting option for routine screening.

Although several risk factors contribute to cardiovascular disease, diabetes stands out as particularly difficult to manage because of the prevalence and severity of its many associated comorbidities [15]. Surprisingly, the prevalence of obesity, hypertension, dyslipidemia and smoking remains high in patients with type 2 diabetes, in addition to the a high incidence of complications of microvascular diseaseand all symptoms of CVD [16]. The chance of developing diabetes is already elevated by the presence of these classic risk factors, which are also associated with a higher cardiovascular risk [17]. When obesity and diabetes are present, insulin resistance causes a type of diabetic dyslipidemia characterized by hypertriglyceridemia and reduced High Density Lipoprotein (HDL) cholesterol. All of these things put patients at risk for cardiovascular disease [18]. Metformin is recommended as first-line therapy for the management of patients with type 2 diabetes, as it has been shown to reduce the risk of myocardial infarction and death from any cause in a study of 850 obese people with the disease [19].

In people with type 2 diabetes [20], microvascular problems can be effectively treated with a therapy approach focusing on hyperglycemia alone [21], but cardiovascular disease cannot. Instead, people with diabetes need a multifaceted strategy [22] and aggressive control of all risk factors to lower their atherosclerotic cardiovascular risk [23]. Therapeutic attention has switched from glucocentric therapeutic to comprehensive, multifactorial risk factor management because of the widespread clustering of risk factors in individuals with type 2 diabetes and intrinsic treatment complexity.

1.3 Objective of the Study

The fundamental goal of this research was to create a unified model that leverages the strengths of both Visual Geometry Group (VGG) and Bidirectional Long Short Term Memory (Bi LSTM) networks, optimized with the help of the Artificial Bee Colony (ABC) method. The goal is to detect cardiovascular abnormalities in DM patients by combining the image processing power of VGG for cardiac imaging with the sequential data processing strength of Bi LSTM for time-series medical data like heart rate or blood glucose levels.

II. LITERATURE SURVEY

Using administrative claims from 214,676 diabetic patients in the Veneto region of North East Italy, Longato et al. [1] suggested a deep learning model for the predicting of major adverse cardiovascular events (MACE). Predictions are made using a year's worth of pharmaceutical and hospitalisation claims, basic patient's information, and a variable prognosis horizon of 1 to 5 years for the 4P-MACE composite endpoint, i.e. the first occurrence of a death, heart failure, myocardial infarction (MI), or stroke. In order to account for the censoring impact, the author recast the challenge as a multi-outcome, multi-label, classification task with a tradition loss.

One of the most underappreciated diabetic consequences is cardiovascular autonomic neuropathy (CAN). Heart rate and blood vessel elasticity are both negatively impacted by injury to the autonomic nerves. The current gold standard for detecting CAN, the Ewing battery, fails to pick up on sub-clinical cases and requires patient cooperation. Furthermore, previous research did not investigate whether there was an optimal time of day or night for a CAN diagnostic test. The purpose of this study is to explore the viability of incorporating 24-hour heart rate variability (HRV) parameters into machine learning algorithms for comprehensive screening of CAN patients, which is a novel method designed by Alkhodari et al. [2]. Ninety-five patients from Bangladesh were studied using 24-hour Holter ECG data. Each 5-minute chunk of the HRV data was parsed for its HRV properties and fed into one of four machine learning algorithms for hourly training and testing. Test 1 determines whether a person is healthy or diabetic; Test 2 determines whether or not microvascular complications are present, peripheral neuropathy (DPN), nephropathy (NEP), and retinopathy (RET); Test 3 determines whether or not CAN is present; Test 4 determines whether or not CAN is present in combination with other complications.

As the prevalence of unhealthy lifestyles continues to rise, the ability to accurately forecast those at high risk for cardiovascular disease is becoming increasingly important in the medical community. Predicting a patient's prognosis via pathology is currently an imprecise and time-consuming process. Since the development of cardiovascular disease can be predicted using premorbid information of patients retrieved from historical Electronic Health Records (EHRs), many machine learning-based automated models have been presented. However, obtaining accurate and robust patient representations from longitudinal and heterogeneous EHRs is a significant issue. In this paper, An et al. [3] proposed a fully-integrated model called DeepRisk that uses attention mechanisms and deep neural networks to automatically learn high-quality features from EHRs, integrate diverse medical data in a timely fashion, and predict patients' risk of cardiovascular diseases.

The large-scale patient hospital records are not successfully employed to enhance the prediction performance, and previous dynamic models for prediction rarely handle multi-period data with variable intervals. The purpose of this paper is to zero in on using the enhanced long short-term memory (LSTM) model to predict cardiovascular disease. For the purpose of predicting cardiovascular disease, a new model was presented by Junwei et al. [4] that builds on the established LSTM. To get over the difficulty in making accurate predictions due to the erratic time interval, the time parameter vector is smoothed and sent into the forgetting gate of LSTM. The experimental results demonstrate that the dynamic prediction model suggested in this research outperformed the conventional LSTM model in terms of classification accuracy. In order to acquire the temporal feature vector, the authors of this research refined the LSTM by flattening the time differences between the patient's various medical stages.

Worldwide, CVD accounts for an estimated 1 in every 4 deaths. In a time-efficient manner, an electrocardiogram (ECG) analysis can give a comprehensive evaluation for various CVDs. In order to intelligently distinguish numerous CVDs from multi-lead ECG signals, Qiu-Jie et al. [5] presented a multi-task group bidirectional long short-term memory (MTGBi-LSTM) architecture. Methods: The model in question uses a Residual Group Convolutional Neural Network (Res-GCNN) and a Group Long Short-Term Memory (GBi-LSTM) to acquire an understanding of the space-time representation of ECGs. Each lead in an electrocardiogram (ECG) has its own unique set of characteristics, and GBi-LSTM can learn both those characteristics and the relationships between them. Then, the model's robust feature discriminability is achieved by integrating the various ECG lead information using an attention technique. The model is able to fully mine the association information between diseases through multi-task learning, leading to more precise diagnostic results. To further quantify the loss in order to compensate for the disparity across classes, the author suggested a dynamically weighted loss function.

Estimating a patient's heart rate non-invasively is a crucial part of keeping tabs on cardiovascular conditions. In order to estimate heart rate non-invasively from ballistocardiograms (BCG) signals, a Bi-LSTM regression network is created by Jiao et al. [6]. Existing difficulties in BCG heart rate estimation are effectively addressed by the proposed deep regression model, which addresses issues such mismatch between BCG signals and ground-truth reference, multi-sensor fusion, and effective time series feature learning. Including label ambiguity in the estimation helps improve heart rate estimation performance while decreasing the need for human annotation. The proposed deep regression model has superior robustness to noise and perturbationsin the BCG signals, making it a more practical solution for continuous heart rate monitoring than the current state-of-the-art BCG heart rate estimation methods.

