INTERNET OF MEDICAL THINGS ENABLED CLOUD-BASED BREAST CANCER IDENTIFICATION WITH MACHINE LEARNING

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ABSTRACT: Breast cancer occurs when cells in the breast grow out of control. Breast cancer can spread outside the breast through lymph vessels and blood vessels when it spreads to other parts of the body, it is said to have metastasized. Most breast cancer cases are reported in women who are 50 years and/or o40 years older. According to facts and figures shared by WHO (World Health Organization), it impacts 2.1 million women every year and also causes the greatest number of cancer-related deaths amongst women. Whilst breast cancer rates are higher among women in more developed regions, rates are increasing in nearly every region globally. Different machine learning algorithms have been applied to the dataset like Naïve Bayes (NB), J48 Decision tree, K-Nearest Neighbor (KNN) and ANN (Gradient Descent) have been applied among them ANN (Gradient Descent) produces the optimal results among these classification algorithms. The proposed Internet of Medical Things Enabled Cloud-Based Breast Cancer Identification with Machine Learning system model with 98.07 % accuracy has been achieved. For the proposed model 97.64 % sensitivity and 98.32 % specificity have been recorded. From the results produced by the proposed expert system, it's satisfactory to utilize it for breast cancer diagnosis. The Proposed system model will be helpful for the diagnosis of breast cancer.

Keywords: Internet of medical things (IoMT), ANN (Gradient Descent), prediction model, Breast cancer.

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INTRODUCTION

A significant number of (about 2.1 million) women develop breast cancer every year, and more than 50% become dead due to frequent causes of cancer-related deaths among women, worldwide. Every year incidences of breast cancer are reported to increase in developing countries where early detection is inadequate but also in developed countries i.e. about 12% in the USA (WHO, 2019). Early detection of this fatal problem is important to prevent breast cancer incidences and survival. In developing countries, the majority of women are prone to this problem due to a lack of awareness and resources in health systems for timely detection and diagnosis (NBCF, 2019). Henceforth, for positive outcomes connected to breast cancer diagnosis; inexpensive, and available screening facilities should be planned for identifying its early symptoms and signs (Ahmad, A. 2019).

An innovation is witnessed in cancer screening by Computer Aided Diagnosis (CAD) of specific (biomarkers) cancer features. Patricio *et al*. (2018) reported that these techniques vary from the conventional test methods of mammography/clinical breast investigations as these let more vigorous predictive approaches and outcomes for treatment preferences. Such strategies need the identification of the potential biomarkers achieved from the routine blood investigation of clinical samples to scrutinize their sensitivity, accuracy, and specificity. Such information/prediction model patterns are established to augment huge/complex data sets using various statistical methodologies. Curently these screening procedures are gaining more significance in providing important contributions to fetching early screening quality procedures (Patrício *et al.,* 2018).

A number of studies have authenticated that the use of machine-learning methods is considered to increase the accuracy of foreseeing cancer incidences and their prognosis. Furthermore, these techniques aid to improve the basic knowledge of cancer development/progression at the primary level. Machine learning has been used in various cancer research for the last 3 decades, however, its applications have become more common in distinctive and predicting cancer-causing factors, which is currently indispensable in determining the probability of rising breast cancer in women (Osareh *et al.,* 2010). These causative agents included molecular biomarkers, metabolic parameters, cellular parameters, and anthropometric data e.g. body mass index, age). Combining these factors with clinical information (such as a patient's general health), a good set of screening parameters can be developed through a machine learning. A range of causative agents has been investigated for early detection, dependent on their sensitivity and specificity with the increasing breast cancer incidences (Brody *et al.,* 2003).

Through conventional screening-methods i.e. mammography, these parameters can be possibly be identified in routine blood samples. This research study is therefore aimed to combine the predictive and probabilistic approach of machine learning technique with potential screening candidates or biomarkers of breast cancer to gain statistically organized data about their specificity and sensitivity in cancer screening. In addition, using machine learning we could develop a comparative study to analyze the most favorable and least favorable screening candidates for achieving refined and more sophisticated outcomes. These outcomes would provide promising alternative solutions and therefore have great applications in early breast cancer detection and prevention(Birdwel *et al.,* 2001).

