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Cyber-Physical System (CPS) Based Heart Disease's Prediction Model for Community Clinic Using Machine Learning Classifiers

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Abstract: There are 13000 community clinics in Bangladesh to resolve rural people's health problems. The people in the rural area of our country have been affected by various common diseases, and these diseases are not properly diagnosed due to a lack of modern technologies. In this context, the risk of uncertainty in health management and treatment is not at a controllable level. Modern technology like Cyber-Physical systems (CPS) based health care can be considered an effective data collection, processing, and prediction tool for rural medical infrastructure to resolve the complexity of different diseases. In this paper, a CPS-based health care architecture is proposed. In addition, a methodology is suggested to process the real-time data for further taking the strategical decision in a very special way using different machine learning algorithms. A heart disease-related case study is considered to understand the proposed method clearly in practical application. Because of this, a heart disease dataset is collected from Kaggle resources. Using this dataset, different machine learning classifiers are used to develop a heart disease prediction model. The different classifier models associated with Random Forest (RF), K-Nearest Neighbors (K-NN), Naive Bayes (NB), Adaptive Boosting (AdB), Decision Tree Classifier (DTC), and Binomial Logistic Regression (BLR) are used. The results obtained from the prediction model are in good agreement with the experimental results, and accuracy is about 87% for the classifiers DTC. In comparing other available state-of-art models, the proposed model exhibits better efficiency in predicting future decision-making. Among the classifiers, DTC shows 87% accuracy for predicting heart disease. Using this Model diagnosis will be faster, correct, and help patients predict heart disease. When compared to other state-of-the-art models, our model outperforms them.

Keywords: heart disease, cyber-physical system, community clinics, classifier algorithm, decision trees.

使用機器學習分類器的基於網絡物理系統的社區診所心髒病預測模型

摘要: 孟加拉國有 13000 個社區診所，用於解決農村人口的健康問題。我國農村地區的人們受到各種常見疾病的影響，由於缺乏現代技術，這些疾病沒有得到正確的診斷。在此背景下，健康管理和治療的不確定性風險並未處於可控水平。為了解決不同類型疾病的複雜性，基於信息物理系統的醫療保健等現代技術可以被視為農村醫療基礎設施的有效數據收集、處理和預測工具。在本文中，提出了一種基於的醫療保健架構。除此之外，建議使用一種方

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法來處理實時數據，以便使用不同的機器學習算法以非常寶貴的方式進一步做出戰略決策。心髒病相關的案例研究被認為可以在實際應用中清楚地理解所提出的方法。因此，心髒病數據集是從 卡格尔資源中收集的。使用這個數據集，不同的機器學習分類器被用來開發心髒病的預測模型。使用與隨機森林、最近鄰、樸素貝葉斯、自適應增強、決策樹分類器和二項式邏輯回歸相關的不同分類器模型.從預測模型獲得的結果與實驗結果非常吻合，分類器的準確率約為 87%。與其他可用的最先進模型相比，所提出的模型在預測未來決策方面表現出更好的效率。在分類器中，顯示預測心髒病的準確率為 87%。使用此模型診斷將更快、更準確，並將幫助患者預測心髒病。與其他最先進的模型相比，我們的模型優於它們。

关键词： 心臟疾病, 网络物理系统, 社区诊所, 分類器算法, 決策樹。

1. Introduction

The cyber-physical system is an emerging technology in which integration of the dynamic physical world and the cyber world is attributed. Physical processes in the physical world are monitored and controlled by embedded computers and networks through a feedback loop. The idea is to integrate intelligence of everyday life using objects to execute critical tasks in CPS. Where physical processes affect the cyber process, and cyber process affects the physical process. Sensors must capture numerous data types from the real world—captured data transmitted to the cyber world for processing and analysis [1].

Because the physical world is dynamic and complex, the difference between the physical world and the cyber world leads to many challenges in the development of CPS. Network, heterogeneous, and availability are most of them [2].

