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Intelligent Cloud Based Heart Disease Prediction System Empowered with Supervised Machine Learning

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Abstract: The innovation in technologies related to health facilities today is increasingly helping to manage patients with different diseases. The most fatal of these is the issue of heart disease that cannot be detected from a naked eye, and attacks as soon as the human exceeds the allowed range of vital signs like pulse rate, body temperature, and blood pressure. The real challenge is to diagnose patients with more diagnostic accuracy and in a timely manner, followed by prescribing appropriate treatments and keeping prescription errors to a minimum. In developing countries, the domain of healthcare is progressing day by day using different Smart healthcare: emerging technologies like cloud computing, fog computing, and mobile computing. Electronic health records (EHRs) are used to manage the huge volume of data using cloud computing. That reduces the storage, processing, and retrieval cost as well as ensuring the availability of data. Machine learning procedures are used to extract hidden patterns and data analytics. In this research, a combination of cloud computing and machine learning algorithm Support vector machine (SVM) is used to predict heart diseases. Simulation results have shown that the proposed intelligent cloud-based heart disease prediction system empowered with a Support vector machine (SVM)-based system model gives 93.33% accuracy, which is better than previously published approaches.

Keywords: Cloud computing, machine learning, healthcare.

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1 Introduction

Disease prevention and health promotion programs are aimed at keeping people healthy. The purpose of these two is to empower the masses to choose a healthy lifestyle such that they have a low risk of chronic diseases. The new millennium marks the unprecedented rise of biomedical sciences. The advances in technology have made it possible to examine medical problems on the cellular level and if needed generate antibodies.

The services provided by Cloud computing (CC) are giving an on-demand Information technology (IT) delivery of applications and resources through the Internet [Prasanth, Bajpei, Shrivastava et al. (2015)]. CC empowers the initiatives to meet the modern age needs of the health care domain as well.

A cloud-based application can be used in the health care industry to share information about medical reports more conveniently and efficiently. With the help of emerging technologies test reports, medical charts, and other documents related to the patient are updated within no time. Big data set of different tests like CT scans, radiology images, X-rays, etc. are managed by the innovation of cloud computing and the health care domain.

The cloud application in the domain of health care needs a high level of security, accuracy, privacy, and availability for its implementation. In previous literature, presents different health care applications utilize the technology of cloud computing for example diabetes disease [Kumar and Chaithra (2015)], cancer diseases [Maithili, Kumari and Rajamanickam (2012)], [Mulimani and Kulkarni (2015); Wang, Yu, Kang et al. (2014)], cardiovascular diseases [Xia, Asif and Zhao (2013); Wang, Gui, Lui et al. (2014)], and brain tumor detection [Kagadis, Alexakos, Papadimitroulas et al. (2015)]. Among these several diseases, heart disease is one of the primary reasons behind the high death rate is high due to heart disease in several countries.

In 2012, the World health organization (WHO) estimated that the disease of cardiovascular has been the reason behind 31% of the deaths [WHO (2015)]. One more study conducted by the Registrar General of India states and the Indian Council of Medical Research showed that in the age range of 25 to 69, 25% of the deaths happened for the reason of cardiovascular diseases [NCD (2015)].

Hassan et al. [Hassan, Bilal, Khan et al. (2018)] proposed a system for the prediction of heart disease by using a fuzzy inference system, it takes 14 different input parameters for the prediction of heart disease and indicates the risk level as moderate, high with the help of mathematical calculations.

Multilayer Mamdani inference system was used by Ahmad et al. [Ahmad, Khan, Abbas et al. (2019)] to the proposed system to classify the stages of hepatitis B with the help of 2 input variables in layers 1 and 7 input variables at layer 2 respectively. The multilayer Mamdani based hepatitis B system developed is very easy as any medical expert or non-medical expert can use it and find the severity of the disease.

The diseases under the umbrella of the name "cardiovascular" include all the heart diseases and circulation i.e., pain of angina, heart attack, as well as coronary heart disease. In this paper, supervised machine learning algorithm SVM for prediction of heart disease output is investigated to achieve the highest accuracy. In the training and validation phases of estimation of heart disease output with supervised machine learning, a data set named heart disease with 303 data instances, is being used so that each instance includes different and diverse characteristics. Consequently, the examination and comparison with state-of-the-art techniques in the same field have been done.

