# AI based Dynamic Prediction Model for Mobile Health Application System

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***Abstract*—In recent decades, mobile health (m-health) applications have gained significant attention in the healthcare sector due to their increased support during critical cases like cardiac disease, spinal cord problems, and brain injuries. Also, m-health services are considered more valuable, mainly where facilities are deficient. In addition, it supports wired and advanced wireless technologies for data transmission and communication. In this work, an Artificial Intelligence (AI)-based deep learning model is implemented to predict healthcare data, where the data handling is performed to improve the dynamic prediction performance. It includes the working modules of data collection, normalization, AI-based classification, and decision-making. Here, the m-health data are obtained from the smart devices through the service providers, which comprises the health information related to blood pressure, heart rate, glucose level, etc. The main contribution of this paper is to accurately predict Cardio Vascular Disease (CVD) from the patient dataset stored in cloud using the AI-based m-health system. After obtaining the data, preprocessing can be performed for noise reduction and normalization because prediction performance highly depends on data quality. Consequently, we use the Gorilla Troop Optimization Algorithm (GTOA) to select the most relevant functions for classifier training and testing. Classify his CVD type according to a selected set of features using bidirectional long-term memory (Bi-LSTM). Moreover, the proposed AI-based prediction model's performance is validated and compared using different measures.**

***Keywords*—Artificial Intelligence (AI); M-Health System; Data Collection; Cloud Storage; Gorilla Troop Optimization (GTO); Bi-directional Long Short-Term Memory (Bi-LSTM); dynamic prediction***

## I. INTRODUCTION

The healthcare industry faces several challenges in diagnosing disease and providing affordable services [1, 2]. Providing patients with the best possible care based on a review of their medical histories, medical decisions, and the variability of their molecular properties is one of the fundamental requirements of any healthcare system. Due to the rapid development of new technologies, these systems have been dealing with several problems with data gathering, information association, data retrieval, and decision-making [3]. Due to logistical constraints caused by mobile phone use in developing nations, many healthcare sectors have significantly transformed. Mobile technology [4] has recently been crucial in several technological domains among subscribers in practically all countries. The advancement of new technologies and their use in the healthcare industry, known as "m-health" [5, 6] are aided by mobile devices and communications. The general framework of m-health system is shown in Fig. 1. Still, the m-health framework [7, 8] has many challenges and issues, which include the followings:

- Better interpret the data from multiple sources produced by numerous mobile and information sources after 2021.
- Enabling smarter, more personalized behavior change and engaging tools to inspire more meaningful users and patients to improve their health and well-being. The vast amount of health data from 5G mobile health users also needs to be intelligently adapted and transformed. It is essential to accurately estimate the relationship between the genomic data sequence and other medically relevant data.

The interpretation of large medical imaging datasets and other relevant diagnostic/imaging data generated by the latest generation of mobile imaging devices requires reliable, accurate and secure data analysis methods.

For instance, the cardiac arrest is now more likely in the situation where life is currently halted. Patients' health conditions deteriorate when they put off getting medical care because they are worried about contracting a communicable illness. For diagnosis and therapy, accurate predictions are essential. Researchers are constantly creating useful decision assistance systems, but CVD diagnosis is still difficult. Several intelligent tools have been developed based on machine learning and data-driven methodologies to address these issues. These methods have all included connecting many data sources to create a collective understanding for future research and predictive analysis [9, 10]. Several research have demonstrated that the severity of heart diseases may be automatically diagnosed using various machine learning approaches, such as combining numerous classification algorithms and augmentation algorithms to create reliable automated prediction systems. The CVD dataset was utilized in the research to test seven models, including SVM, KNN, LR, DT and various ensemble methods. Moreover, the AI-assisted diagnosis can help doctors make diagnoses more quickly and cheaply, which can help save patients' lives earlier in the process when there is a shortage of medical professionals.

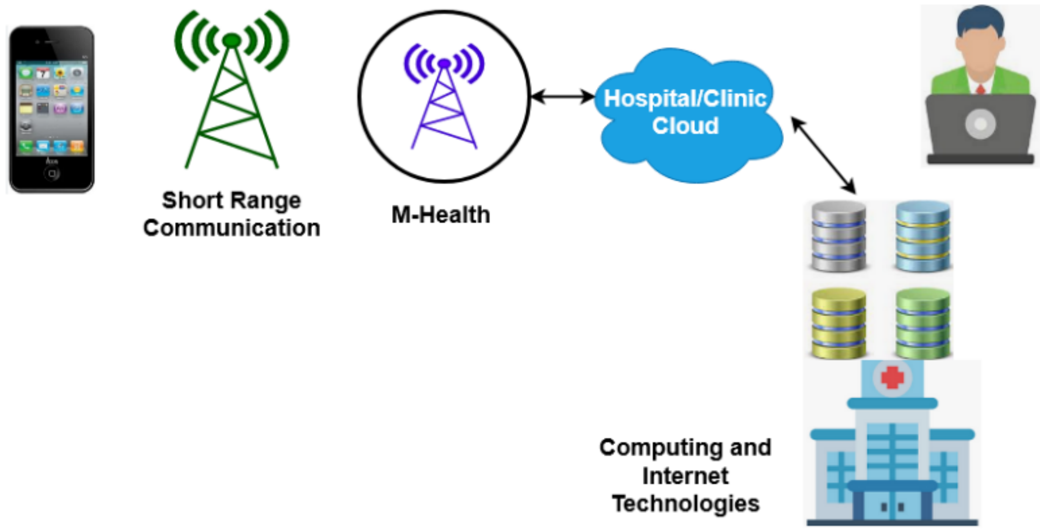


Fig. 1. General framework of M-Health systems.