The structure Model of CPS is divided into three segments: the physical layer, information system layer, and user segment [3].

- The physical system layer encompasses many sensor networks, embedded smart chips, etc. The role of a physical system is collecting and transmitting information and signals. As a result, it serves as the foundation of the CPS.
- The role of the information system segment is processing and transmitting data acquired from the physical system.
- The role of the user layer mainly completes the work like data query and safety that should be guaranteed to all CPS users.

CPS applications have many advantages, including interoperability with cloud computing and WSNs, the interaction between human and system, dealing with certainty, better system performance, scalability, autonomy, flexibility, optimization, and faster response time.

Social life can be improved by using the intelligence of the Cyber-Physical system. When CPS is used in the medical sector, it is called Medical Cyber-Physical System (MCPS). In the area of cyber-physical systems (CPS), the solution to improve health care services was pointed out as a powerful solution [4]. , the traditional clinical scenarios are closed-loop systems [5], which include controls for the caregiver, medical devices, and physical plants, which serve as sensors and actuators. As a distinct CPS class, Medical Cyber-Physical Systems (MCPS) modify this scenario by introducing other computational entities to help the caregiver control the system by supporting the decision [6]. MCPS is a context-aware and life-critical system that focus on patient safety, which requires rigorous validation processes to ensure compliance with the user's requirements and specified accuracy.

Bangladesh is a South Asian country that is poor and densely populated. The population is increasing day by day. More than 70% of the people are a farmer and live in rural areas. They suffer from various diseases like family planning treatment, blood pressure, heart disease, etc. That is why the government of Bangladesh took the initiative in 1998 for Community Clinics (CC) in rural areas, added to the health sector of Bangladesh for primary, integrated healthcare [7]. The initiative was closed for political reasons and revitalized in 2009 by the Government of Bangladesh, which has established more than 13000 community clinics in rural areas. Each community clinic covers around 6,000 villages, especially women [8].

The establishment of a CC in the country is a revolutionary initiative to provide basic healthcare delivery to reach the doorstep to people within half an hour's walk. Community clinics are truly helpful for rural people. Community people donate land for infrastructure and are involved in the management process. Community people maintain security. Health is the major factor in human life. In Bangladesh, the health system relies on Government [9]. Community clinics operate across Bangladesh and are designed to provide a range of critical, basic health and family planning services to the people. One thousand four hundred trained healthcare providers are delivering critical primary healthcare. Awareness is necessary for rural people [10].

Heart disease is the number 1 cause of death, and about 80% of deaths occur in low-and middle-income countries for heart disease. It is almost equal for men and women. Reduction of oxygen and blood supply in the heart leads to heart disease. If these trends are continued till 2030, an estimated death will be 23.6 million people from heart disease [11]. Good health is the prerequisite for living a longer, active, stress-free life. Besides, life is dependent on the component functioning of the heart because the heart is a major organ of the human body. Heart disease has remained the leading cause of death globally for the last 20 years.

Heart disease now represents 16 % of deaths from all causes [12]. Death event describes the rate of death and survival of patients. Prediction of death events of heart diseases in the medical field is a major concern nowadays. A huge amount of heart disease patient-related data can be useful for predicting the occurrence of death events. Recently computer technology and machine learning techniques have developed software to assist doctors in deciding heart disease early. Clinical and pathological data is useful for the diagnosis of heart disease. Specifically, the cardiovascular breakdown happens when the heart is incapable of siphoning enough blood to the body, and it is generally brought about by diabetes, hypertension, or other heart conditions or illnesses [13].

Artificial Intelligence (AI) applied to clinical records, specifically, can be a powerful device both to foresee the endurance of every patient having cardiovascular breakdown indications [14], furthermore, to identify the main clinical highlights (or danger factors) that may prompt cardiovascular breakdown [15]. Researchers can exploit AI not just for the clinical forecast, yet also for highlight positioning [16]. In particular, computational insight is advantageous when applied to clinical records or combined with imaging. This paper introduces a noble work for predicting heart disease events using heart disease symptoms applying different machine learning algorithms.