Breast malignant growth has gotten one of the most widely recognized sicknesses among ladies that prompt passing. Breast malignancy can be analyzed by ordering tumors. There are two distinct sorts of tumors, example, dangerous and kind tumors. Doctors need a dependable determination strategy to recognize these tumors. In any case, for the most part, it is hard to separate tumors even by specialists. Subsequently, the computerization of the demonstrative framework is required for diagnosing tumors. Numerous specialists have endeavored to apply AI calculations for identifying the survivability of malignant growths in individuals and it is additionally been demonstrated by the analysts that these calculations work better in distinguishing disease analysis. This paper sums up the use of AI calculations in recognizing diseases in humans. In this review area, 2 gives the data of the neural system, and its learning rules. Area 3 determines about writing survey dependent on Artificial Neural Network (ANN). Section 4 indicates other related chips away at breast cancer utilizing neural systems. Area 5 infers with other AI calculations and their sorts, with related work on those calculations (Praseetha, *et al.,* 2019; Khan, *et al.,* 2020; Siddiqui, *et al.,* 2021).

LITERATURE REVIEW

The contribution of the Internet of Medical Things (IoMT) in the healthcare domain is to enhance medical and healthcare services for individual health and healthcare departments. Their study reviewed the researchers who successfully applied IoMT-based techniques specifically in different medical fields to provide accurate, productive, and reliable service in a digitized format. They proposed that IoMT is a challenging technique with huge potential that would dynamically revolutionize our healthcare structure (Joyia *et al.,* 2017).

The researchers demonstrated the efficacy of IoMT in monitoring big data in healthcare departments. In their research, they critically examined the productivity, time management, and all other features of IoMT enabled devices and software. They concluded that IoMT enabled wearables or mobile apps are user-friendly and support fitness, disease symptom tracking, health education, and can raise preventive strategies. They believed it IoMT is a novel personalized preventive technology that can store, analyze and predict large data files in medical departments by interlinking and reducing inefficiencies (Ross, *et al.,* 2016).

In artificial intelligence, machine learning is the branch used for high precision in medical applications. In this study, the researchers surveyed different types of machine learning techniques to highlight the success of its predictive properties in cancer prediction and progression by comparing machine learning with other detection and predictive methods, this research survey found out that machine learning techniques substantially improve result accuracy by almost 15 to 20 percent in cancer studies such as breast cancer. Moreover, these techniques are gaining marked importance in understanding how cancer develops, its root causes, and the development of personalized medicines against its incidence and recurrence. Due to its widespread applications, the researchers highly recommend machine learning methods for studying cancer-related difficulties (Cruz, *et al.,* 2006).

The importance of computer-aided detection (CAD) in screening for breast cancer is to improve the early-stage diagnostic rate. After undergoing an extensive review study they revealed that CAD improves detection rates, breast tumor imaging, and time-consuming double reading observations. However, regarding these benefits, the reviewers declare that the applications of CAD methods are still limited in clinical settings due to inadequate perceptions about their effectiveness in cancer detection. In the future, it is hoped that by implementing CAD as a diagnostic strategy incidence of breast cancer can be progressively (Ahmad, *et al.,* 2013) .

Delicate Computing strategies assume a significant job in choice in applications with loose and dubious information. The utilization of delicate figuring disciplines is quickly developing for the determination and anticipation in clinical applications. Among the different delicate processing methods, the machine learning framework exploits the fuzzy set hypothesis to give register questionable words. In a fluffy master framework, information is spoken to as a lot of unequivocal etymological standards. Analysis of bosom malignancy experiences vulnerability and imprecision related to loose information measures and inadequacy of information on specialists. Notwithstanding, there are a few innovation situated examinations revealed for bosom disease determination, and hardly any investigations have accounted for the bosom malignant growth visualization.