Furthermore, many prediction-based techniques have been developed for various conditions, including neurological and cardiovascular heart disorders. In m-health systems, patient data is gathered to help with disease tracking, diagnosis, and prompt services, particularly in places where immediate care is complicated. Another online platform with a substantial library of medical content built on multimedia is called E-Medicine. Despite the availability of these new communication channels [11, 12], the technological support for the healthcare industry often needs to meet expectations due to scalability and other technical issues. To make the service more accessible to providers, users, and medical professionals, a more suitable m-health architecture needs to be designed. In addition, all data transmissions must be quick and secure to ensure timely delivery [13]. Security is one of the most crucial elements, particularly in relation to wearable sensors and handheld devices. The major research objectives of this paper are as follows:

- To develop a computationally efficient M-Health framework by using an advanced Artificial Intelligence (AI) mechanism.
- To accurately predict the cardiovascular disease from the obtained patient health information with reduced time and computational complexity.
- To improve the prediction rate of the M-Health systems, a Gorilla Troop Optimization Algorithm (GTOA) mechanism is deployed.
- A bidirectional long-short-term memory (Bi-LSTM) model has been implemented to ensure efficient and accurate disease diagnosis.

A comprehensive analysis was performed using various performance measures to validate and test the results of the proposed GTOA using the Bi-LSTM model.

The following sections make up the remaining parts of this article: The traditional approaches and methods for dynamic disease prediction in m-health systems are reviewed in Section II. In accordance with its primary disease prediction outcomes, it also analyses the benefits and drawbacks of each technique. The entire description of the proposed approach, including its workflow and extensive illustrations, is provided in Section III. Using a variety of parameters, Section IV compares and validates the results of the proposed and existing disease prediction models. In Section V, the study concluded with its findings, implications, and future scope.

## II. Related Works

This section gives an exhaustive assessment of the literature on the current AI development approaches. Additionally, it looks at each work's benefits and drawbacks in relation to its performance, core concepts, and processing method.

The most popular machine learning approaches are classification algorithms. Based on their preferred method of learning, machine learning models can be broadly categorized into three categories: reinforcement learning, unsupervised learning, and supervised learning. When a machine learns how to assign labels to each class of data that process is known as classification. Moreover, the ANN, NB, DT, and LR are the most popular machine learning models specifically used in the healthcare applications for disease prediction. To identify patterns and address AI issues, the ANN is constructed using a network of neurons and weighted connections. During training, the random forest generates a number of decision trees and produces the results that receive the most votes. This method is applied to tasks involving classification and regression. NB is a Bayes' rule-based classification system that works under the presumption that all of the features that forecast the ideal value are unbiased. Based on the likelihood that the data belong to a particular class, the Nave Bayes model can determine the class of a given set of data. A straightforward method known as "nearest neighbors" can be used to save all existing cases and categorize new cases based on how similar they are as determined by distance functions.

Istepanian and Anzi [14] utilized a new m-health framework for an intelligent healthcare delivery systems. The purpose of this work was to investigate the relevant big data issues, and technological innovations for developing an effective m-Health framework. Moreover, we validated different types of data analysis approaches for the M Health system, including descriptive models, diagnostic models, predictive models, and prescriptive models. Based on this research, machine learning and deep learning tools are analyzed to be of great importance and play an important role in the m-Health framework. Mishra et al. [15] pursued a new approach to improve the effectiveness of m-health systems using big data and IoT technologies. This paper targets to construct a new IoT based m-Health framework for disease monitoring and patient empowerment. Also, it intends to minimize the cost and enable an effective utilization of the medical components for proper m-Health management and control. However, the system model of the suggested framework could be difficult to understand, and it failed to demonstrate the efficiency and reliability of this systems. Alotaibi, et al. [16] analyzed the major applications of using AI and big data analytical models for developing a highly proficient m-Health systems. Here, a systematic review is conducted for investigating the different types of AI mechanisms to improve the performance of m-health systems. Moreover, this work used various performance measures to assess the quality of m-health systems that includes interactivity, veracity, usefulness, effectiveness, user satisfaction, and customization. The major drawbacks of this framework are inaccurate system response, various privacy and security problems.

Al-Marridi, et al. [17] employed an AI technique for optimizing the energy efficiency of m-health systems. The purpose of this work is to effectively minimize the latency and jitter by properly providing the resources and services from the cloud data centers. Moreover, it mainly concentrated on the optimal allocation of resources in the m-health systems. For this purpose, the deep learning based neural network algorithm was deployed, which supports to reduce the distortion and maximize the compression ratio of the healthcare framework. The primary advantages of this framework are reduced time consumption, optimized energy consumption, and delay. Elhishi, et al. [18] deployed a mobile health application system for identifying the leukemia cancer, where a straightforward medication management scheme was also used to remind the patients about their schedules. Specifically, it intends to develop a construct a new prototype for identifying the suitable solution with reduced time and cost. In addition, the Convolutional Neural Network (CNN) based deep learning classifier has been utilized to detect the leukemia cancer using the blood film input. Lano, et al. [19] utilized an AI mechanism to assist the m-health application systems. Here, the machine learning model is utilized to analyze the behavior elements of the medical systems. Mendo, et al. [20] provided a thorough analysis of the many machine learning models employed to raise the capability of mobile health systems. We also explored the rise of mobile healthcare devices and applications for reviewing patient health records. Pankaj et al. [21] used a machine learning approach to diagnose diabetes using the M-Health application. Abed et al. [22] introduced an integrated electronic medical system that enables efficient medical monitoring. Here, the machine learning based traffic flow classification model was utilized for reducing the time delay and traffic during data transmission/communication.