In this paper, we have discussed a CPS-based community clinic for collecting real-time data and showing a prediction model of heart disease by analyzing the dataset using the decision tree classifier. We used a dataset collected from the Kaggle platform for the data analysis.

The rest of the paper is organized as follows. We discuss the literature study in section 1. In section 2, the proposed architecture is stated. The methodology is stated in section 3. The experimental result analysis is shown in part 4. Finally, we completed the paper in section 5.

2. Literature Review

CPS is a new trend in our country. In every sector, researchers are trying to include the concept. Many types of research have been done using cyber-physical systems in the healthcare field worldwide. Especially CPS-based community clinic system or any research work has not been done in Bangladesh. In [17], the authors proposed a cost-efficient fog computing MCPS. The limitation of this paper is that no data are analyzed using machine learning models. In [18], the authors presented a system to capture images of medical to store data in the cloud. However, data is not explained to provide the result automatically. A therapy system using CPS is established [19].

However, more works have been done on the medical dataset like ECG, heart disease, etc. Recently, many data mining and machine learning algorithms in medical sectors have been performed related to disease prediction systems. [20] developed a heart disease prediction method using different classifiers.

FCBF, PSO, and ACO outperform other classifiers based on performance matrices. The authors focused on predicting chronic disease using different data mining techniques on historical health records [21]. The support vector machine (SVM) gives the highest accuracy rate from this experiment. The prediction of the chance of having heart disease is recommended using data mining techniques for early automatic diagnosis of the disease within the result in a short time [22]. It uses different medical attributes such as heart rate, blood sugar, age, and sex to predict if a person has heart disease or not. In the paper [23], Sharmila *et al.* proposed nonlinear classifiers for heart disease prediction.

Big data tools like Hadoop Distributed File System (HDFS), Map-reduce, and SVM are proposed to predict heart disease with an optimized attribute set. Only two papers have been published using the utilized dataset from the Kaggle platform. Ahmed *et al.* [24] described this dataset. They explained a case study. Authors [25] approached a machine learning model on the two parameters only of the dataset. The authors [26] used a random forest model for another dataset to predict heart failure. Chen *et al.* [27] did the feature analysis on another dataset using a support vector machine and got 75.26% accuracy.

There are 11 parameters to cause the heart attack in the analyzed dataset. Table 1 shows the value of a normal range of parameters of the dataset which causes the heart attack.

Table 1 Normal range of heart disease's parameters

Parameter of risk factor	Standard range
Age	Below 40 years
Anemia	10.0–11.5 g/dl
Creatine phosphokinase (CPK)	10-120 mcg/L, or micrograms per liter
Ejection fraction	50% to 70%
Serum creatinine	0.6–1.1 mg/dL in ladies and teenagers matured 16 and more established 0.8–1.3 mg/dL in men and young people matured 16 and more seasoned 0.2 or more in newborn children,
Serum sodium	135 to 145 milliequivalents per liter (mEq/L)
Platelets	150,000 to 450,000 platelets per microliter
High blood pressure (HBP)	90/60mmHg -120/80mmHg
Diabetes	>7.8 mmol/L
Smoking	Male, Female
Sex	Men, Women

3. Proposed Architecture

Detailed block diagram of CPS-based architecture in future shows in Fig. 1. There are a few components in this architecture.

• *Community Clinic:* This is the primary component or starting point in this process. The patient will come to the community clinic, and data will be collected through various sensors such as mechanical, electrical, optical, and chemical sensors.

• *Data collection tools:* Collecting data from body to machine using sensors in community clinic patients are coming mostly pregnant women, chest pain and fever patients. Our architecture will predict heart diseases using ECG sensors and transfer them to the cloud using Wi-Fi, ZigBee, etc.