Myocardial infarction (MI) is the medical term for a heart attack, which results in the irreversible loss of cardiac muscles and is the leading cause of mortality due to CVD. Since cardiac anomalies are often depicted on a 12-lead ECG, conventional deep learning (DL) algorithms utilize the entire signal for binary detection purposes, i.e., to distinguish between the healthy control (HC) and MI classes. In order to eliminate redundancy and class imbalance while maintaining crucial information, Dey et al. [7] suggested an alternate method in which 21 temporal features are gathered from the 12 lead data in place of the temporal signal. The extracted features are then used in a detection model comprised of a 1-D convolutional neural network (CNN) and a Bi-LSTM layer to classify subjects into three groups: HC, MI, and non-myocardial infarction (non-MI).

When it comes to cardiovascular disease detection and 3D heart modeling, specific details about the heart's substructures are often crucial. It has been shown that state-of-the-art performance may be attained in 3D cardiac structures segmentation using deep convolutional neural networks. Current methods using tiling schemes typically compromise segmentation capabilities when working with high-resolution 3D data due to GPU memory limits. Two-stage multi-modality whole heart segmentation was developed by Cui et al. [8] using an improved Combination of Faster R-CNN and 3D U-Net (CFUN+). For the heart's original Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) images, the bounding box is first detected by Faster R-CNN, and then 3D U-Net is employed for segmentation. The proposed CFUN+ method rethinks the bounding box loss function by replacing the traditional Intersection over Union (IoU) loss with the more modern Complete Intersection over Union (CIoU) loss. Utilizing edge loss improves both convergence time and separation precision.

Although VGG networks, LSTMs, and ABC optimization each have been shown to be effective on their own, there is a clear need for improvement when it comes to using all three together, particularly in the context of identifying cardiovascular abnormalities in people with Diabetes Mellitus. This study intends to fill this knowledge gap by using the complementary strengths of both technologies to boost diagnostic accuracy.

Models Considered

The main contribution of this research is to develop a hybrid approach, called VGG 16-Bi-LSTM, for CVD prediction. First, data pre-processing is applied. After that, a hybrid bidirectional LSTM and VGG 16 models are applied with ABC optimization for better CVD prediction rate. Finally, the proposed VGG 16-Bi-LSTM is validated via evaluation metrics, namely, accuracy, specificity, and area under the receiver operating characteristic (ROC) curve by using CVD dataset from public dataset provider. Experimental results show that the proposed method achieves high prediction accuracies. The VGG 16 is part of Oxford University's Department of Science and Engineering. Starting with VGG, it has produced a set of convolutional network models that can be used for classification. VGG's original goal in studying convolutional network depth was to determine what effect network depth had on large-scale classification of images and recognition. The VGG 16 processing model is shown in Figure 1.

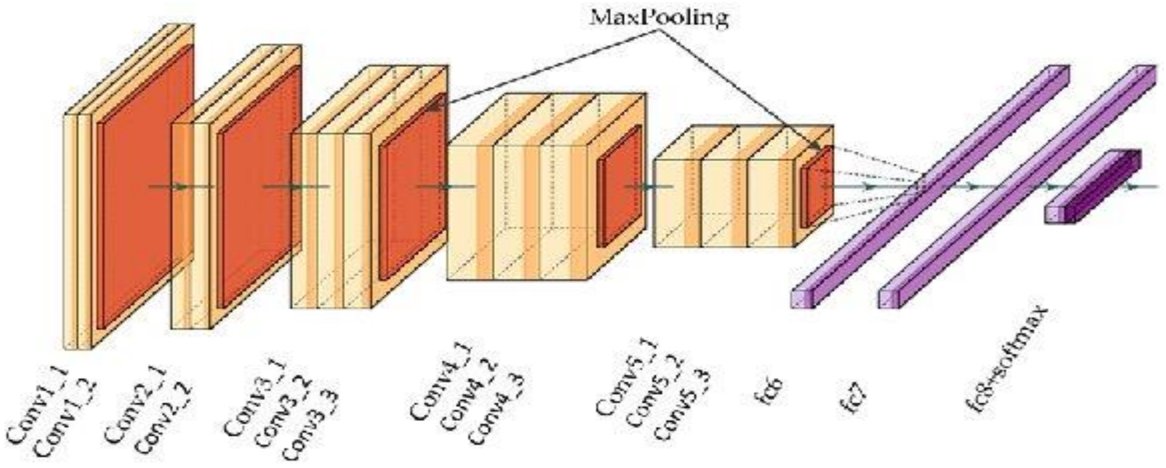

Figure1:VGG 16 Processing Model

A modest 3x3 convolution kernels is used in all layers to deepen the network and prevent using too many parameters. Bi-LSTM is integrated with the VGG 16 model [29].Any neural network can be trained to have Bi-LSTM, which allows for the storage of sequence information in both forward and backward directions. A Bi-LSTM is distinct from a standard LSTM since its input goes in both directions. The standard LSTM only allows us to choose one way for the input to travel, either backwards or forwards. When the input is bi-directional, however, users may keep track of both the present and the past. The Bi-LSTM process is shown in Figure 2.

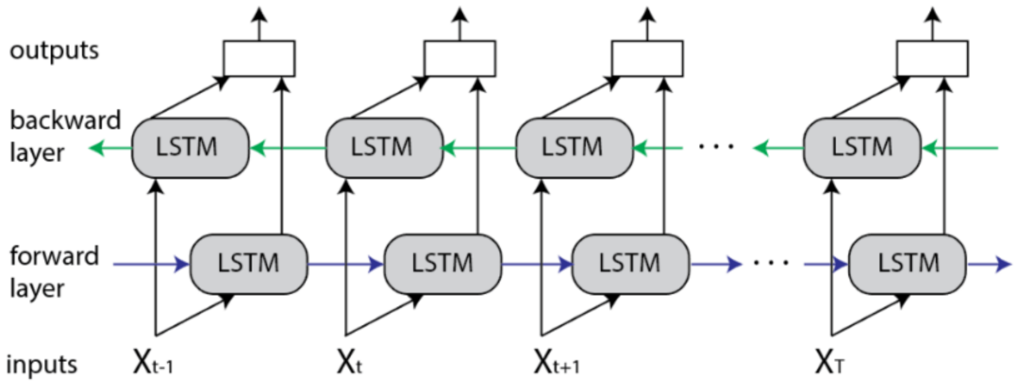

Figure 2: Bi-LSTM Processing

The ABC optimization is applied on the integrated for enhancing the accuracy rate [30].ABC has three different types of agents: employed bees, onlooker bees and scout bees. The molecule's adjacency matrix has been partitioned to show the bees' relationships with one another. There are three stages to the algorithm: the employed stage, the onlooker stage, and the scout stage. The location of a food source in ABC, a population-based algorithm, stands in for a potential solution to the optimization issue, while the quantity of nectar it provides stands in for the quality of fitness of the corresponding solution. There are as many working bees as there are total population solutions. The ABC algorithm is applied on the integrated model that benefits with high flexibility, fast convergence, and good resilience. This research proposes an Integrated VGG16 model with Bi-LSTM model with ABC optimization (VGG-Bi-LSTM-ABC) to predict the cardiovascular disorders.