The remainder of this paper is organized as follows. Section 2 briefly describes the related work. Section 3 presents the method to carry out a comprehensive evaluation for the prediction of heart disease output. Section 4 discusses the simulation and results of the proposed SVM approach. Sections 5 discuss the conclusions from the study.

2 Literature review

Fuzzy and neural network-based methods were used by Atamanyuk et al. [Atamanyuk and Kondratenko (2015); Galper, James, Mauch et al. (2011)] to recognize cardiovascular sickness among sufferers. The technique used an alternate physical and restorative arrangement of parameters like chest pain, electrocardiogram. The investigation of that group applied the neural method and gets the results about 83 percent for the prediction of disease.

To diagnose heart disease is as difficult another disease; Kim et al. [Kim and Kang (2017)] used the technique of artificial neural networks. The proposed model is viewed as a single layer model and a single input layer of 16 coronary illness structures by utilizing various neurons. In the testing phase, 4146 information tests and 3031 informational collections for low risk and 1115 for high threat were used. The activity and verification of exactness stages are correspondingly 87.04% and 81.09%. In this consideration, a propelled correctness level was achieved because of the analysis of past work and forecast.

Performance evaluation was analyzed by Classification and regression trees (CART) and Artificial neural network (ANN) by Ata et al. [Ata, Abbas, Khan et al. (2018); Ata, Khan, Abbas et al. (2019)]. A detailed comparison also made by Linear Regression on a small amount of data. Big data not considered. Recently different approaches of Computational intelligence (CI) are used in the emerging field of science also in the medical domain, Smart city, Health, etc. [Ata, Abbas, Khan et al. (2018); Ata, Khan, Abbas et al. (2019)].

Gu et al. [Gu, Wu, Yin et al. (2019)] purposed a stable cloud and fog application query system. In this system, the cloud service tests the query details from the fog network as the fog network sends the query details to the users. The cloud server may pre-select some of the data aggregation trees on the fog network, and then it will review some of the fog network data to test the final results delivered to the users. The cloud infrastructure model promotes a limited pool of virtualized services on requests, on a pay-per-use basis.

Li et al. [Li, Li, Zhang et al. (2019)] study the virtual machine packaging dependent on page sharing, which takes into account constraints in several resources. Provided a collection of virtual machine variants that access a wide set of specific memory pages, they are compressed into a limited number of physical machines, subject to various space restrictions on physical machines.

Siddiqui et al. [Siddiqui, Athar, Khan et al. (2020)] proposed the multi-technique model for human health care. The automated model proposed Diagnosis cardiovascular disease (DCD) which includes fuzzy logic (DCD-MFIS), Artificial neural network (DCD-ANN), and Deep extreme machine learning (DCD-DEML) approach using backpropagation system. These frameworks support in achieving more precision and accuracy.

Rehman et al. [Rehman, Athar, Khan et al. (2020)] proposed the model using deep extreme machine learning for diabetic patients. This research predicted the patient's condition with a minimum rate of error and shows the highest rate of accuracy.

Hussain et al. [Hussain, Syed, Abeer et al. (2020)] design a TDI-EFL expert system that diagnoses the thyroid disease using fuzzy logic. The proposed TDI-EFL Expert System designed for both medical professionals and non-professionals which detect the disease accurately with specifies time.

3 Experimental

3.1 Proposed system model

The proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning is presented in Fig. 1. In this proposed method data is collected through the Internet of medical things (IoMT) enabled devices. The proposed model is divided into two phases: The training phase and the Validation phase. The training phase consists of four layers named as: sensory layer, object layer, preprocessing layer, and application layer. The sensory layer contains various IoMT enabled sensors like BP, Sugar, ECG, etc., which sense the data from the patient and pass into the object layer through a wireless link. The data which is received by the object layer is raw because it might contain some missing values and noisy data due to wireless link. Therefore, the data is processed in the preprocessing layer. In this layer, predict the missing values using moving average method, mean or mode, and mitigate the noise using normalization. Processed data further sent to an application layer, this layer is further categorized into two sub-layers: prediction and performance layer. In the prediction layer, a supervised machine learning technique named Support vector machine (SVM) is used to train the model.

After the training prediction layer evaluates the accuracy of the training prediction layer concerning different statistical methods like accuracy, miss rate, sensitivity, etc. If the required training learning criteria are not meet then again retrain the prediction layer and evaluate the performance. After achieving the required threshold learning criteria or required number of cycles, a successful training model is a store on a cloud which can use in various applications.