Alhussein, et al. [23] developed a voice pathology detection system with the help of CNN model for mobile health applications. The purpose of this work was to design a smart m-health framework by using the transfer learning mechanism. In addition, various types of features such as mel-frequency cepstral coefficients (MFCC), pitch frequencies, and linear prediction cepstral coefficients (LPCC) are also used. Shaban-Nejad, et al. [24] presented a detailed analysis demonstrating the importance of using AI in personalized healthcare systems. The scope of this paper was to improve the speed, accuracy, and reduce the time in the health systems. Shatte, et al. [25] presented a comprehensive survey for examining various ML methodologies used for developing a computationally proficient healthcare monitoring framework. Moreover, it discussed about the importance of using ML techniques in the field of medical treatment and diagnosis. It includes the mechanisms of active learning, Bayesian network, ensemble learning, regression, KNN, multivariate classification, random forest, linear discriminant analysis, and discriminative dictionary learning. Dargan, et al. [26] presented a comprehensive survey for examining the different types of deep learning mechanisms used in a health application systems. Key factors for using deep learning methodologies are layered or multi-level nonlinear processing and whether learning is guided or unguided. Garcia et al. [27] developed a framework for mental health monitoring systems (MHMS) based on machine learning models. The main consideration of this paper is to ensure the properties of increased privacy, high storage capacity, reliable data transmission, reduced energy consumption, and flexible data labeling. Tian, et al. [28] intended to design a smart healthcare framework with the specific parties of efficiency, convenience, and personalization. This framework includes the major participants of doctors, patients, hospitals and research institutions.

Based on the literature review, the problems associated to the conventional M-Health frameworks are as follows:

- Complex system design.
- Increased error prediction rate.
- Computational burden.
- High time consumption.
- More resource utilization.

Therefore, the proposed work motivates to develop a new M-Health framework for dynamic disease prediction.

## III. Proposed Methodology

This section provides the complete explanation for the proposed m-health systems with the overall workflow and illustrations. The original contribution of this work is to predict the cardiovascular disease according to the patient information collected from the cloud storage by using an advanced AI mechanism. The architectural model of the proposed M-Health framework is shown in Fig. 2. The development of mobile systems, especially for emergency applications, is usually a product of information and communication technology. Moreover, the emergency applications are highly crucial for the patients who suffered with heart disorders, brain injuries, spinal injuries, and etc. The M-Health services are beneficial, particularly in areas without many medical facilities, where hospitals are dispersed among the population, or where the cost of medical care is high. Also, it is built on new wireless and wired technologies, including cloud computing, Global System for Mobile Communications (GSM), and $4^{th}$ or $5^{th}$ generation technologies. Smart sensors are a feature of M-Health systems, which also have 5G connectivity capabilities linked with Web 2.0, online communities, and cloud - based services. Furthermore, the majority of M-Health-capable sensors and gadgets use low-power Bluetooth and ZigBee technologies to transmit data to other endpoints. The information is then shared to the distant systems or cloud data storage over communication networks for additional processing and decision-making. The modules involved in the proposed M-Health framework are as follows:

- Data collection using smart sensors.
- Data transmission to cloud.
- Deep learning based cardiovascular disease prediction.

Initially, the data collection is performed through smart sensors that are planted inside the human body, which are further connected with the mobile devices or gateways. Then, the smart devices like mobile can be used to enable communication between the patients and healthcare professionals at anywhere. After that the obtained health information is transmitted to the cloud systems for further operations. Furthermore, the deep learning based AI mechanism is applied to accurately predict the cardiovascular disease from the obtained patient health information. As shown in Fig. 3, the proposed AI based disease prediction system comprises the following operations:

- Secure data collection from cloud or data centers.
- Data preprocessing.
- Gorilla Troop Optimization Algorithm (GTOA) for feature selection.
- Bi-directional LSTM based classification.

After obtaining the health data from cloud systems, the data preprocessing is applied to generate the balanced dataset by performing the operations of cleaning, normalization, noise removal and balancing. Since, the raw dataset comprises some un-related attributes or information that may disrupt the accuracy of disease detection. Hence, the data preprocessing is more essential for an accurate disease prediction and diagnosis. After that, an intelligent and computationally efficient GTOA is applied for reducing the dimensionality of the dataset by choosing the most relevant features. It is also helps to improve the disease detection rate and reduce the overall time consumption of the processing system. Finally, the deep learning based AI model, named as, Bi-LSTM has been applied to accurately predict the type of cardiovascular disease according to the set of extracted feature set. The performance of the proposed GTOA using the Bi-LSTM model is validated and tested with various parameters. The primary advantages of the proposed model are as follows: easy to understand, reduced complexity in processing, less time consumption, accurate disease prediction, and computationally proficient.

### A. Cloud Model

In this framework, the cloud system comprises two layers such as data annotation & analysis, and storage & access layers, in which the storage layer stores the M-Health information obtained from the mobile devices through network service providers. The data is related to the patient's medical information like previous history, glucose level, BMI, heart rate, etc. Typically, the cloud is one of the most suitable and convenient platform for the users to store and retrieve the information. Specifically, the cloud has the major benefits of reduced cost, stability, and efficiency for the M-Health applications. Here, isolation strategies are used to enable secure data storage operations that ensure privacy and confidentiality of patient medical information. The data storage model of the cloud system for the proposed M-Health application system is shown in Fig. 4.