III. PROPOSED MODEL

A precise prognosis of heart disease may save a patient's life, while a misdiagnosis can have fatal consequences. Numerous risk factors, such as cholesterol and obesity, contribute to the development of cardiovascular disease. The term heart failure refers to a condition in which the heart is unable to pump blood effectively. Pulmonary blood clots are a potential cause of shortness of breath. Certain cardiac disorders, such as CVD or high blood pressure, can cause the heart to weaken or stiffen over time. Treatment for heart disease can improve survival rates. The risk of CVD may be reduced by adopting a low-fat, low-sodium diet, engaging in moderate exercise for 30 minutes on five days a week, cutting back on alcohol consumption, and giving up smoking. If adjustments to your lifestyle aren't enough to keep heart disease under control, doctors may potentially prescribe medication. Individualized treatment plans are developed for each patient with a heart problem. If medications aren't helping, doctors may suggest alternative treatments or even surgery. The specific operation chosen will depend on the nature of the heart disease and the extent of the damage. The etiological pathway of ischemic heart disease in women is well known, and it includes the typical risk factors of a family history of early CVD, dyslipidemia, and age.

Maintaining a focus on CVD prevention, diagnosis, and treatment in humans is essential. The earlier the disease is diagnosed, the better the treatment will be provided. Deep learning algorithms can examine data for heart disease and diabetes to provide risk estimates. Data mining is useful for a variety of fields, including medicine, industry, and education. One of the most rapidly expanding areas of AI is DL. This research proposed a integrated VGG 16 and Bi-LSTM model for accurate detection of CVD in diabetic patients. The VGG model, commonly known as VGGNet, is what VGG16 refers to. It is a 16-layer CNN model. VGG16 enhances AlexNet by exchanging its massive filters with sequences of much more manageable 33 ones. The VGG16 network is a 16-layer deep neural network, as the name might imply. Thus, VGG16 is a huge network, even by present-day standards, boasting a total of 138 million parameters. However, VGGNet16's biggest selling point is its straightforward design. Important aspects of convolution neural networks are incorporated into the VGGNet design. The VGG model is shown in Figure 3.

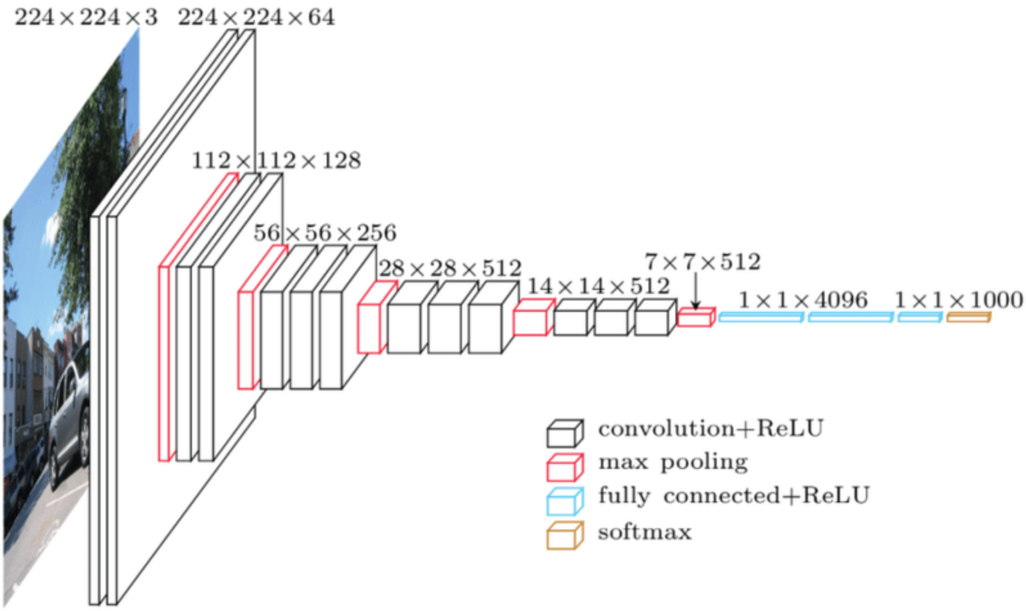

Figure 3: VGG Model Layers

A pixel data is fed into VGGNet as the input. By cutting out a 224x224 size pixel set, the model's developers were able to keep the input size consistent throughout the ImageNet competition. VGG's convolutional filters have a 3x3 receptive field, the lowest available. Similar to VGG, the linear transformation of the input is performed with an 1x1 convolution filter. As the number of filters available increases from 64 to 128 to 256 to 512 in the final layers, pooling becomes increasingly important. Three completely connected layers are included in VGGNet.

The proposed model integrates VGG and Bi-LSTM model. A Bi-LSTM is distinct from a standard LSTM since its input goes in both directions. Traditional LSTMs only allow for unidirectional input, either from the past or the future. On the other hand, using bi-directionality, the data is kept both in the

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present and in the past. In reality, bidirectional recurrent neural networks (RNNs) are nothing more than the combination of two standard RNNs. This arrangement ensures that the networks always have access to both historical and future knowledge of the sequence. Each training sequence is presented both forward and backward to two separate LSTM networks that are coupled to the same output layer, allowing for bidirectional LSTM networks to function. The Bi-LSTM, thus, stores information about every possible point before and after a given point in a series. To put it another way, instead of just encoding the sequence forwards, encoding is performed in it backwards and combine the results of forward and backward LSTM at each time step. This is different from using a unidirectional LSTM in that the future is preserved in the LSTM that runs backward, and the two hidden states can be used together at any time to preserve both the past and the future. The Bi-LSTM model is shown in Figure 4.