For the intelligent prediction of heart disease evaluation then the second phase of the proposed model is executed. In the validation phase, the input data is received from IoMT enabled devices and the trained model is inherited through a cloud. In the validation phase when input is received, it predicted the heart disease using an inherited trained model as an output. In this paper dataset collected from the Cleveland Heart Disease dataset from the UCI repository. Input and output variable of the proposed model shown in Tab. 1 to predict heart disease.

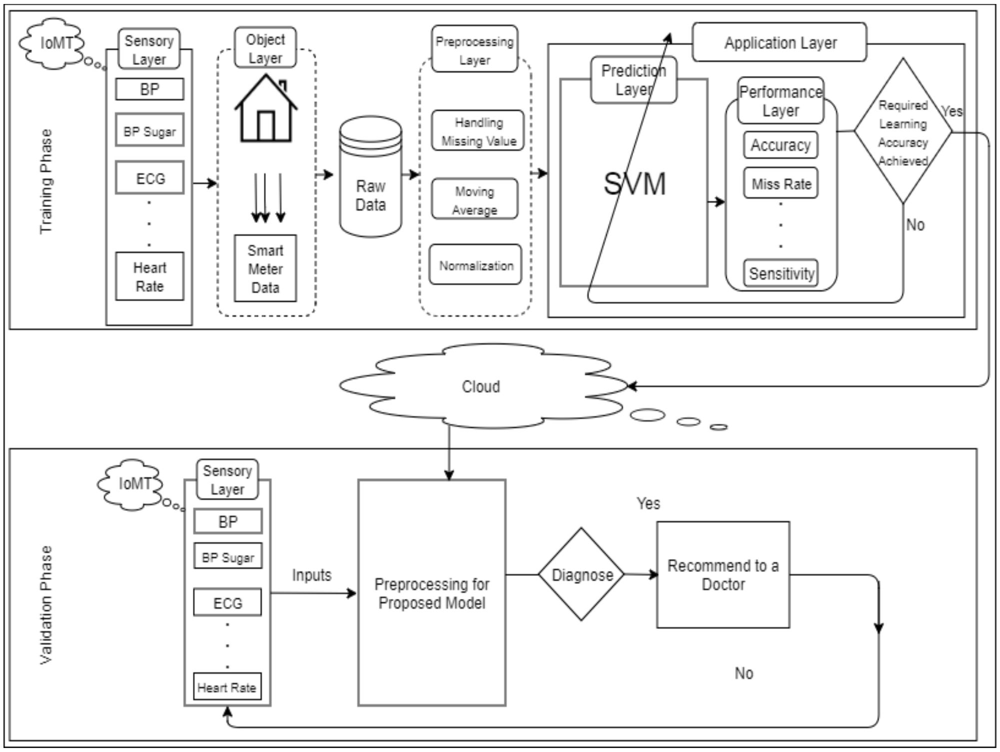

Figure 1: Proposed intelligent cloud based heart disease empowered with supervised machine learning system model architecture

Table 1: Input/output variables of the proposed system

Sr. No	I/O Variable Name	Sr. No	I/O Variable Name
Input 1	Age	Input 8	Heart Rate
Input 2	Sex	Input 9	Angina
Input 3	Chest pain	Input 10	Depression
Input 4	Blood Pressure	Input 11	ST-Segment
Input 5	Cholesterol	Input 12	Major Vessels
Input 6	Blood Sugar	Input 13	Thal
Input 7	ECG	Output	Hear Disease Result

As we know that the equation of the line is

$$x_2 = a x_1 + b \tag{1}$$

where ‘a’ is a slope of a line and ‘b’ is the intersect, therefore

$$a x_1 - x_2 + b = 0$$

Let $\bar{x} = (x_1, x_2)^T$ and $\bar{w} = (a - 1)$ then above equation can be written as

$$\overrightarrow{\hat{w}}.\bar{x} + b = 0 \tag{2}$$

This equation is derived from 2-dimensional vectors. but in fact, it also works for any number of dimensions, Eq. (2) also known as the hyper lane equation.

