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Research Article

An Ensemble Filter based Feature Selection with Deep Learning Classification for Breast Cancer Prediction using IoT

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Abstract—Artificial intelligence and data mining have played an increasingly important part in the evolution of the Internet of Things (IoT) during the last few years, allowing researchers to evaluate both current and historical data. In contrast to men, women are more likely to be diagnosed with breast cancer than men. In an IoT healthcare system, early-stage breast cancer recovery and treatment are dependent on an accurate and quick diagnosis. There are currently no effective methods for detecting early breast cancer stages, and many women succumbed to the disease as a result. As a result, medical specialists and researchers face a significant barrier in identifying breast cancer at an early stage. We developed a deep learning-based diagnostic system that accurately distinguishes between malevolent and healthy people in the IoT environment. Our suggested approach uses a 1-D convolutional neural network (1D-CNN) as a deep learning classifier to distinguish between cancerous and benign individuals. To recover the classification presentation of the classification system, we employed an ensemble filter based feature selection approach to choice more relevant features from the breast cancer dataset. Use of the splits strategy for training and testing of a classifier for the finest prediction model is employed here. The dataset "Wisconsin Diagnostic Breast Cancer" was used in this study to test the proposed method. Classifier 1D-CNN obtained optimal classification performance on this best subset of data, as demonstrated by the experiments, which show that the suggested feature selection strategy selects the most useful features.

Keywords— *Breast Cancer; Internet of Things; Healthcare; Machine Learning Classifier; Feature Selection; Training Data.*

I. INTRODUCTION

A person is said to be healthy if they are in a condition of complete bodily, mental, and social well-being, rather than just being free of disease. For many people, health is a fundamental requirement for a higher quality of life. Many causes, including poor health care services, vast inequalities between rural and urban areas and the absence of physicians and nurses during the most critical times of need, have contributed to the global health crisis [1-2]. In the IoT, all ordinary Internet-enabled and non-internet-enabled devices can sense, communicate and share data via wireless or cable connections. Microcontrollers and integrated circuits are used to create and collect data that is subsequently transmitted to other devices via networking connections [3]. Using this method, data can swiftly spread over multiple devices and be viewed by multiple users without the need for human intervention. The IoT merely enhances the capabilities of gadgets and improves the user experience [4]. The Internet of Things (IoT) is used in healthcare monitoring because it is fast, dependable, and versatile, and because cloud computing provides a crucial part of data storage. Having access to a patient's medical records allows healthcare providers to have an overall picture of the patient's treatment and to track the patient's condition over time.

Health and environmental conditions may be tracked using IoT in healthcare management, which is the most significant use of the technology. Different body sensor nodes [6] are used to imprisonment the patient's data (such as temperature, and blood glucose levels). Additionally, the acquired data is sent through the cloud network via IoT agents and mobile devices. Data is efficiently processed and stored on the cloud network. Data is processed and uploaded into the cloud, where doctors can take action remotely. [7] The ability to accurately diagnose disease and provide patients with appropriate therapies is a key component of any healthcare endeavor. Diagnosis is a difficult task, but it is one that must be completed successfully. In many cases, the doctor's knowledge and understanding is used to make the forecast, which may at times be incorrect, resulting in unpleasant outcomes [8-10]. An automated medical analysis system that makes use of the data gathered and provides decision assistance is therefore required. Even before the patient experiences any significant symptoms, this technique can assist in making a diagnosis of a problem using only a few simple medical tests. In order to meet this need, authors rely on hospital-managed health information systems [11]. Their goal was to construct an intelligent disease prediction system that uses a history database of various diseases to diagnose illness by extracting hidden information from massive amounts of data. As a result, machine learning techniques are used to procedure a massive amount of patient data and extract meaningful information from it in an efficient manner in the e-healthcare network [12].

Among women worldwide, breast cancer (BC) is regarded to be the leading cause of death from disease. [13] Cancer is made up of aberrant cells in an individual's body that can spread throughout the body, not just to the affected area. Cancer of the breast has become more deadly as it has spread to other regions of the body, making it a top cause of death worldwide [14]. Regional differences in the discriminative prognosis have been predicted by several different researches. Selecting the most relevant characteristics from the dataset is done using an ensemble filtering technique in this study. The 1D-CNN model is then used to make a final prediction about the likelihood of breast cancer.