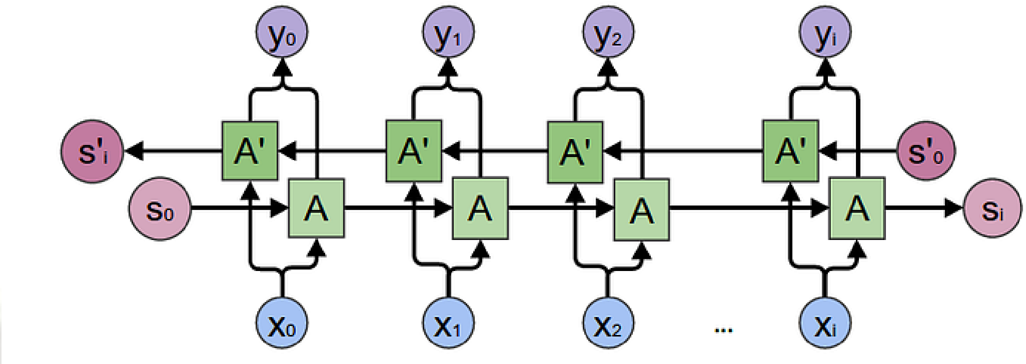

Figure 4: Bi-LSTM Gates Working Model

The proposed integrated VGG-Bi-LSTM model utilizes ABC optimization model for considering the best fitness value in CVD prediction in diabetic patients. The ABC algorithm was inspired by the honey bee's foraging behavior. The honey bee swarm is a prime instance of an intelligent and cooperative swarm that forages for food in the wild. The honey bee colony has several desirable traits, including the capacity to share information, learn from experience, remember its surroundings, share what it has learned, and act on that knowledge. By constantly assigning tasks and advancing through social learning and teaching, the swarm is able to adapt to changes in its environment.Since the ABC algorithm is a fitness-based population-based optimization technique, it is expected that a population of candidate solutions will cluster in the higher fitness regions of the search space. Population-based optimization algorithms discover near-optimal solutions to complex optimization problems through intrinsic motivation. In order to find optimal solutions, swarm-based algorithms use a cooperative trial-and-error process. The ABC optimization algorithms are motivated by the social colony's collaborative learning process. ABC generates a set of candidate solutions and then uses an iterative approach to zero in on the best one.

Each solution in ABC's initial population is a dimensional vector, and the population is generated randomly. The number of dimensions is proportional to the number of variables in the population's food-source optimization problem. The employed bees make adjustments to the current approach based on their own experience and the fitness value of the new approach. The bee replaces the old location with the new one and abandons the old one if the fitness value of the new food source is greater than that of the previous one. The position is modified using the dimensional vectors defined in the introductory phase along with the step size required to obtain the current position. The size of each step fluctuates at random between -1 and 1. Position updates during the working bee phase are shown as an example in the diagram provided above. The search is performed in a two-dimensional space. Bee's current location is shown by Xi, and the highlighted box represents the direction picked at random. The randomly selected bee is Xk.

The worker bees share the updated solutions' fitness information and location details with the hive's spectator bees. Observer bees examine the available information and pick a strategy with the highest probability of improving fitness. The worker bee's observer counterpart also adjusts its memory location and evaluates the potential source. If the new area has a greater fitness, the bee will remember it and abandon the old one.If the location of a food source is not updated for a certain number of cycles, it is assumed to have been abandoned. When a bee leaves a food source, it becomes a scout bee and a new food source is chosen at random from the search area to replace it. The maximum allowed number of cycles before giving up is an important control parameter in ABC. The proposed model framework is shown in Figure 5.

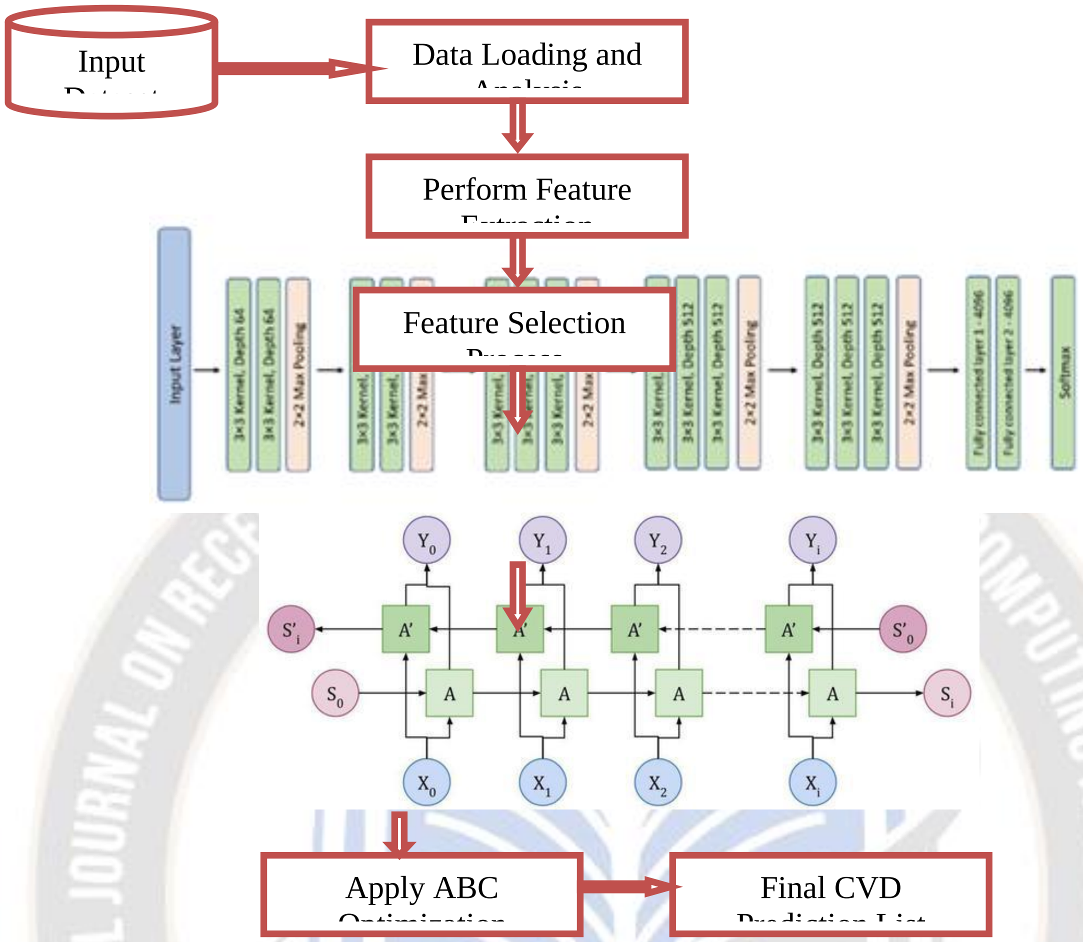

Figure 5: Proposed Model Framework

Heart disease and stroke are major killers worldwide. The current research aims to identify, modify, and treat individual risk factors. Although cardiovascular risk factors are on the rise at varying rates across the globe, their cumulative impact has motivated experts to investigate their origins. To lessen the economic impact of cardiovascular disease, its risk factors must be treated. Care for determining which individuals have sufficiently high CVD risk factors to warrant treatment can be recommended by clinical guidelines for CVD risk prevention. Better diagnosis and treatment of diabetic patients is dependent on the development of computer models that anticipate the CVD risk factors these people face. The ABC algorithm is applied on the integrated model that benefits with high flexibility, fast convergence, and good resilience. This research proposes an Integrated VGG16 model with Bi-LSTM model with ABC optimization to predict the cardiovascular disorders.