The direction of a vector $\bar{x} = (x_1, x_2)^T$ is written as $\bar{w}$ and is defined as

$$\hat{w} = \frac{x_1}{||x||} + \frac{x_2}{||x||} \tag{3}$$

where

$||x|| = \sqrt{x_{1+}^2 x_{2+}^2 x_{3+}^2 \dots\dots\dots.. x_n^2}$

As we know that

$\cos(\varrho) = \frac{x_1}{||x||}$ and $\cos(\sigma) = \frac{x_2}{||x||}$

Eq. (3) can also be written as

$$\hat{w} = (\cos(\varrho), \cos(\sigma))$$

$\overrightarrow{w}.\vec{x} = ||\hat{w}||\, ||x||\, \cos(\varrho)$

$$\varrho = \beta - \sigma$$

$$\cos(\varrho) = \cos(\beta - \sigma)$$

$= \cos(\beta)\cos(\sigma) + \sin(\beta)\sin(\sigma)$

$= \frac{\hat{w}_1}{||\hat{w}||} \frac{x_1}{||x||} + \frac{\hat{w}_2}{||\hat{w}||} \frac{x_2}{||x||}$

$$= \frac{\hat{w}_1 x_1 + \hat{w}_2 x_2}{||\hat{w}||||x||}$$

$\hat{w}.x = ||\hat{w}||||x|| \left[\frac{\hat{w}_1 x_1 + \hat{w}_2 x_2}{||\hat{w}||||x||}\right]$

$$\overrightarrow{\hat{w}}.\vec{x} = \sum_{i=1}^{n} \hat{w}_i x_i \tag{4}$$

The dot product can be computed as the above equation for n-dimensional vectors

Let,

$f = y\,(\hat{w}\,.\,x + b)$

If sign (f)>0 then correctly classified and if sign (f)<0 then incorrectly classified

Given a dataset D, we compute f on a training dataset

$f_i = y_i\,(\hat{w}\,.\,x + b)$

Then F which is called the functional margin of the dataset

$F = \min_{i=1.....m} f_i$

When comparing hyperplanes, the hyperplane with the largest F will be complimentary selected. Where F is called the geometric margin of the dataset. Our objective is to find an optimal hyperplane, which means we need to find the values of $\overrightarrow{\hat{w}}$ and Ƃ of the optimal hyperplane.

The Lagrangian function is

$$\mathcal{L}\,(\hat{w}, Ƃ, \sigma) = \frac{1}{2}\,\hat{w}.\hat{w} - \sum_{i=1}^{m} \sigma_i\,[y : (\hat{w}.x + Ƃ) - 1]$$

$$\nabla_{\hat{w}}\mathcal{L}\,(\hat{w}, Ƃ, \sigma) = \hat{w} - \sum_{i=1}^{m} \sigma_i\, y_i\, x_i = 0 \tag{5}$$

$$\nabla_{Ƃ}\mathcal{L}\,(\hat{w}, Ƃ, \sigma) = -\sum_{i=1}^{m} \sigma_i\, y_i = 0 \tag{6}$$

From the above two Eqs. (5) and (6) we get

$$\hat{w} = \sum_{i=1}^{m} \sigma_i\, y_i\, x_i \;\text{ and }\; \sum_{i=1}^{m} \sigma_i\, y_i = 0 \tag{7}$$

After substitute the Lagrangian function $\mathcal{L}$ we get

$$\hat{w}(\sigma, Ƃ) = \sum_{i=1}^{m} \sigma_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \sigma_i\,\sigma_j y_i\, y_j\, x_i x_j$$

thus

$$\max_{\sigma} \sum_{i=1}^{m} \sigma_i - \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} \sigma_i\,\sigma_j y_i\, y_j\, x_i x_j \tag{8}$$

Subject to

$\sigma_i \geq 0,\; i = 1 \ldots .\, m,\; \sum_{i=1}^{m} \sigma_i\, y_i = 0$

Because the constraints have inequalities, so we extend the Lagrangian multipliers method to the Karush-kuhn-tucker (KKT) conditions. The complementary condition of KKT states that

$$\sigma_i\,[y_i(\hat{w}_i.x^* + Ƃ) - 1] = 0 \tag{9}$$

x^* Is the optimal point.