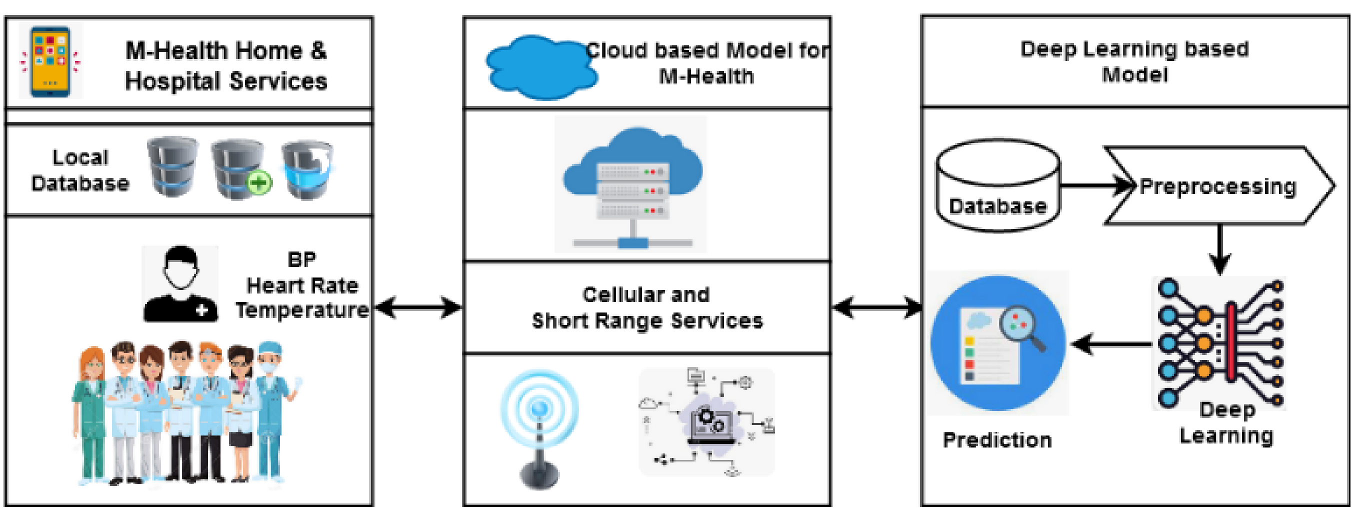


Fig. 2. M-Health framework of the proposed system.

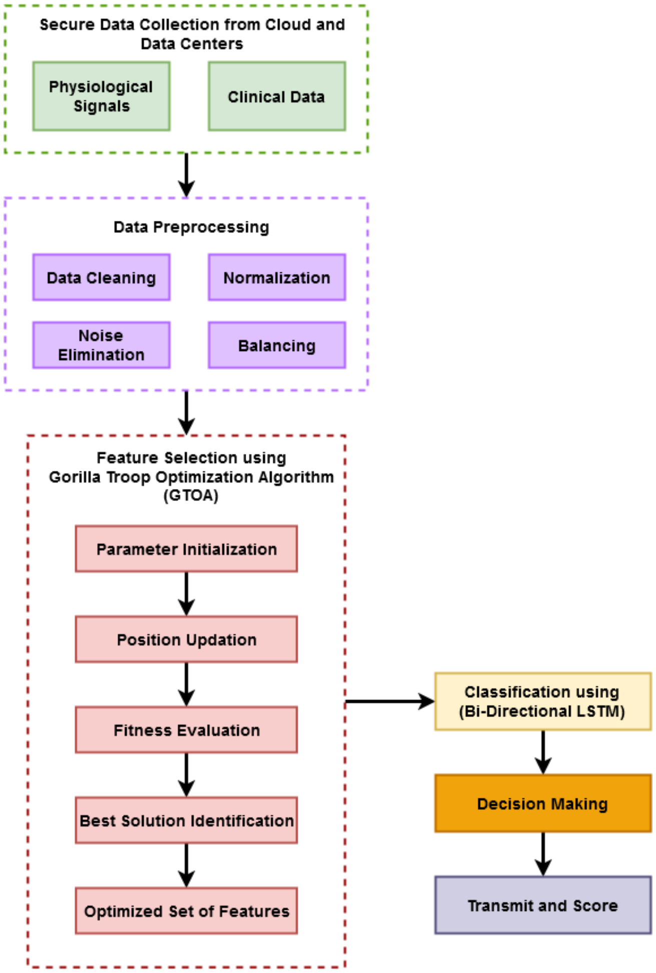


Fig. 3. Flow of the proposed dynamic prediction system.

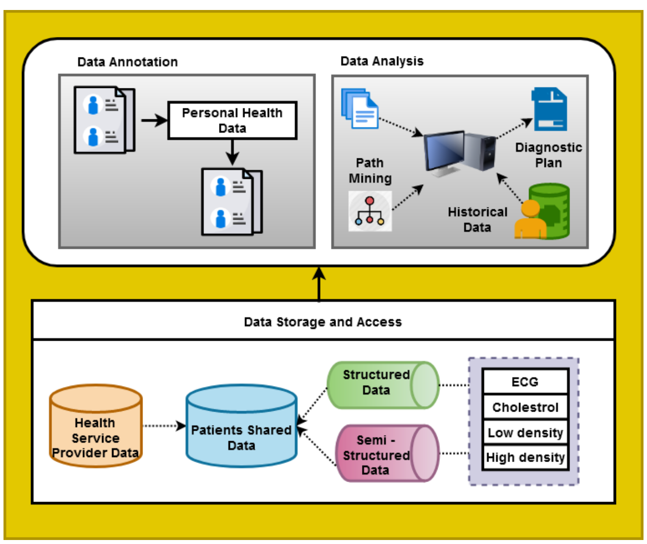


Fig. 4. Cloud data storage model.

## B. Secure Data Collection

The health or medical information about the patients like clinical records, and physiological signals are gathered from the smart sensor devices. Here, the wearable smart devices monitor the patients' data, and transmits the obtained information to the mobile device. Since, the existing data are gathered from the cloud systems, which comprise the information of patient history, age, BMI, gender, blood pressure, etc. This information is updated by the medical centers, and it can be used to predict that whether the patient is affected by the CVD or not.