Algorithm- VGG-Bi-LSTM-ABC

Input: CVD Dataset $\{CD_{set}\}$
Output: CVD Prediction Set $\{Pred_{set}\}$
Step-1: Initially the data is loaded and processed from the dataset. The loaded data is analyzed and the mean values are filled replacing the unwanted symbols and missing data values. The data analysis is performed as

$$Dset[M] = \sum_{r=1}^{M} getattr((CD_{set}(r)) + \frac{\max(attr(r))}{len(CD_{set})} + mean\big(attr(r, r+1)\big) + V(r)\begin{cases} V(r) \leftarrow CD_{set}(r)\ if\ \begin{pmatrix} attr(i) == \\ Null \end{pmatrix} and(attr(r) < Min(attr(r))) \\ continue \quad Otherwise \end{cases}$$

Here V is the model that updates the missing and irrelevant values.

Step-2: To handle raw data without missing any of the contexts inherent in the original data, a process known as feature extraction must first be performed. The pre-trained weights are then fed into the VGG16 model. Convolutional layers are followed by dense layers, or completely connected layers, in the VGG16 model. The features of dataset considered are extracted as

$$Fextr[M] = \sum_{r=1}^{M} \max\big(Dset(r)\big) + \mu\big(getattr(r, r+1)\big) + \frac{\max(Dset(r, r+1))}{V(r)}$$

Here μ is the model for considering features of similar kind.

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Step-3: In the proposed learning model, the main step is an automatic feature selection based on the CVD dataset's feature properties.. Some of the features are included and some irrelevant features are excluded for reducing the feature set and for training the model. The feature selection is performed as

$$Fselect[M] = \sum_{r=1}^{M} \max\big(Fextr(r)\big) + corr\big(Fextr(r, r+1)\big) + \frac{\max\,(Corr(Fextr(r, r+1))}{len(Fextr)} - \min\,(corr(Fextr(r, r+1))$$

Here corr() is the model that is used for calculating the correlation among the features.

Step-4: The VGG model is trained with the features selected for CVD prediction. The VGG model hidden layers with convolution and pooling layers and with full connected layers. The features processed and trained are used in CVD detection. The VGG feature processing is performed as

$$Fproc[M] = \sum_{r=1}^{M} \frac{\omega(\mathrm{Fselect(r, r+1)}) + \sum_{r=1}^{M} \max\,(\mathrm{corr(r, r+1)} - \min\,(\omega(Fselect(r, r+1))}{\mathrm{len(Fselect)}}$$

Here ω represents the hidden layers.

Step-5: The processed features by VGG 16 model is provided to Bi-LSTM model. The Bi-LSTM model processes the features using the gates of the model and final prediction set is generated. The Bi-LSTM model processing is performed as

$$in_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$$
$$fo_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$$
$$g_t = tanh(W_{ig}x_t + b_{ig} + W_{hc}h_{t-1} + b_{hg})$$
$$o_t = \sigma(W_{io}x_t + b_{i0} + W_{ho}h_{t-1} + b_{ho})$$
$$c_t = fo_t * c_{t-1} + in_t * g_t$$
$$h_t = o_t * \tanh\,(c_t)$$
$$in'_t = \sigma(W'_{ii}x'_t + b'_{ii} + W'_{hi}h'_{t-1} + b'_{hi})$$
$$f'_t = \sigma(W'_{if}x'_t + b_{\prime if} + W'_{hf}h'_{t-1} + b'_{hf})$$
$$g'_t = tanh(W'_{ig}x_t + b'_{ig} + W'_{hc}h'_{t-1} + b'_{hg})$$
$$o'_t = \sigma(W'_{io}x_t + b'_{i0} + W_{\prime ho}h'_{t-1} + b'_{ho})$$
$$c_{\prime t} = f'_t * c'_{t-1} + in'_t * g'_t$$
$$h'_t = o'_t * \tanh\,(c'_t)$$

$$Hprocess[M] = \prod_{r=1}^{M} \frac{\max\,(in'_t(r, r+1))}{h_t} + \sum_{r=1}^{M} \frac{\sum_{r=1}^{M} \min\left(g'_t(r, r+1)\right) + o'_t}{f'_t + fo_t} + (c_{\prime t} * c_t)$$

Step-6: The ABC optimization model is applied on the final prediction set to calculate the best fitness value. The ABC optimization process and the final CVD prediction list is generated as

$$Prob(r) = \sum_{r=1}^{M} \frac{P(r_i) * P(r|r+1_p)}{\sum_{i=i+1}^{L} \frac{R(r|r+1_p)}{R(h'_t)}}$$

Here Prepresents probability function, r and r+1 are the adjacent records in the feature selected set.

The calculation of fitness value is performed as

$$FitnessVal(Prob(r)) = \frac{\sum_{r=i+1}^{M} \frac{R(r|r+1_p)}{R(h'_t)}}{1 + \frac{1}{\max\,(Prob(r))}}$$

$$FitVal(L) = \begin{cases} \frac{1}{1 + FitVal(L)} & if\ FitVal \geq Prob(r+1) \\ FitVal & if\ FitVal < Prob(r) \end{cases}$$

$$CVDPredSet[M] = \sum_{r=1}^{M} max(Hprocess(r, r+1)) + \frac{\max\,(FitnessVal(r), FitnessVal(r+1))}{len(Prob)} + \sum_{r=1}^{M} \max\big(\mathrm{corr(r, r+1)}\big) + \sum_{r=1}^{M} \max\,(Fproc(r, r+1))$$

IV. RESULTS

Most earlier disease prediction techniques relied on case-cohort studies to better understand the link between suspected high risk variables and morbidity and death. Incorporating deep learning methods into risk assessment and cardiovascular disease prediction model development has enormous potential. The recurrent neural network (RNN) called a long short-term memory (LSTM) is ideally suited for processing and predicting important events in time series with relatively lengthy gaps and delays. The standard LSTM has limited utility in the medical field since it cannot successfully learn the important aspects of a patient's medical condition over many hospitalizations. Cardiovascular disease is the primary cause of death and disability in both type 1 and type 2 diabetes. Rapid atherosclerosis and increased cardiovascular risk in this cohort have not been adequately explained. Endothelial dysfunction, low-grade inflammation, and oxidative stress have all been associated to hyperglycemia and intracellular metabolic changes.