σ Is the positive value and σ for the other points are$\approx$0

So,

$$y_i\big((\hat{w}_i.x^* + Ƃ) - 1\big) = 0. \tag{10}$$

These are called support vectors, which are the closest points to the hyperplane. According to the above Eq. (10)

$$\hat{w} - \sum_{i=1}^{m} \sigma_i\, y_i\, x_i = 0$$

$$\hat{w} = \sum_{i=1}^{m} \sigma_i \, y_i \, x_i \tag{11}$$

To compute the value of Ƃ we get

$$y_i\big((\hat{w}_i . x^* + Ƃ) - 1\big) = 0 \tag{12}$$

Multiply by both sides Ƃy y in Eq. 12 then we get

$y_i^2\big((\hat{w}_i . x^* + Ƃ) - y_i\big) = 0$, Where $y_i^2 = 1$

$$\big((\hat{w}_i . x^* + Ƃ) - y_i\big) = 0$$

$$Ƃ = y_i - \hat{w}_i . x^* \tag{13}$$

Then

$$Ƃ = \frac{1}{S} \sum_{i=1}^{S} (y_i - \hat{w} . x) \tag{14}$$

S is the number of support vectors. On one occasion we will have the hyperplane, and then we can use the hyperplane to make predictions. Where the hypothesis function is

$$h\,(\hat{w}_i) = \begin{bmatrix} +1 \text{ if } \hat{w}.x + Ƃ \ \geq 0 \\ -1 \text{ if } \hat{w}.x + Ƃ \ < 0 \end{bmatrix} \tag{15}$$

The above point on the hyperplane will be classified as class +1 (Heart Disease found) and the point below the hyperplane will be classified as -1 (Heart Disease not found).

So, the goal of the proposed intelligent cloud-based heart disease prediction system empowered with a supervised machine learning algorithm is to find a hyperplane that could separate the data accurately and we need to find the best one, which is often referred to as the optimal hyperplane.

4 Results and discussion

MATLAB 2019 is used for simulation purposes. The proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning has been applied on the dataset having 303 total instances [Kim and Kang (2017)]. 213 samples (70%) are used for training whereas 90 samples (30%) are used for validation. Different metrics are used for the evaluation of the proposed system predicted output.

$$\text{Miss rate} = \frac{\left({}^{P_1}/_{I_{-1}} + {}^{P_{-1}}/_{I_1}\right)}{I_{-1} + I_1} \tag{16}$$

$$\text{Accuracy} = \frac{\left({}^{P_{-1}}/_{I_{-1}} + {}^{P_1}/_{I_1}\right)}{I_{-1} + I_1} \tag{17}$$

$$\text{Sensitivity} = Y_F / (Y_F + N_{NF}) \tag{18}$$

$$\text{Specificity} = \mathrm{Y_{NF}}/(\mathrm{Y_{NF}} + \mathrm{N_F}) \tag{19}$$

$$\text{Negative prediction value} = \frac{{I_1}/{P_1}}{\left({P_1}/{I_1} + {P_{-1}}/{I_1}\right)} \tag{20}$$

$$\text{Positive prediction value} = \frac{{\mathrm{P}_{-1}}/{\mathrm{I}_0}}{({\mathrm{P}_{-1}}/{\mathrm{I}_{-1}} + {\mathrm{P}_1}/{I_{-1}})} \tag{21}$$

$$\text{False positive ratio} = 1 - \text{specificity} \tag{22}$$

$$\text{False negative ratio} = 1 - \text{sensitivity} \tag{23}$$

$$\text{Negative prediction value} = \frac{{I_1}/{P_1}}{\left({P_1}/{I_1} + {P_{-1}}/{I_1}\right)} \tag{24}$$

$$\text{Positive prediction value} = \frac{{\mathrm{P}_{-1}}/{\mathrm{I}_{-1}}}{({\mathrm{P}_{-1}}/{\mathrm{I}_{-1}} + {\mathrm{P}_1}/{I_{-1}})} \tag{25}$$

The proposed model predicts the output as negative (-1) and positive (1). In the resultant output (-1) shows no symptoms of heart disease found, whereas (1) represents that system diagnosis the presence of heart disease.

Table 2: Training performance of the proposed supervised machine learning empowered system model during the prediction of heart disease

Total Sample (N=213)	Result P_{-1}, P_1	
Input	P_{-1}	P_1
I_{-1}=88	82	06
I_1=125	4	121

While Tab. 2 shows the proposed system model performance during training. In which 213 total patient samples are taken which further divided into 88 negative and 125 positive patient samples. it is clearly shown that 82 patient samples are estimated correctly in which no heart disease found, whereas 06 patient samples are wrongly estimated as positive in which heart disease found, but heart disease not exist. Similarly, 121 patient samples are correctly estimated as positive in which heart disease found and 04 samples are estimated wrongly in which heart disease not found, but in real heart disease exists.