Soft Computing approach systems fuzzy system 13 (Hussain *et al.,* 2019), 14 (Fatima, *et al*. 2019; Atta *et al*. 2019) neural network (Khan *et al*. 2019), and swarm intelligence (Khan *et al.,* 2015), and evolutionary computing (Khan, *et al.,* 2015) like genetic algorithm (Ali *et al.,* 2016), (Umair, *et al.,* 2015; Umair *et al.,* 2013; Kashif *et al.,* 2018; Alqudah *et al.,* 2019) are the strong candidate in the field of smart heath and smart cities.

Proposed Model: The suggested model consists of 2 major phases i.e. Training phase and the Relation phase. The Training phase is further divided into three major layers; (1) Data Acquirement layer (2) Pre-processing layer (3) Application layer. In the Data Acquisition layer, we use multiple sensors which are IoMT enabled with the parameters of our research study. They are connected with the IoMT-enabled devices to store the data in a database that is called raw data. It's a wireless linked data in which the pre-processing is applied using Normalization, Moving Average, and Mean (See figure 1).

After the pre-processing, the application layer is activated. This application layer is further divided into two other layers; the Prediction layer and the Performance evaluation layer. In the Prediction layer, we use Machine learning which is going to predict our model or train our model. After training, we evaluate the performance of our trained model in the performance evaluation layer for RMSE, Accuracy, and Regression. Here we have to check if the learning criterion is met or not. If the criterion does not meet then the prediction layer is retained again and again until our learning criteria are met. Once the learning criterion is accomplished the trained model is stored on a cloud. The data then enters the Validation phase that can be conducted anywhere or in any place such as a hospital. The validation is on a client-server interconnected with IoMT devices. It imports the trained model from the cloud and gives input for prediction, the input is then further checked for accuracy of prediction. If the diagnosis is positive then it is recommended to a doctor and if it is negative then it is discarded and the system moves back to the next record.