## C. Data Preprocessing

After collecting the information, we apply data preprocessing to create a noise-free and balanced dataset for accurate disease prediction and classification. The main goal of this work is to accurately detect CVD disease in order to provide appropriate treatment and recommendations to patients. Data normalization and noise reduction techniques are used to make the data noise-free at this stage. Noise and other environmental influences are present in the raw data that comes from the sensor nodes. Moreover, it includes the preprocessing operations of cleaning, normalization, noise elimination, and data balancing. This technique is used to tune the noisy data into a clean dataset. In other words, anytime data is acquired from various sources, it is done in a primary manner that makes analysis impossible. So that the deep learning model being used can produce better outcomes, data must be presented in the correct format. Pre-processing describes the changes made to our data before the algorithm receives it. The removal of mistakes, inconsistencies, and missing values from the dataset is the focus of the data cleansing/cleansing stage. Various approaches or techniques have been developed to address this issue. The data value missing from the cell in the corresponding column is known as a missing value. In healthcare, missing values may occur due to human error, non-applicability, sensor omission, patient absence from the ventilator due to medical decisions, or patient state unrelated to a particular variable. Moreover, the missing values can be handled by either rejecting them or imputing the missing information. In addition, the data scaling is performed by using the min-max algorithm, which scales the features in the range of [0, 1], and [-1, 1]. It is estimated as follows:

$$\boldsymbol{D} = \frac{d - d_{mn}}{d_{mx} - d_{mn}} \tag{1}$$

Where, $\boldsymbol{d_{mn}}$ and $\boldsymbol{d_{mx}}$ are the minimum and maximum values of the dataset. Based on this operation, the balanced and quality improved data is produced as the output, which can be used for an accurate CVD prediction.

## D. Gorilla Troop Optimization Algorithm (GTOA)

After preprocessing, the GTOA is applied to optimally select the features from the balanced dataset for accurately predicting the disease. This technique provides the best solution for setting features to train the classifier. Finding the best viable or desirable solutions to a specific problem that is frequently faced in a variety of fields is referred to as optimization. Multiple factors have contributed to the popularity of met heuristics in engineering applications. For instance, they are simple to execute, contain reasonably simple concepts, perform better than local search algorithms, have many different applications, and knowledge of the derivative function is not required. In the existing disease prediction frameworks, various meta-heuristics optimization techniques are deployed for feature optimization and dataset dimensionality reduction. However, it faces some complications associated with slow convergence, a high number of iterations, complexity in computation, and more time consumption. Hence, the GTOA is utilized in this work, which supports reducing the dimensionality of the preprocessed dataset by selecting the most relevant features used for CVD prediction.

In this technique, the five distinct operators are used to simulate exploration and exploitation optimization procedures based on the behaviors of gorilla, and its phases are shown in Fig. 5. During exploration, three distinct operators have been used such as:

- Migration to unknown place for increasing the capability of exploration.
- Migration to other gorillas for balancing both exploration and exploitation.
- Move in the direction of an identifiable place to increase the capability of GTO.

These operations are mathematically performed as shown in below:

$$\boldsymbol{AG}\,(\boldsymbol{h}+\boldsymbol{1}) = \begin{cases} (\boldsymbol{Up_b} - \boldsymbol{Lo_b}) \times \boldsymbol{\alpha} + \boldsymbol{Lo_b} & \boldsymbol{r} < \boldsymbol{d} \\ (\boldsymbol{\beta} - \boldsymbol{K}) \times \boldsymbol{G_r}(\boldsymbol{h}) + \boldsymbol{H} \times \boldsymbol{B} & \boldsymbol{r} \geq 0.\boldsymbol{5} \\ \boldsymbol{G}(\boldsymbol{i}) - \boldsymbol{K} \times (\boldsymbol{K} \times (\boldsymbol{G}(\boldsymbol{h}) - \boldsymbol{AG_r}(\boldsymbol{h})) + \boldsymbol{\gamma} \times (\boldsymbol{G}(\boldsymbol{h}) - \boldsymbol{AG_r}(\boldsymbol{h}))) & \boldsymbol{r} < \boldsymbol{0.5} \end{cases} \tag{2}$$

Where, $\boldsymbol{AG}\,(\boldsymbol{h}+\boldsymbol{1})$ indicates the candidate position vector of gorilla at iteration $h$, $\boldsymbol{G}(\boldsymbol{h})$ denotes the current vector of gorilla, $\boldsymbol{r}, \boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}$ are the random numbers from [0 to 1] that can be updated at each iteration, $d$ is the parameter that is used before optimization ranging from 0 – 1, $\boldsymbol{Up_b}$ and $\boldsymbol{Lo_b}$ are the upper and lower bounds respectively. Moreover, the optimization parameters $K$, $H$ and $B$ are computed by using the following equations:

$$\boldsymbol{K} = \boldsymbol{U} \times \left(\boldsymbol{1} - \frac{\boldsymbol{itr}}{\boldsymbol{max_{itr}}}\right) \tag{3}$$

$$\boldsymbol{U} = \boldsymbol{\cos(2} \times \boldsymbol{\rho}) + \boldsymbol{1} \tag{4}$$

$$\boldsymbol{H} = \boldsymbol{K} \times \boldsymbol{a} \tag{5}$$

where U is the function computed using equation (4), iteration denotes the current iteration, and 〖max〗 iteration denotes the total number of iterations used to perform the optimization, $\boldsymbol{\rho}$ is the random number from 0 to 1, and $\boldsymbol{a}$ is the random number from -1 to 1. Consequently, the other optimization parameter $B$ is estimated by using the following equation:

$$\boldsymbol{B} = \boldsymbol{w} \times \boldsymbol{G}(\boldsymbol{h}) \tag{6}$$

$$\boldsymbol{w} = [-\boldsymbol{K}, \boldsymbol{K}] \tag{7}$$

Where, $\boldsymbol{w}$ indicates the random value in the range of [-K to k]. Similarly, the other two operators are used in the exploitation stage that supports to increase the performance of searching. During exploitation, the following operations are performed:

$$\boldsymbol{AG}(\boldsymbol{h}+\boldsymbol{1}) = \boldsymbol{H} \times \boldsymbol{Q} \times (\boldsymbol{G}(\boldsymbol{h}) - \boldsymbol{G_{sb}}) + \boldsymbol{G}(\boldsymbol{h}) \tag{8}$$

$$\boldsymbol{Q} = \left(\left|\frac{\boldsymbol{1}}{\boldsymbol{P}} \sum_{\boldsymbol{i}=\boldsymbol{1}}^{\boldsymbol{P}} \boldsymbol{AG_i}(\boldsymbol{h})\right|^{\boldsymbol{v}}\right)^{\boldsymbol{1/v}} \tag{9}$$

$$\boldsymbol{v} = \boldsymbol{2^L} \tag{10}$$

Where, $\boldsymbol{G}(\boldsymbol{h})$ indicates the vector position of gorilla, $\boldsymbol{G_{sb}}$ is the silverback of gorilla, $\boldsymbol{Q}$ is the function estimated by using equ (9), $\boldsymbol{v}$ is the setting parameter, and $P$ is the number of gorillas. Then, the vector position of each candidate gorilla $AG(i)$ is updated at iteration $h$ as shown in below:

$$AG(i) = G_{sb} - (G_{sb} \times I - G(h) \times I) \times CV \tag{11}$$

$$I = 2 \times rand - 1 \tag{12}$$

Where, $I$ is the impact force, and $CV$ is the coefficient vector. Finally, the cost of all solutions is estimated, and based on this the best solution is obtained as the optimal solution.

*Algorithm 1 – GTO for feature selection*

Input: Population size $P$, maximum number of iterations $N$, parameters $\delta$ and s;
Output: Location of gorilla and fitness value;
Step 1: Initialize the random population as $G_i$ , where $i = 1,2 \ldots P$;
Step 2: Estimate the fitness value of Gorilla;
Step 3: While (Until reaching the stopping criterion) do
Update the parameter K by using equation (3);
Update the parameter H by using equation (5);
For (each Gorilla $G_i$) do
Update the current location of gorilla by using equation (2);
End for;
Compute the fitness value;
If $AG$ is better G
Set $G_{sb}$ as the best location;
For (each Gorilla $G_i$) do
If ($|K| \geq 1$) then
Update the current location of gorilla using equation (9);
Else
Update the current location of gorilla by using equation (11);
End if;
End for;
Estimate the fitness value of gorilla;
If (New solution is greater than previous)
Update $G_{sb}$ as the best position;
End while;
Return $G_{best}$, $Best_{fit}$;

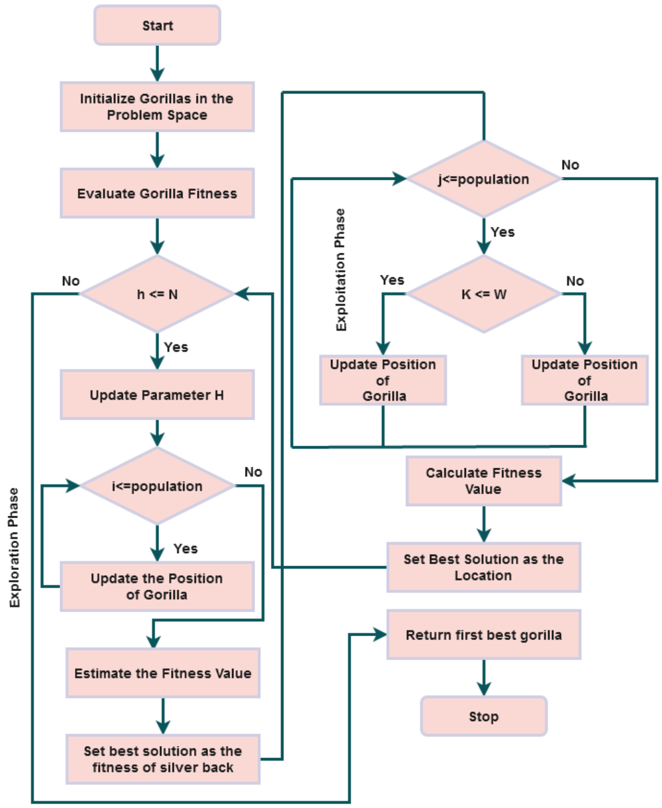


Fig. 5. Flow of GTOA.

### E. Bi-Directional LSTM

Finally, the Bi-LSTM algorithm is applied to precisely classify the CVD with high reduced complexity and high accuracy. Typically, the Recurrent Neural Networks (RNNs) are the foundation of the LSTM method [29], Input gates, output gates, and forget gates that form the primary LSTM unit cell. The LSTM creates an internal feedback state due to processing various inputs close to one another, which helps the network comprehend time and the significant variability of the displayed data. Through gate control, the LSTM network incorporates resolving gradient vanishing to a certain level. While an LSTM framework can understand and preserve past data, it cannot accurately include new data to support a final prediction. As a result, a Bi-LSTM with two-way functionality was made using the LSTM network. In sequence prediction modelling, bi-LSTM networks perform better than other RNN and LSTM architectures, especially regarding speech or handwriting recognition and machine translation. Bi-LSTM contains two separate LSTMs that can integrate and aggregate data from both forward and backward directions. It is useful to have access to past and future context when performing sequence labeling tasks. Bi-LSTM proposes to transfer and invert each sequence to her two hidden entities, to produce a result by integrating the two logical states, and to obtain knowledge of the future and the past. Although they have identical sentence embedding, two opposing directions' parameters in the Bi-LSTM framework are different. By using this mechanism, the CVD is properly predicted and categorized with less time consumption.