• *Algorithm for analysis, design, processing, and synthesis:* Getting data from sensors needs analysis. We will use machine learning classifiers or deep learning models.

• *Tools and techniques:* After analyzing, we will get a result sent to clinics or patients' mobile devices using Wi-Fi or ZigBee protocols.

• *Output device:* Smart mobile laptop with a connectivity.

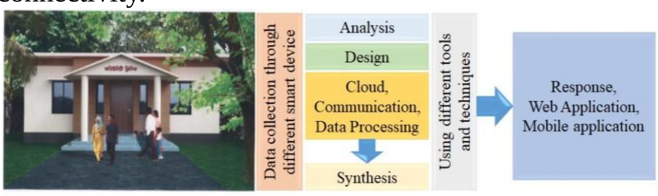

Fig. 1 Proposed architecture

4. Proposed Methodology

In this section, we represent the methodology of our proposed model. Fig. 2 illustrates the detailed block diagram of our methodology.

This diagram shows that data will be collected in two ways from community clinics by health professionals. One way is through IoT, wearable devices, and smart devices automatically using wearable sensors in the patient's body, and the other is through the web and other devices and sent to cloud servers. Collected data will be merged and organized for processing. Data will be analyzed according to desire-related attributes to get output. The whole system will be tested in different ways. Training can be started when the test is completed—training for health professionals and users for the final dataset model.

We analyzed a heart disease dataset collected from the Kaggle platform as a case study. The following section predicted the heart disease and analyzed the dataset using machine learning models.

4.1. Dataset Description

The used dataset in our methodology is taken from the Kaggle platform. The dataset consists of 12 columns and 299 rows. The columns represent the feature and the target variable. The feature variables are age, anemia, CPK, diabetes, ejection fraction, high blood pressure, platelets, serum creatinine, serum sodium, smoking, and sex. Heart disease is the target variable of the data set. The dataset contains 299 heart failure patients [28]. That is why we utilized supervised machine learning algorithms for finding heart disease cases.

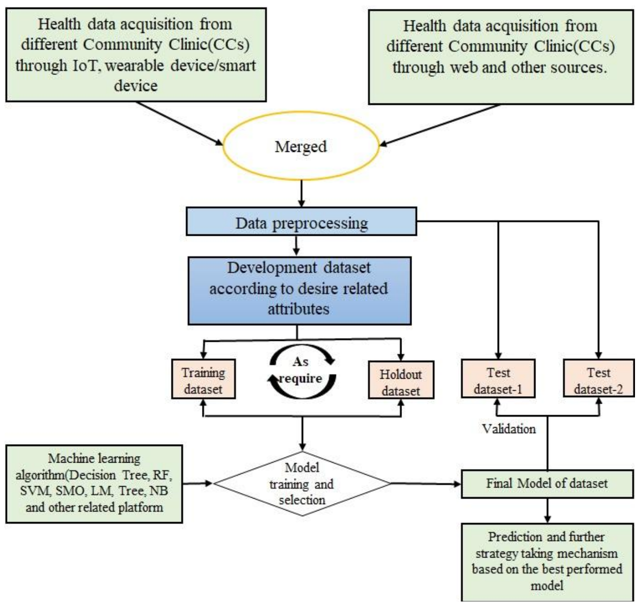

Fig. 2 Block diagram of proposed methodology

4.2. Exploratory Data Analysis

First, we import our data set, and then we get a clear concept of the data set using the EDA step. EDA alludes to the basic cycle of performing starting examinations on data to find patterns, spot anomalies, test the theory, and check presumptions with the assistance of outline insights and graphical portrayals. After applying EDA, we get noise-free and error-free data as data has only floated integer values, and no variable column has null/missing values.

4.3. Test-Train Splitting

In the experiment, we split the data set into two categories: 90% of the data for training and 10% for testing. This is called test-train splitting.