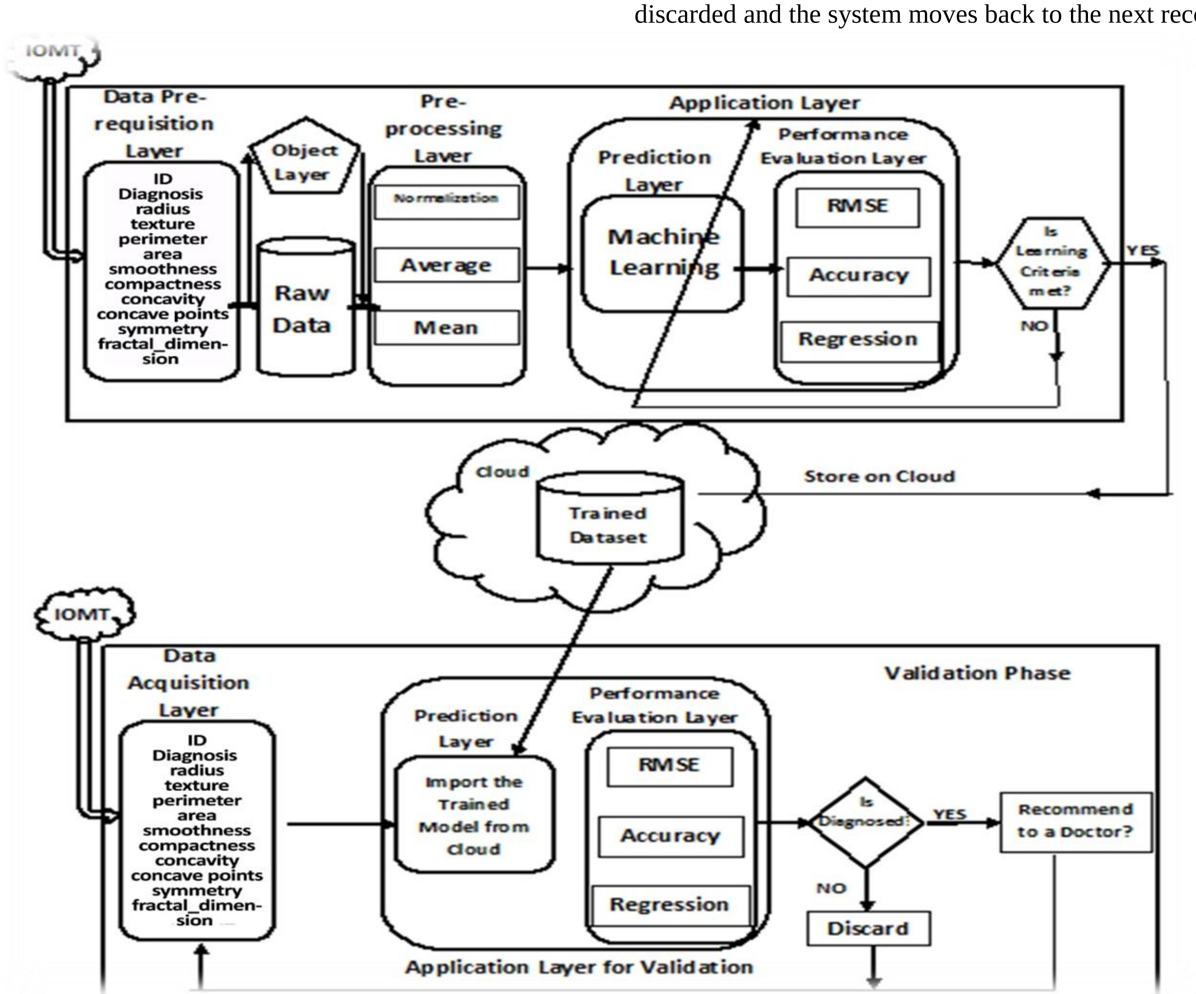

Figure 1 Theoretical Framework of the study

Mathematical Model: The ANN architecture with the Back-Propagation algorithm incorporates the input layer, hidden layer, and output layer are being used for convergence and bit per data (BPD) rate. The steps incorporate initialization of weight, Back Propagation of error and updating of weight and bias, and Feedforward.

$$¥_j = c_1 + \sum_{i=1}^{ñ} (\quad v_{ij} * t_i) \quad 1$$

$$ß_j = \frac{1}{1 + e^{-¥_j}} where j = 123 \dots \dots u. \quad 2$$

The input is fetched using the equation below

$$¥_k = c_2 + \sum_{j=1}^{ñ} (µ_{ij} * ß_j) \quad 3$$

Whereas the equation below represents the output activation function

$$£ = \frac{1}{2} + \sum_j (†_k - ¥_k)^2 \quad 4$$

Here $†_k$ $u$denotes the desired output. Whereas, out as a calculated output. However, the change in weight for the output layer is calculated using the formula below

$$\Delta \mathrm{W} \propto \frac{Œ£}{ŒÄ}$$

$$V_{i,j} \propto \boldsymbol{\epsilon} \frac{Œ£}{Œµ_{i,j}}$$

The equation below denotes the chain rule.

$$V_{i,j} = -\boldsymbol{\epsilon} \frac{Œ£}{Œß_j} * \frac{Œß_j}{Œ¥_j} * \frac{Œ¥_j}{Œµ_{i,j}} 5$$

After substituting the values in the equation above, the value of weight changed is obtained using the equation below.