Tab. 3 shows the performance of the proposed system model during Validation. A total of 90 samples are used that further distributed as 37, 53 negative, and positive patient samples respectively. it is clearly shown that 33 patient samples are estimated correctly in which no heart disease found, whereas 04 patient samples are wrongly estimated as positive in which heart disease found, but heart disease not exist. Similarly, 51 patient samples are correctly estimated as positive in which heart disease found and 02 samples are estimated wrongly in which heart disease not found, but in real heart disease exists during the validation phase.

The performance of the proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning model during training and validation by using different statistical metrics are shown in Tab. 4.

It is clearly shown that the proposed system during training produces 4.69% and 95.31% miss rate and accuracy, respectively. During validation, the proposed system produces 6.67% and 93.33% miss rate and accuracy, respectively. Tab. 4 also shows the proposed system model performance in terms of sensitivity, specificity, during training & validation phase. It clearly shows that the Proposed system during training gives 95.35% & 95.28% sensitivity and specificity respectively. And during validation proposed system gives 94.29% & 92.73% sensitivity and specificity respectively. Also, some more statistical measures are added to predict the values such as false positive, false negative, as well as positive and negative prediction values gives the result during training 94.28%, 94.35%, 93.18%, and 96.8%. And during validation, the proposed system gives 93.29%, 91.73%, 96.23%, and 89.19% respectively.

Table 3: Validation performance of the proposed supervised machine learning empowered system model during the prediction of heart disease

Total Sample (N=90)	Result P_{-1}, P_1	
Input	P_{-1}	P_1
I_{-1}=37	33	04
I_1=53	2	51

Table 4: Statistical performance evaluation of proposed supervised machine learning empowered system model during training & validation

	Miss Rate	Accuracy	Sensitivity	Specificity
Training	4.69%	95.31%	95.35%	95.28%
Validation	6.67%	93.33%	94.29%	92.73%
	Positive prediction value	Negative prediction value	False-positive value	False-negative value
Training	93.18%	96.8%	94.28%	94.35%
Validation	96.23%	89.19%	93.29%	91.73%

Table 5: Comparison of performance measure of proposed supervised machine learning empowered system model during validation & training with previously published methods

	Training		
	Positive predictive value (PPV)	Negative predictive value (NPV)	Accuracy
Logistic regression (LR) **[Kim and Kang (2017)]**	57.24%	87.63%	86.11%
Neural network (NN) **[Kim and Kang (2017)]**	63.04%	88.67%	87.04%
Framingham risk score (FRS) **[Kim and Kang (2017)]**	2.54%	85.48%	6.67%
Proposed System Model	93.18%	96.8%	95.31%
	Validation		
	Positive predictive value (PPV)	Negative predictive value (NPV)	Accuracy
Logistic regression (LR) **[Kim and Kang (2017)]**	67.53%	83.63%	80.32%
Neural network (NN) **[Kim and Kang (2017)]**	67.55%	85.08%	81.09%
Framingham risk score (FRS) **[Kim and Kang (2017)]**	21.49%	54.41%	28.87%
Proposed System Model	96.23%	89.19%	93.33%

Tab. 5 shows the comparison of proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning model with previously published state of art methods. Different algorithms of machine learning named as Neural network (NN) [Kim and Kang (2017)], Logistic regression (LR) [Kim and Kang (2017)] and Framingham risk score (FRS) [Kim and Kang (2017)] are used for comparative analysis using different performance metrics, for example, Positive predictive value (PPV), Negative predictive value (NPV), and Accuracy. It also is shown that the performance of the proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning-based system model gives 93.18%, 96.8% & 95.31% and 96.23%, 89.19% & 93.33% Positive predictive value (PPV), Negative predictive value (NPV) and accuracy during training and validation respectively. It's clearly observed that the proposed SVM based system model gives better results as compared to the previously published approaches during training as well as in validation.

5 Conclusions

In this article, an intelligent cloud-based heart disease prediction system empowered with supervised machine learning is proposed. The simulation results have shown that the performance of the proposed system model gives better results as compared to the previous [Kim and Kang (2017)] proposed approaches like Logistic regression, Neural network & Framingham risk score. Further, it also observed that the proposed intelligent cloud-based heart disease prediction system empowered with supervised machine learning-based system model gives 95.31% & 93.33% accuracy during training and validation respectively.

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