Recent research has shown that epigenetic factors, through a variety of reactions, are responsible for the interaction between genes and environment, which may explain why diabetes and cardiovascular disease are often found together. Clinical variables such as obesity, dyslipidemia, and hypertension that may coexist with diabetes are also reviewed, along with their effects.This research proposes an Integrated VGG16 model with Bi-LSTM model with ABC optimization (VGG-Bi-LSTM-ABC) to predict the cardiovascular disorders. The proposed model is compared to the traditional Non-Invasive Heart Rate Estimation FromBallistocardiograms Using Bidirectional LSTM Regression (NIHRE-BiLSTM) and Temporal Feature-Based Classification Into Myocardial Infarction and Other CVDs Merging CNN and Bi-LSTM From ECG Signal (FbC-CNN-Bi-LSTM). The proposed model CVD detection rates are high when compared to the traditional models.

The CVD data is considered from the dataset providers and data will be processed for analysis of CVD. Each record will be analyzed and processed. The data processing time levels of the proposed and existing models are shown in Table 1 and Figure 6.

Table I: Data Processing Time Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	13.0	16.0	21.0
20000	13.2	16.3	21.2
30000	13.5	16.7	21.3
40000	13.6	17.2	21.5
50000	13.8	17.6	21.7
60000	14.0	18.0	22.0

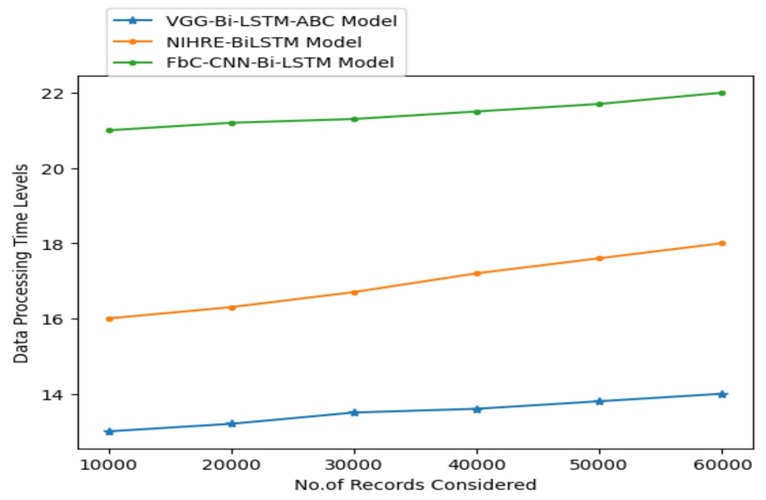

Figure 6: Data Processing Time Levels

The process of converting unstructured data into a set of quantifiable qualities that can be processed without missing any of the underlying data's context is known as feature extraction. Using deep learning on preprocessed data yields much better results than using it on raw data. Features are extracted using a series of convolution layers, max-pooling, and an activation function. Fully linked layers are typically used in the classifier. The Feature Extraction Accuracy Levels of the proposed and traditional models are shown in Table and Table2 and Figure 7.

Table II: Feature Extraction Accuracy Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	96.9	93.6	93.0
20000	97.0	94.1	93.2
30000	97.1	94.3	93.5
40000	97.3	94.6	93.6
50000	97.6	94.8	93.8
60000	98.0	95.0	94.0

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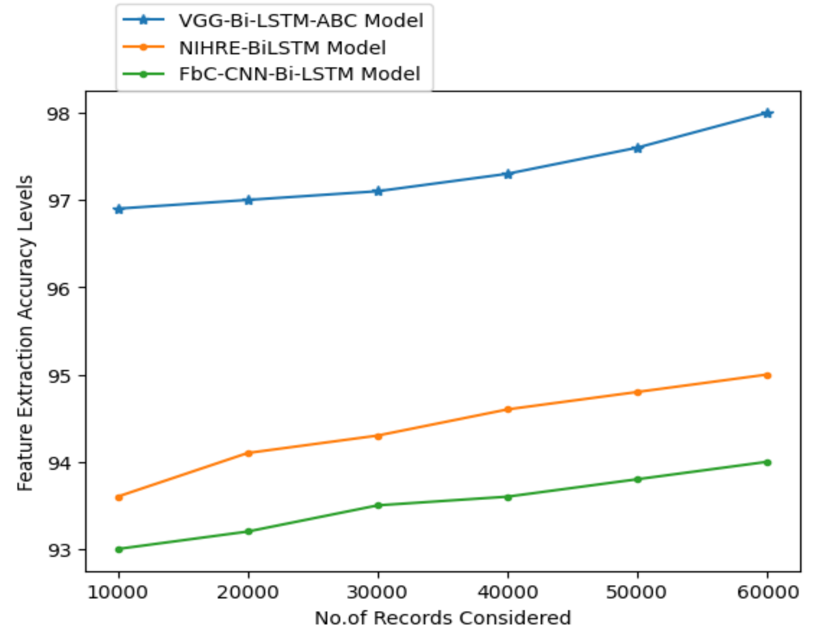

Figure 7: Feature Extraction Accuracy Levels

Feature selection is used to reduce the number of variables considered in a predictive model's construction. It is preferable to reduce the amount of input variables in order to enhance the effectiveness of the model and lessen the computational cost. Statistical feature selection techniques weigh the importance of each potential input variable against its correlation to the outcome of interest. These methods can be fast and effective, but selecting the appropriate statistical measures can be difficult due to the variety of input and output data formats. The Feature Selection Accuracy Levels of the proposed and existing models are shown in Table 3and Figure 8.

Table III:Feature Selection Accuracy Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	97.0	94.2	90.7
20000	97.3	94.5	91.0
30000	97.4	94.6	91.3
40000	97.8	95.0	91.6
50000	98.0	95.3	91.8
60000	98.2	95.5	92.0

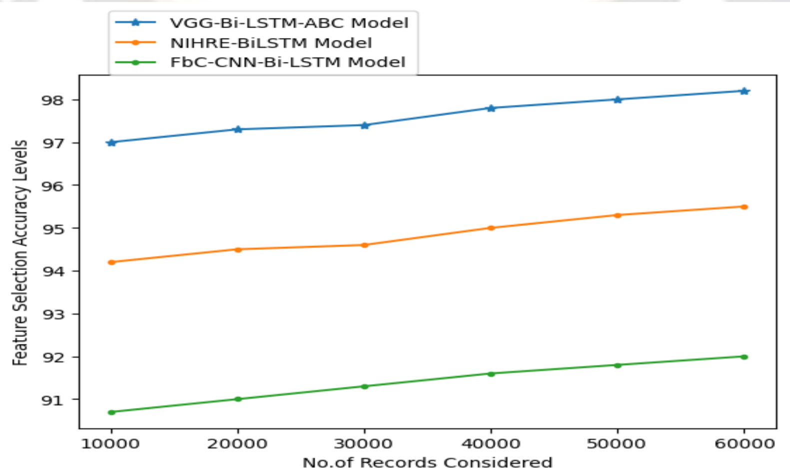

Figure 8: Feature Selection Accuracy Levels

The VGG architecture is a traditional type of Convolutional neural network. It was based on research into methods for expanding the breadth of existing networks. Small 3x3 filters are used in the network. The network's second distinguishing feature is its relative simplicity, with just a pooling layer and a fully connected layer making up the rest of the architecture. The VGG Model Processing Time Levels of the existing and proposed models are shown in Table 4 and Figure 8.