$$V_{i,j} = \boldsymbol{\epsilon}(†_k - ß_k) * ß_k(\mathbf{1} - ß_k) * (ß_j) 6$$

$$\xrightarrow{\Delta v_{i,j}} = \boldsymbol{\epsilon} fkß_k \quad 7$$

Where,

$$f_k = (†_k - ß_k) * ß_k(1 - ß_k) \qquad 8$$

$$Z_{i,j} \propto -\left[\sum_{\boldsymbol{k}} \frac{Œ£}{Œß_k} * \frac{Œß_k}{Œ¥_k} * \frac{Œ¥_k}{Œß_j}\right] * \frac{Œß_j}{Œ¥_j} * \frac{Œ¥_j}{Œž_{i,j}}$$

$$Z_{i,j} = -\boldsymbol{\epsilon} \left[\sum_{\boldsymbol{k}} \frac{Œ£}{Œß_k} * \frac{Œß_k}{Œ¥_k} * \frac{Œ¥_k}{Œß_j}\right] * \frac{Œß_j}{Œ¥_j} * \frac{Œ¥_j}{Œž_{i,j}}$$

$$Z_{i,j} = \boldsymbol{\epsilon} \left[\sum_{\boldsymbol{k}} (†_k - ß_k) * ß_k(\mathbf{1} - ß_k) * (v_{j,k})\right] * ß_k(\mathbf{1} - ß_k) * (\boldsymbol{\alpha}_i)$$

$$Z_{i,j} = \boldsymbol{\epsilon} \left[\sum_{\boldsymbol{k}} (†_k - ß_k) * ß_k(\mathbf{1} - ß_k) * (v_{j,k})\right] * ß_j\left(\mathbf{1} - ß_j\right) * (\boldsymbol{\alpha}_i)$$

$$Z_{i,j} = \boldsymbol{\epsilon} \left[\sum_{\boldsymbol{k}} fk(v_{j,k})\right] * ß_j\left(\mathbf{1} - ß_j\right) * (\boldsymbol{\alpha}_i)$$

$$Z_{i,j} = \boldsymbol{\epsilon} fk \boldsymbol{\alpha}_i \quad 9$$

Where,

$$fk = \left[\sum_{\boldsymbol{k}} fk(v_{j,k})\right] * ß_j\left(\mathbf{1} - ß_j\right)$$

The output and the hidden layer and updation of the weight and bias between layers is visualized through the equation below

$$v_{j,k}^{+} = v_{j,k} + \Lambda_{è} \Delta v_{j,k} \; 10$$

$$ž_{j,k}^{+} = \Delta\, ž_{i,j} + \Lambda_{è} \Delta ž_{j,k} \quad 11$$

Dataset Evaluation: The Breast Cancer Dataset (BCD) utilized by us has been given to the University of California, Irvine (UCI). 11 traits exist there, what's more, the first is the ID that we will evacuate (it's anything but an element we need to take care of in our grouping). The nine measures are as talked about before in bosom malignant growth order segment, they are intended to decide whether lump acts amiable otherwise defame, the preceding element comprises of parallel worth (2 aimed at the amiable lump in addition to 4 aimed at defame lump).

The dataset utilized to conduct this research is the updated version of the Wisconsin Diagnostic Breast Cancer Data Set (WDBC) downloaded from Kaggle. It predicts that either it is the benign or malignant state of breast cancer. The features of the datasets were determined through an analysis of an image of an FNA i.e. fine needle aspirate of a breast mass. The analysis performed incorporates the following traits. However, the real-valued features from – numbered below, describe the characteristics of the cell nuclei.

Table1 Dataset Attributes.

Sr.No.	Name of Attributes	Symbol	Data type
1	Id	ID	Integer
2	diagnosis (M=1, B=0)	diagnosis	Integer
3	radius_mean	Radius	Numeric
4	texture_mean	Texture	Numeric
5	compactness_mean	compactness	Numeric
6	area_mean	Area	Numeric
7	smoothness_mean	smoothness	Numeric
8	symmetry_mean	symmetry	Numeric
9	concavity_mean	concavity	Numeric

10	concave points_mean	concave points	Numeric
11	perimeter_mean	perimeter	Numeric
12	fractal_dimention_mean	fractal_dimention	Numeric

The data set values are numeric so to apply different classification techniques it is first converted to a stringto a wordvector then numeric tonominal. Data Values is converted from numeric to nominal to implement other techniques which are shown in figure 2 that are classified into healthy and Diseased form.