## IV. Results and Discussions

In this section, we describe and compare the full results of the proposed disease prediction models. The CVD dataset is used to verify and contrast the outcomes of the suggested prediction mechanism. This data comprises extensive patient information and medical records. Moreover, the different types of parameters used to validate the results, and are computed as shown in below:

$$Precision = \frac{TrP}{TrP+FaP} \tag{13}$$

$$Recall = \frac{TrP}{TrP+FaN} \tag{14}$$

$$F1-score = 2 \times \frac{(Precision \times Recall)}{(Precision+Recall)} \tag{15}$$

$$Accuracy = \frac{Correct\ Prediction}{Total\ Prediction} \tag{16}$$

Where, $TrP$ is the true positive, $FaP$ is the false positive, and $FaN$ is the false negative. The attributes and descriptions of the CVD dataset used in this study are shown in Table I.

Fig. 6 presents a comparative analysis of conventional [30] and proposed AI mechanisms used for CVD prediction and classification. For this analysis, the parameters precision, recall, f-measure and accuracy have been considered. The proposed model offers improved computation capabilities and system efficacy as a result of the best feature processing and selection.

The accuracy of CVD prediction is significantly increased when the proposed optimization and classification model is used; however ordinary machine learning and deep learning methods perform less well due to insufficient feature processing and selection.

TABLE I. CVD Dataset Description

| Attributes | Descriptions |
|---|---|
| Age | In years |
| Gender | Male or Female |
| Chest Pain | Type of CP |
| Blood Pressure | BP level in mm Hg |
| Serum Cholesterol | In mg/dl |
| Fasting blood sugar | >120 mg/dl (1 true and 0 false) |
| Rest ECG | 0 – Normal<br>1 – Abnormal<br>2 – Maximum heart rate |
| Max_heart rate | Maximum heart rate |
| Exercise induced angina | 0 – No<br>1 – Yes |
| ST depression | Depression induced by exercise |
| Slope | 1- Up<br>2- Flat<br>3- Down |
| No of vessels | Vessels colored by fluoroscopy |
| Thalassemia | Normal, irreversible, and fixed |
| Num | No of risk, low risk, high risk, and very high risk |

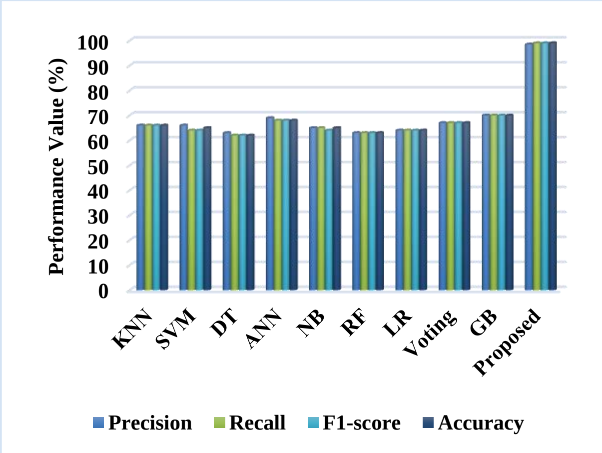


Fig. 6. Performance comparative analysis with machine learning techniques.

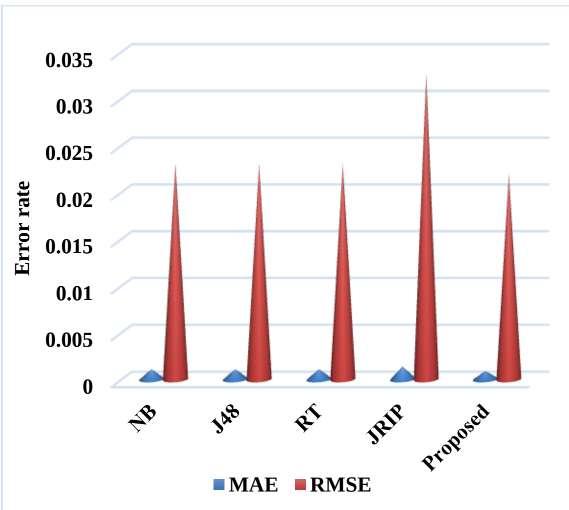


Fig. 7. Error analysis.

Fig. 7 compares the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) rate of the existing [31] and proposed classification methodologies. Absolute error is the term used to describe the size of a measurement error. Estimate using the difference between the measured value and the actual value. Mean Squared Error, or MSE, measures how inaccurate a statistical model is. The mean squared difference between observed and expected values is computed. Additionally, the MSE increases as model error increases and is equal to 0 when a model is error-free. Mean squared error, also called mean squared error, is a commonly used technique to assess the accuracy of predictions. It exemplifies the Euclidean gap between predictions and measured actual values, and is indicated in the results that the MAE.

Table II and Fig. 8 [32] provide an overall comparison of existing and proposed prediction methods used for CVD detection and classification in terms of recall, f1 score, accuracy, precision, and time shows the analysis. Based on our results, we conclude that the proposed BTOA-integrated Bi-LSTM model provides better results than other techniques. The GTOA helps to extract the most relevant and optimal features for classifying the disease. Hence, the training and testing operations of the classifier are improved, so the overall prediction efficacy of the proposed model is highly improved.

Fig. 9 to Fig. 11 validates the CVD prediction performance of the baseline [33] and proposed mechanisms. Here, the similarity coefficients are also estimated for determining that how accurately the classifier predicts the disease from the dataset. From the overall results, it is determined that the combination of proposed GTOA integrated Bi-LSTM provides a highly improved results over the other techniques.