According to this structure, the break of the paper is: Section 2 focuses on existing methods for predicting breast cancer. Section 3 delivers a brief summary of the suggested methodology. Section 4 delivers the validation of the proposed methodology with existing methodologies, and Section 5 depicts the conclusion of the work. 5.

II. Related Works

IoT and computer-supported diagnosis can be used to monitor patients with heart failure, according to Abdel-Basset et al. [16]. It was initially communicated using Bluetooth technology to the cloud database via a smart gateway, which was connected to the mobile phones of the patients with heart failure. Patients were divided into many categories by the doctors based on the symptoms they presented with. Heart failures can be detected, monitored, and controlled using the IoT and techniques. The high-level system's performance was confirmed by the results of the experiments.

There is now an automated framework for the diagnosis of cardiac disease that was developed by Ali and colleagues [17]. In order to create training datasets, the feature vectors had to be normalized first. The training data was then used in a statistical framework to perform assortment and feature ranking. During the data testing phase, the same subset of features was used as during the framework's training phase. A neural network (NN) used training data with a smaller amount of characteristics for training drives. The test data was used to evaluate the trained NN's performance.

New healthcare frameworks can be built using block chain technology, according to Rathee et al [18]. Transparency in document accessibility, healthcare data, and the shipment process between providers and clients were all made possible thanks to the block chain. Experiential evaluation of the framework was measured through malevolent IoT objects' illicit behaviors or communications. Healthcare IoT systems face a number of hurdles, and Mutlag et al. [19] attempted to address these issues by focusing on three primary factors: load balancing, interoperability, and compute offloading. [19]

Using a secure, lightweight authentication framework, Zouka and Hosni [20] ensured that personal health data was protected and that communication was safe. Patients' real-time bio signals can be monitored by clinicians using a machine-to-machine (M2M) patient monitoring screen and remote health app in the proposed framework. Because it reduced access time while still achieving good results, the proposed structure proved effective. When the verification and transfer times are taken into account, the structure has the longest key generation time.

An Artificial Neural Network (ANN) objective function for breast cancer analysis was proposed by Hajiabadi et al. [21]. Correntropy, Hinge, and Cross Entropy are three loss functions that the author used to evaluate the dataset at various noise levels and find the loss functions. Two-layer nested ensemble classifier was created by MoloudAbdar et al. [22]. Models are evaluated using K-fold cross-validation. Voting ensembles and stacking were both used. This model increased the Nave Bayes algorithm's ability to detect breast cancer.

Gopal's [23] team proposed a strategy for combining the IoT and machine learning such as random forest, logistic regression and Multi-Layer Perceptron to undertake early detection of breast cancer (MLP). The obtained findings showed that the MLP classifier has a higher accuracy and a lower error rate than LR and RF. Using the classifier we proposed, we got precision of 98%, recall of 97%, F Measure of 96.7% and accuracy of 98%, respectively. According to our findings in this study, a classifier's minimum error rate is 34.21 percent of the Mean Absolute Error (MAR), 45.82 percent of Root Mean Square Error (RMSE), or 64.47 percent of the Relative Absolute Error (RAE).

The most precise set of features needed to detect breast cancer is described by Mate, Y. and Somai, N [24]. While still retaining high accuracy, it can significantly reduce the number of parameters while still maintaining hyper parameter customization and feature selection. To produce the best results, the Extra tree classification algorithm employs feature selection and bayesian optimization, and hyper-parameter tweaking.

Abbas, S., [25] to efficiently identify and classify features. For accurate classification, WOA helps minimize the dimensionality of data and extract useful features. Compared to eight other machine learning methods, untried results on a dataset showed an improvement in performance. There is little doubt that feature selection strategies are useful in enhancing prediction accuracy in this model, which outperformed them all with a precision of 99.30 percent.