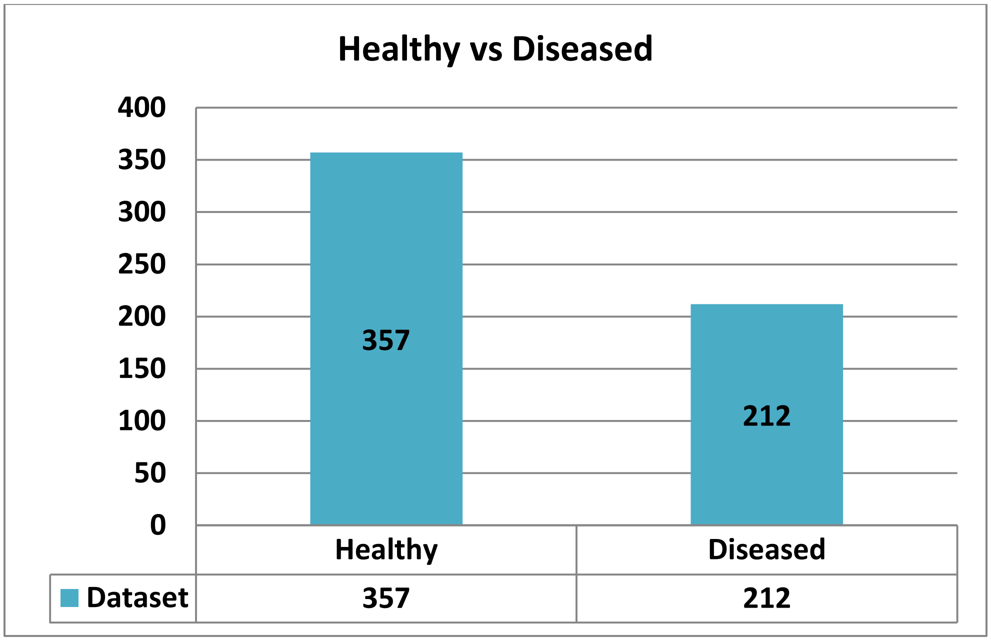

Figure 2 Healthy VS Diseased

RESULTS AND DISCUSSIONS

A confusion matrix is a technique for summarizing the performance of a classification algorithm. Calculating a confusion matrix can give you a better idea of what your classification model is getting right and what types of errors it is making.

$$\textbf{Sensitivity} = \frac{True\_Positive}{True\_Positive + False\_Negative} \quad 12$$

$$\textbf{Specificity} = \frac{True\_Negative}{True\_Negative + \ False\_Positive} \quad 13$$

$$\textbf{Accuracy} = \frac{True\_Psitive + True\_Negative}{True\_Positive + True\_Negative + \ False\_Positive + False\_Negative} \quad 14$$

Table 3ANN (Gradient Descent) Confusion Matrix.

	a – Malignant	**b – Benign**
a – Malignant	207 (TP)	5 (FN)
b – Benign	6 (FP)	351 (TN)

The ANN Gradient Descent is employed to classify that either the patient had a benign or malignant tumor. Performance of ANN (Gradient Descent) can be visualized by Table 4 and Table 5.

Figure 3 shows the performance analyses of all four machine learning algorithms i.e (Naïve Bayes, J48 Decision tree, KNN, and ANN (Gradient Decent).

It is shown from the experiment performed that Naïve Bayes accuracy is 78.38% that is less than the ANN that has an accuracy of 98.07% and also less than the KNN having an accuracy of 85.59%. It is concluded that decision trees are used both for numeric and categorical data which are shown in figure 4. It is shown that the least significant attribute is class tests in decision trees that have an accuracy of 81.72% while predicting breast cancer causes so it can be neglected.

Table 4:Performance results of ANN (Gradient Decent).

Algorithm	Sensitivity/Recall %	Specificity %	Accuracy %
ANN (Gradient Decent)	97.64	98.32	98.07

Table 5:Performance Analysis of Machine Learning Algorithms.