TABLE II. COMPARATIVE ANALYSIS

| Methods | Recall | F1-score | Precision | Accuracy | Time (s) |
|---|---|---|---|---|---|
| DT | 64.40 | 63.94 | 63.42 | 63.69 | 0.53 |
| KNN | 61.46 | 67.02 | 73.68 | 69.87 | 5.78 |
| LR | 67.99 | 71.13 | 74.58 | 72.36 | 2.52 |
| NB | 32.30 | 44.43 | 71.11 | 59.44 | 0.63 |
| SVM | 64.21 | 70.17 | 77.35 | 72.66 | 296.67 |
| Proposed | 99 | 99 | 99 | 99.5 | 0.32 |

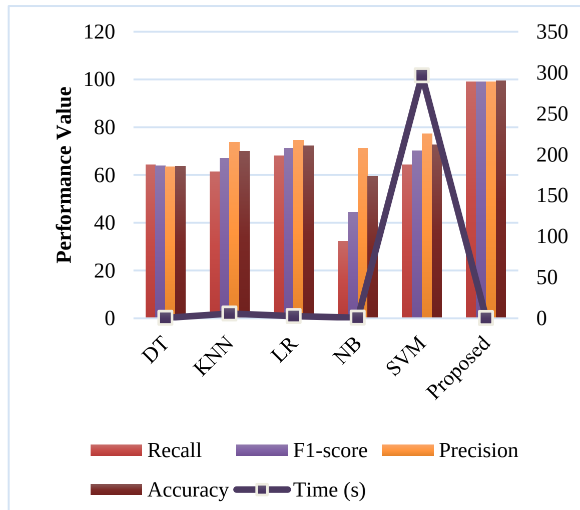


Fig. 8. Overall analysis.

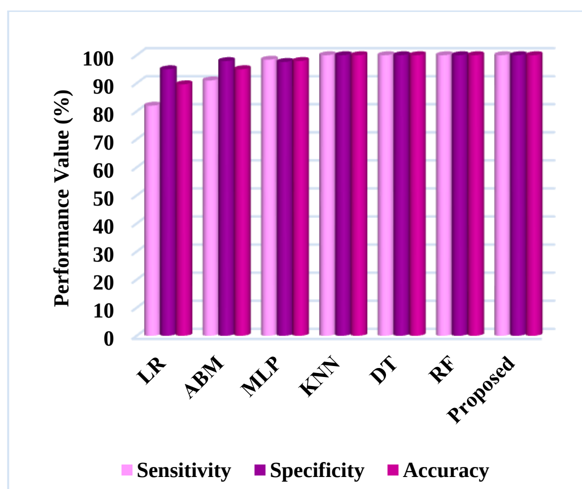


Fig. 9. Sensitivity, specificity, and accuracy analysis.

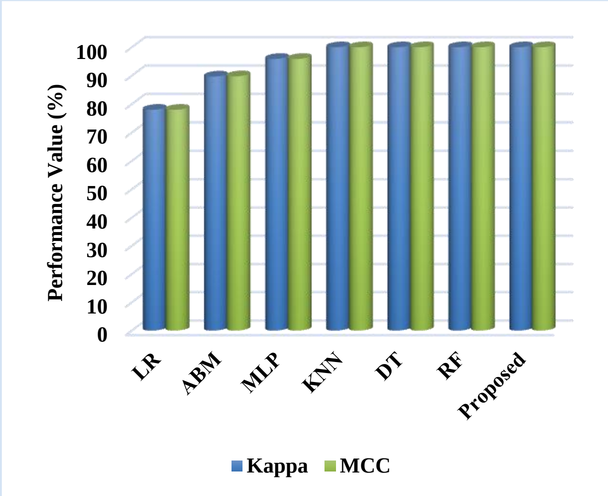


Fig. 10. Similarity coefficients.

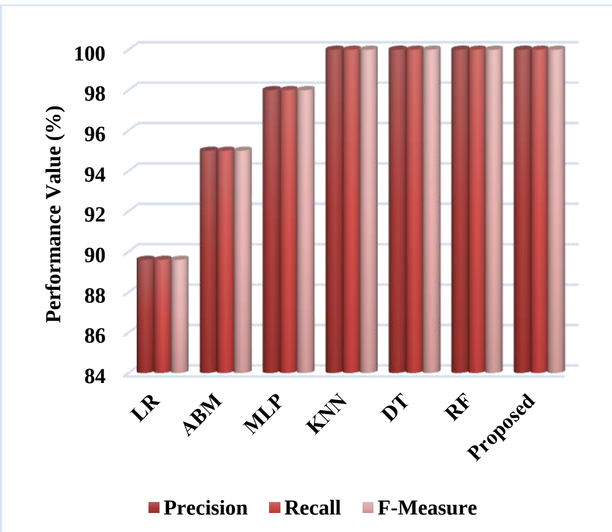


Fig. 11. Prediction performance evaluation.

## V. Conclusion

CVD is a life-threatening condition brought on by sudden heart problems, high blood pressure, and strokes. Early intervention and remote monitoring devices are the best ways to treat CVD patients. Also, the M-Health systems offer a variety of remote management applications for monitoring, and patients benefit from self-reported outcomes and affordable solutions. Recently, sophisticated and intelligent technologies can provide advanced procedures for healthcare services. Such technologies are also connected with m-Health systems to track, handle, and store patient data. This paper proposes a complete M-Health framework for predicting CVD using an advanced AI mechanism. The information collected by the sensors is sent to local databases and stored in cloud storage services with the latest technology enabling mobile networks. Data will be collected via a cloud computing platform or medical facility for further analysis. The GTOA-integrated Bi-LSTM techniques have been adapted for CVD classification. The suggested deep learning model is an excellent choice for CVD prediction based on examining patient attributes from a dataset. During analysis, the performance and results of the proposed GTOA-integrated Bi-LSTM technique are validated and compared using various measures. Overall, the estimated results state that the proposed GTOA integrated with Bi-LSTM outperforms other methods with highly improved results.

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