4.4. Machine Learning Classifiers

In our approach, we simulate all the proposed seven classifiers on heart disease patient data sets to predict patients' heart disease and hence find some interesting results, which we present in our next section.

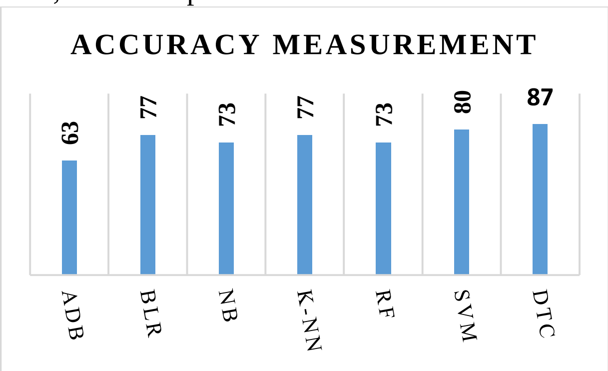

Fig. 3 Accuracy measurement of different classifiers

4.5. Comparison Accuracy

Fig. 3 represents the accuracy of the classifiers for our given data set. Here, DTC is also the first choice, showing 87% accuracy for predicting actual classes. SVM has 80%, which could be the second choice for this classification. K-NN [29] and BLR tie in 77% accuracy. Moreover, RF and NB have the same accuracy of 73%, and finally, Ada Boost shows the worst accuracy, only 63%.

5. Experimental Result Analysis

In this section, we present the analysis and comparison of the classifiers.

5.1. Performance Criteria

In the output step, we get the final result performance of all executed machine learning models. By coding our proposed model, we can exam the results. We can observe the detailed accuracy of running all stated models in this part. We measured accuracy, precision, recall, and f1-score. Moreover, we also measured the weighted and macro average of the scores for each classifier. These terms are obtained from the confusion matrix. An N × N matrix is used to evaluate a classification model's performance, where N is the number of target classes [30]. The matrix compares the actual target values with those predicted by the machine learning model. This gives us a view of how our classification model performs and what kinds of errors it is making. A general sight of the confusion matrix is shown in Table 2.

Table 2 Confusion matrix

	Predicted Yes	**Predicted No**
Actual Yes	TP	FN
Actual No	FP	TN

True Positive (TP): The number of positive events or cases of a data set that are correctly predicted is denoted as TP.

True Negative (TN): The number of negative events or cases of a data set that are correctly predicted is denoted as TN.

False Negative (FP): FP measures positive cases predicted incorrectly as negative.

False Positive (FN): FN measures negative cases predicted incorrectly as positive.

Accuracy: Accuracy is the measure of correctly classified data set cases. It is expressed mathematically in equation 1.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (1)$$

Precision (P): P is the ratio of correctly predicted positive cases to the total positive cases. High precision relates to the low false-positive rate. It is a measure of the exactness of a classifier. It is defined mathematically in equation 2.

$$P = \frac{TP}{TP + FP} \quad (2)$$

Recall (R): R is the ratio of correctly predicted positive cases to all predicted positive cases of a classifier. It is a measure of the completeness of a classifier. R is defined mathematically in equation 3.

$$R = \frac{TP}{TP + FN} \quad (3)$$

F1-Score: It is the weighted average of Precision and Recall. F1 is usually more useful than accuracy when uneven class distribution in the data set. It is shown mathematically in equation 4.

$$F1 - score = \frac{2 \times (P \times R)}{P + R} \quad (4)$$

Weighted Average (WA): It is the weighted average of the sum of all classes' scores (Precision / Recall/ F1-score) after multiplying their respective class proportion. For example, the equation of WA for precision is shown in equation 5.

$$WA_P = \frac{\sum_{i=0}^{N-1} P_{Class\_i} \times D_{Class\_i}}{D} \quad (5)$$

Here, PClass_i is the Precision of class i, DClass_i is the size of the data set of class i, and D is the total size of the data set.