Algorithm	Sensitivity/Recall	Specificity	Accuracy
Naïve Bayes Classifier	69.81	83.47	78.38
J48 Decision Tree	74.53	85.99	81.72
KNN	82.50	87.26	85.59
ANN Gradient Descent	97.64	98.32	98.07

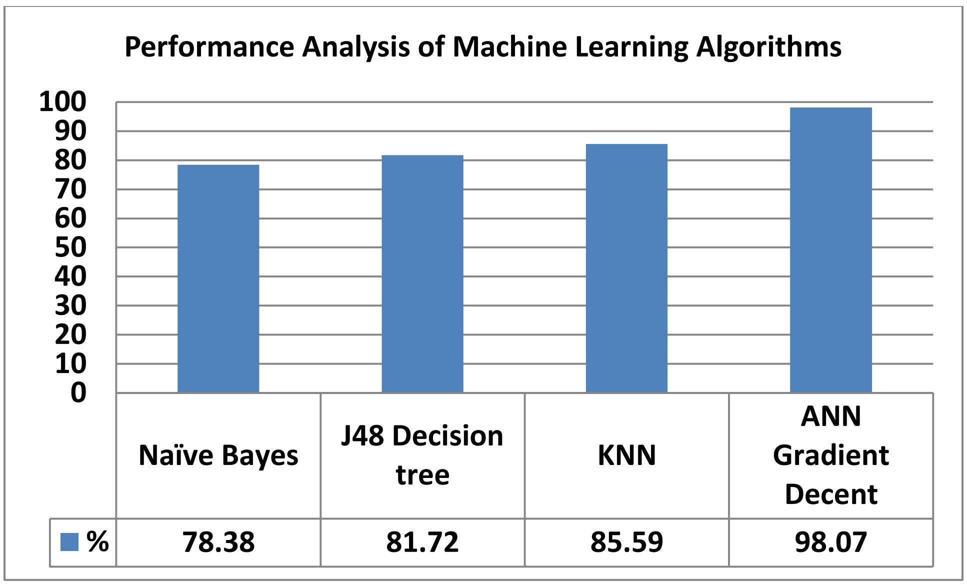

Figure 3 Performance Analyses of Machine Learning Algorithms

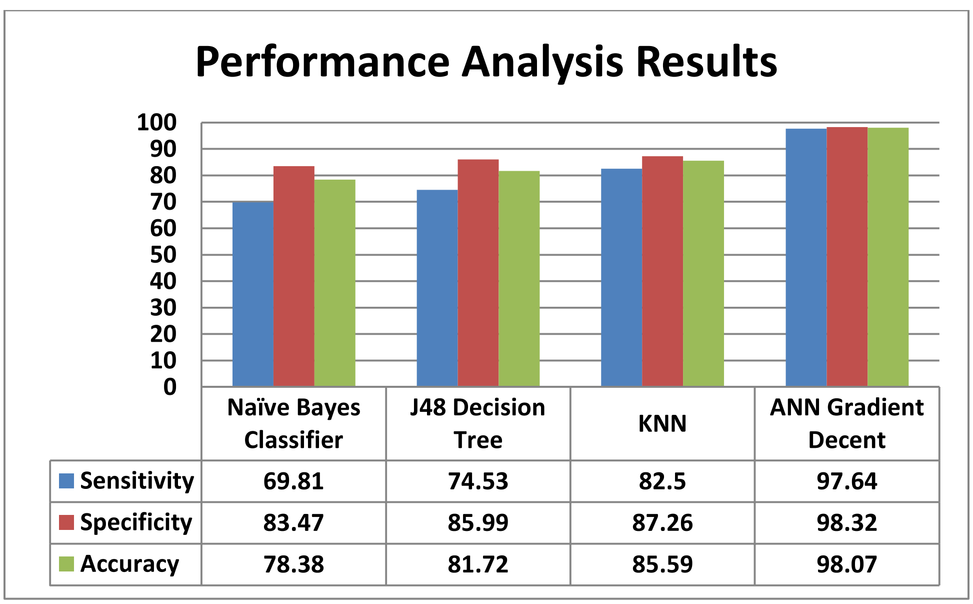

Figure 4 Performance Analysis Results.