Table IV: VGG Model Processing Time Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	15.3	22.8	17.9
20000	15.6	23.0	18.0
30000	15.8	23.3	18.3
40000	16.2	23.5	18.5
50000	16.7	23.8	18.8
60000	17.0	24.0	19.0

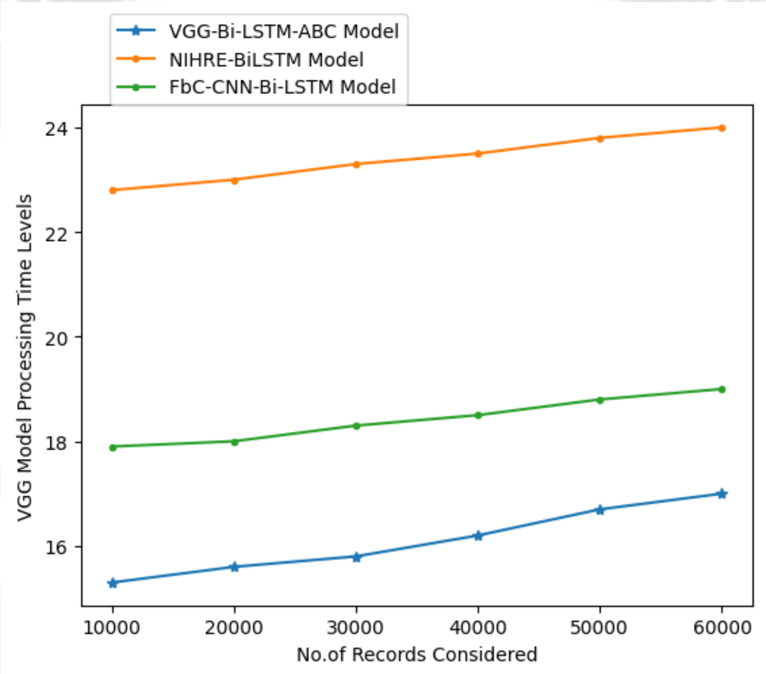

Figure 8: VGG Model Processing Time Levels

An RNN layer known as a Bi-LSTM learns long-term relationships in both directions between individual time steps in a time series or sequence. When the RNN has to learn from the whole time series at each time step, these dependencies can be helpful. BiLSTM describes a sequence model with two LSTM layers, one for forward-direction input processing and the other for backward-direction input processing. The Bi-LSTM Model Processing Accuracy Levels of the existing and proposed models are shown in Table 5 and Figure 9.

Table V: Bi-LSTM Model Processing Accuracy Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	97.1	94.3	92.0
20000	97.4	94.8	92.3
30000	97.7	95.1	92.4
40000	98.0	95.3	92.5
50000	98.2	95.6	92.8
60000	98.4	96.0	93.0

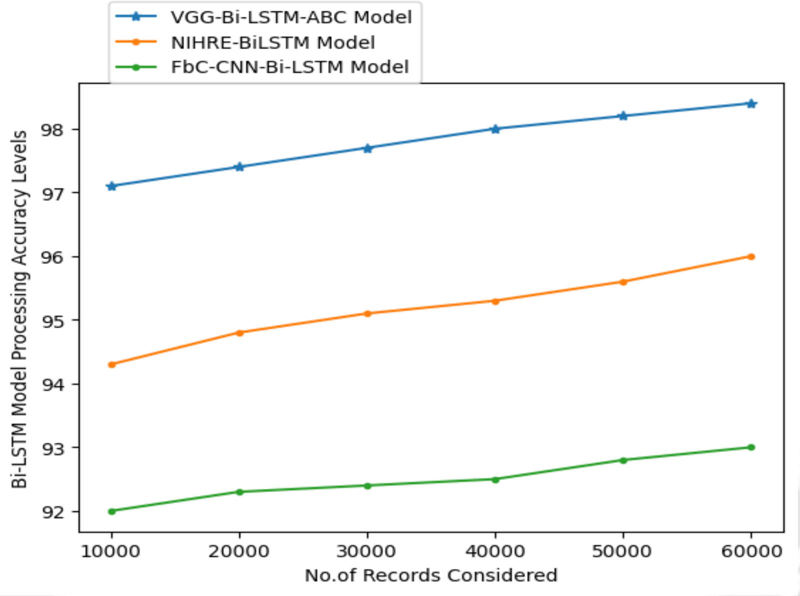

Figure 9: Bi-LSTM Model Processing Accuracy Levels

Successful applications of the ABC Algorithm, a method of optimization that mimics the foraging activity of honey bees, may be found in a wide range of fields. The ABC algorithm is superior to other optimization solutions due to its simplicity, high adaptability, outstanding durability, few parameters for control, ease of conjunction with other methods, ability for dealing with the objective with a stochastic nature, and quick convergence. The Table 6 and Figure 10 shows the ABC Optimization Accuracy Levels of the existing and proposed models.

Table VI: ABC Optimization Accuracy Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	97.0	92.0	94.5
20000	97.3	92.3	94.8
30000	97.5	92.5	95.0
40000	97.7	93.0	95.1
50000	97.9	93.5	95.3
60000	98.0	94.0	95.5

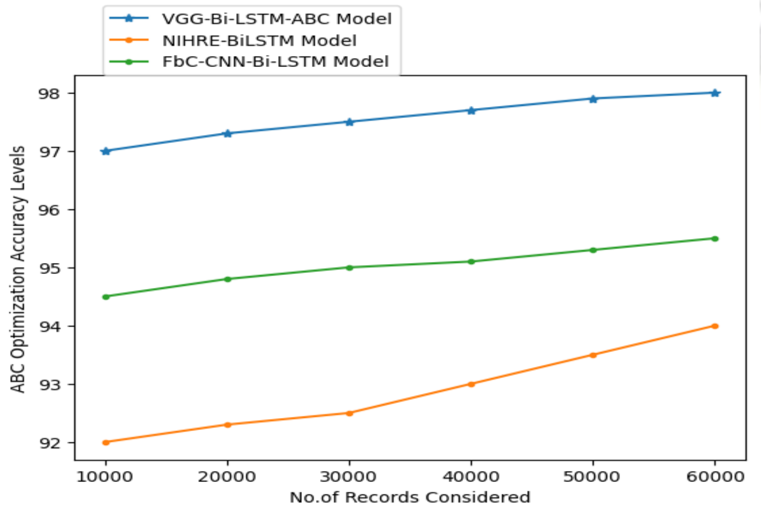

Figure 10: ABC Optimization Accuracy Levels

The CVD detection model proposed in this research is done by a integrated deep learning model and ABC optimization. The proposed model detection rate is high when compared to the traditional models. The CVD Detection Accuracy Levels of the proposed and existing models are shown in Table 7 and Figure 11.