Macro Average (MA): The mean average of a classifier's scores (Precision / Recall / F1-score). For example, the equation of MA for precision is shown in equation 14.

$$M\,A_P = \frac{\sum_{i=0}^{N-1} P_{Class\_i}}{N} \qquad (6)$$

PClass_i is the precision of class i, and N is the number of classes of a data set.

5.2. Result Analysis

This section presents the detailed results and analysis of all the classifiers. Table 3 represents the different score values of the classifiers for their corresponding classes. Here, class 0 represents the event of non-heart disease patients, and class 1 is the event of a patient's heart disease. For an imbalanced data set, only precision and recall could not summarize the performance of a classifier. Therefore, f1-score is also introduced here. The table shows that DTC shows the overall best results of all measurement scores (precision, recall, f1-score) for all classes. However, for class 0, SVM and K-NN show 100% value for recall. Besides, SVM gives 80% and 89%, whereas K-NN has 76% and 86% for precision and f1-score, respectively.

On the other hand, for class 1, DTC also outperforms other classifiers. However, K-NN gives 100% for precision only for the same class. In contrast, SVM, NM, and K-NN perform worst for the class, respectively.

Table 3 Results of scores of different classifiers

Classifiers	Class	Precision (%)	Recall (%)	F1-Score (%)
Ada Boost	0	0.84	0.67	0.74
	1	0.27	0.50	0.35
BLR	0	0.84	0.88	0.86
	1	0.40	0.33	0.44
NB	0	0.79	0.92	0.95
	1	0.00	0.00	0.00
K-NN	0	0.76	1.00	0.86
	1	1.00	0.12	0.22
RF	0	0.83	0.83	0.83
	1	0.33	0.33	0.33
SVM	0	0.80	1.00	0.89
	1	0.00	0.00	0.00
DTC	0	0.92	0.92	0.92
	1	0.67	0.67	0.67

For more clarity, we have presented the macro and weighted average of the scores for all the classifiers in Table 4. From the table, we can see that DTC performs the best for both matrices. Although the average matrices of precision for K-NN are higher than DTC, it could not reach DTC for other scores. Hence, we can conclude that DTC is best among all classifiers for all performance matrices.

Table 4 Result of the weighted and macro average of scores of different classifiers

Classifier	Precision		Recall		F1-Score	
	MA	WA	MA	WA	MA	WA
Ada Boost	0.56	0.73	0.58	0.63	0.55	0.67
BLR	0.62	0.75	0.60	0.77	0.61	0.76
NB	0.39	0.63	0.46	0.73	0.42	0.68
K-NN	0.88	0.82	0.56	0.77	0.54	0.69
RF	0.58	0.73	0.58	0.73	0.58	0.73
SVM	0.40	0.64	0.50	0.80	0.44	0.71
DTC	0.79	0.87	0.79	0.87	0.79	0.87

6. Conclusion

This paper discussed the CPS-based community clinic of Bangladesh. A CPS-based system is proposed for collecting real-time values from the community clinic using various sensors for rural medical infrastructure. Finally, real-time data and data collected from various sources like the web and hospitals are merged. After all, this data is analyzed using machine learning models. We analyzed a heart disease dataset collected from Kaggle resource as a case study. In this dataset, different machine learning algorithms have been carried out to predict the occurrence of heart disease. Among them, the decision tree algorithm has given an accuracy of 87 %. Also, the SVM model provided 80% as performance metrics among other executed models. We accomplished this research to analyze the heart failure medical record dataset of 105 women and 194 male patients. We predicted the rate of heart disease in affected and non-affected patients using 11 heart failure symptoms, including age, anemia, CPK, diabetes, ejection fraction, high blood pressure, platelets, serum creatinine, serum sodium, smoking, and sex. Some limitations are: no infrastructure in the community clinic, connectivity is a big problem for data sending to the cloud server—training required for community clinic staff.

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