Table 6:Comparative Analysis of Results with Different Classifiers

Classifier	Accuracy
Supervised Fuzzy Clustering (Abonyi & Szeifert, 2003).	95.5%
CBRGenetics (Darzi, AsgharLiaei & Hosseini, 2011).	97.3%
Fuzzy Rule Classification (Gadaras & Mikhailov, 2009).	96%
RBF-SVM (Hu, Liu & Yu, 2008).	76%
The proposed model (ANN Gradient Decent)	98.07%

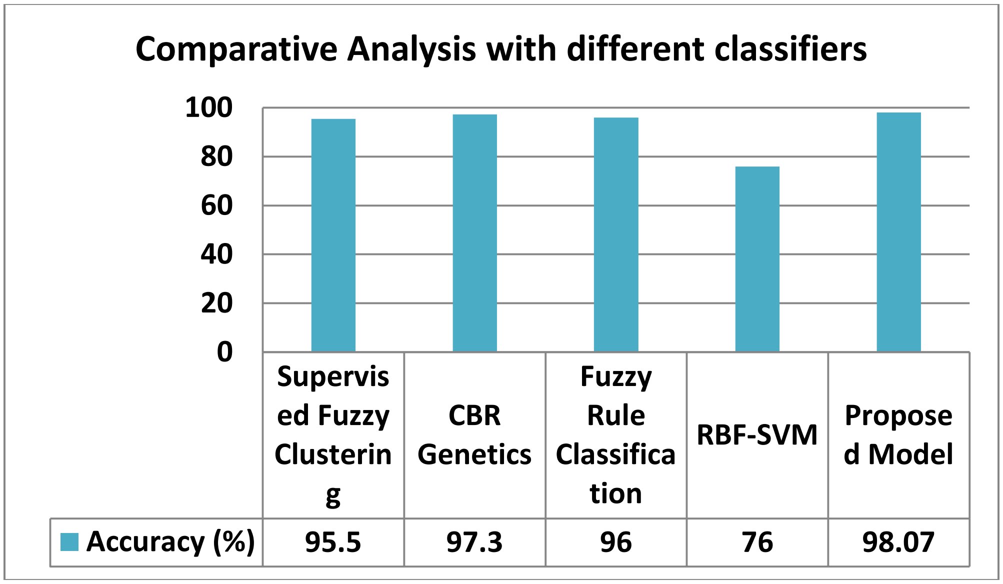

Figure 5 Comparative Analyses of Results with Different Classifiers

Secondly, ANN Gradient Decent shows a high accuracy level of 98.07% with combining three attributes. The results gained i.e. accuracy rate after the experimentation were compared with the research performed by variant researchers can be visualized in Table 6 and Figure 5.

Conclusion: This research is conducted to diagnose breast cancer in women. Certain features are captured to classify a woman in the "benign" or a "malignant" class.Dataset is collect from the UCI repository which contains 569 medical instances. Different data mining techniques and machine learning techniques have been implemented on the dataset for breast cancer predictions. Results produced from these machine learning techniques show that classification is one of the most capable ways to predict the presence of disease. Naïve Bayes, Decision Tree, K-NN, and ANN Gradient Decent produced accuracies 78%, 60%, 85 %, and 98.07 % respectively.

Comparative analysis of the proposed model is carried out from where it's found that the proposed model produced better results than that of the literature models, which made this research worthful. As patients of breast cancer are increasing day by day. The development of the proposed system can help medical practitioners to diagnose the patient who is suffering from such a deadly disease, with easier procedures and better reliability. The sensitivity and specificity produced by this system are more than that of 98% which makes this system useable in real-time.

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