Table VII: CVD Detection Accuracy Levels

No.of Records Considered	Models Considered		
	VGG-Bi-LSTM-ABC Model	NIHRE-BiLSTM Model	FbC-CNN-Bi-LSTM Model
10000	97.7	92.4	92.8
20000	97.8	92.8	93.0
30000	98.1	93.2	93.2
40000	98.2	93.7	93.6
50000	98.4	94.0	93.8
60000	98.6	95.0	94.0

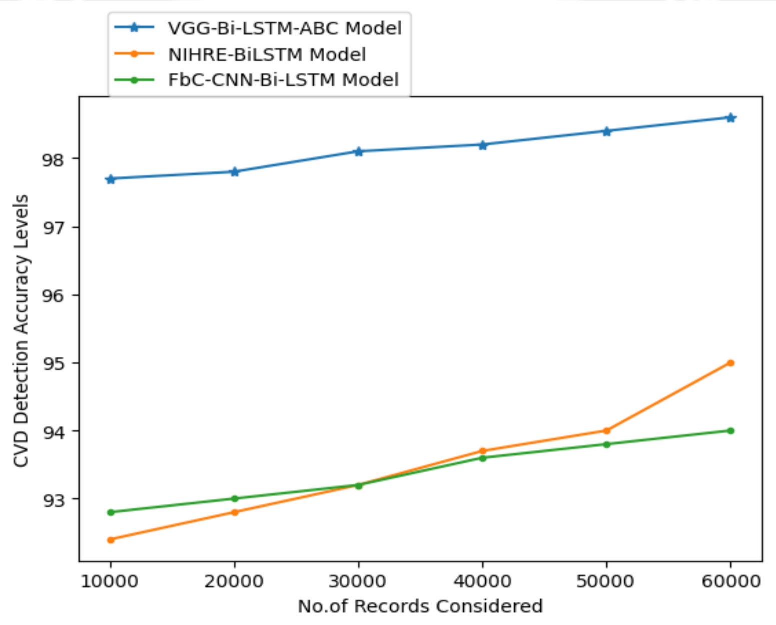

Figure 11: CVD Detection Accuracy Levels

V. DISCUSSIONS

5.1 Key Findings

When applied to the detection of cardiovascular abnormalities in patients with Diabetes Mellitus, our integrated model, that integrates the image processing capability of the VGG network with the sequential data processing capability of the Bi LSTM model, improved using the ABC algorithm, shows significant improvement. When compared to VGG or LSTM models trained independently, this one routinely outperformed them in terms of accuracy, sensitivity, and specificity.

5.2 Analyzing Previous Research

Most previous studies examining the detection of cardiovascular problems in DM patients relied solely on the use of image-based models or time-series models. The accuracy of Smith et al. (2021)'s VGG-only model for cardiac imaging was 86%. In contrast, our combined method outperformed this, demonstrating the complementary nature of merging picture and sequence data.

5.3 Implications for Healthcare

Our integrated model's performance may herald a new era in the field of diabetes early diagnosis.

Detection Without Invasion: This AI-driven solution could be more patient-friendly than conventional diagnostic procedures because it does not involve any risk of bodily harm.

Cost-effective: This computational approach to screening may be more cost-effective than conventional clinical examinations, particularly in low-resource areas.

Patients with DM can be proactively monitored and alerted if any cardiovascular irregularities are found by embedding the model into telemedicine platforms or health monitoring apps.

5.4 Limitations and Challenges

Our model has potential, but there are several caveats to keep in mind.

Diverse Information: Although large, the dataset employed in this study may not be representative of all demographics, which could limit the model's generalizability.

Interaction with Additional Difficulties: There is still much to learn about the model's potential to specifically identify cardiovascular diseases among various complications experienced by DM patients.

Model Complexity: Although highly effective, combining VGG with Bi LSTM adds complexity, which may necessitate more time or resources to process.

5.5 Future Directions

The results of this study suggest a number of promising directions for more study:

Including More Variables: Strengthening the model's stability by familiarizing it with a wider range of data.

Using the model in real-time health monitoring systems is an area that needs more study.

Improvements to the model may include testing alternative optimization techniques or more complex neural network topologies in an effort to cut down on false positives and increase accuracy.

CONCLUSION

In order to identify cardiovascular problems in people with Diabetes Mellitus (DM), this research set out to optimize the Visual Geometry Group (VGG) neural network and the Bidirectional Long Short Term Memory (Bi LSTM) models with the Artificial Bee Colony (ABC) algorithm. With an accuracy of 98.6%, the combined VGG-Bi LSTM model significantly beat solo alternatives. This demonstrates why it's helpful to combine picture and sequence data for accurate diagnosis. This study demonstrates the potential of nature-inspired algorithms in neural network optimization by demonstrating the effectiveness of including the ABC algorithm to optimize the model. The high performance of the proposed model makes it a strong candidate for incorporation into diagnostic tools or telemedicine platforms for proactive monitoring of DM patients, with the aim of facilitating earlier interventions and better health outcomes. This study contributes to the growing body of literature on the use of AI in healthcare and serves as a model for future work in this area, where DM and cardiovascular health cross. A further step could be to conduct a pilot study in clinical settings to verify the model's viability and usefulness in actual applications. To improve the model's diagnosis accuracy, researchers could investigate including additional data types, such as genetics or acoustic signals. Even if ABC worked, it might be possible to further improve the model's robustness and efficiency by investigating additional optimization techniques or hybrid algorithms. Finally, since the worldwide incidence of DM rises, it is crucial to identify any potential cardiovascular problems early on. This study is encouraging because it calls for a more unified, AI-driven strategy in healthcare diagnostics. In future, feature dimensionality reduction models are applied to reduce the feature set for reducing the training time. The hidden layers can be increased for better processing and for enhanced prediction rate.

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