III. Proposed Methodology

Certain operations including sensing and processing data as well as analyzing and transmitting data are used in the proposed architecture because this is how the healthcare system works. Medical and environmental circumstances can affect the sensors' ability to sense. Small, inexpensive, intrusion-sensing smart home sensors could be used in a residential environment to achieve this goal. A comprehensive level of real-time home monitoring is made possible by the incorporation of these sensors, resulting in trustworthy and effective healthcare decisions and a high standard of living for those who want to live independently. In sensor network, each wireless sensor is considered a node that can gather and process sensory input, as well as communicate with other nodes. When deploying, keep in mind the layout of the house and the best places to place sensors. A wide range of radios, such as MiWi, can be used in these perfect sensor sites, as well as the sensitivity of the sensors.
A wireless sensor involves of:

- The platform's microcontroller and radio transceiver both have their own unique set of capabilities.
- the gear that connects external sensors to the computer's processor
- Batteries, capacitors, and other sources of power are found in the Power Layer.

It is extremely difficult for classification techniques to reduce the feature space dimension by finding a limited number of features, which results in superior classification performance. This has been a busy time for feature selection. The deletion of features could drastically reduce the time required for pattern categorization. In addition, this allows the categorization routine to benefit from machine learning capabilities. Eventually, a list of the features (feature contributions will increase) that will be enabled and the ones that will be deactivated can be compiled (feature contribution will be less).

A. *Dataset Description*

WDBC was founded by Dr. William Wolberg at the University of Wisconsin and can be found in machine learning at the University of California, Irvine. "While conducting research on breast cancer detection and therapy, it was used as a dataset to train an artificial neural network. The dataset consists of 569 individuals, each of whom has 32 traits and 30 real-valued characteristics.. A malignant or a benign subject is represented by a label classification in the target output label diagnostic. There are 357 healthy individuals in the group, whereas there are 212 cancerous ones. Consequently, this dataset has 569 features and 32 dimensions.

B. *Data Pre-processing*

Classification problems require data processing before machine learning methods can be used to solve them. Classifier computation time was cut in half, and classification accuracy was improved as a result of the cleaned data. Dataset pre-processing techniques including missing value detection are frequently used. The standard scalar approach assures that all features have the same mean and variance, resulting in the same coefficient for all variables. Shifts the data in such a way that all features fall within the range of zero to one. The feature that has an empty row in the dataset is deleted.

C. *Ensemble Filter-based Feature Selection*

Instead of employing prediction models, the objective function based on filters assesses feature subsets based on their information content. Metrics based on filters are simple and quick to apply, and they can be applied to a wide variety of classifiers. The chi-square statistic is used to compute the value of an attribute in terms of its chi-squared statistic relative to the class. It is compared to the x2 distribution with one degree of freedom in order to determine the degree of dependence between t and c (where t stands for term and c stands for class). Eq. (1) provides the definition of x2measure for text classification (1).

$$x^2_{(t,c)} = \frac{D*(PN-MQ)^2}{(P+M)*(Q+N)*(P+Q)*(M+N)} \tag{1}$$

Documents are counted in this formula: D = D. The number of documents in class c that include the phrase t is denoted by the prefix P. If t occurs without c, then the number of papers that include t is called Q. Documents class c occurring without t are counted as M if M is greater than 0. In other words, N is the number of non-t documents in the other classes.

Correlation – The Pearson correlation coefficient is used to determine the value of an attribute by comparing it to the class. The correlation between the two variables is measured by this metric. Coefficients between +1 and-1 represent total positive linear correlation, zero linear correlation, and zero linear correlation, respectively; +1 is the greatest attainable value. The definition provided by Eq (2).

$$R(i) = \frac{\sum_{k=1}^{m}(\sum_{k=1}^{m}(x_{k,i}-\bar{x}_i)(y_k-\bar{k}))}{\sqrt{\sum_{k=1}^{m}(x_{k,i}-\bar{x}_i)^2 . \sum_{k=1}^{m}(y_k-\bar{y}_i)^2}} \tag{2}$$

the number of data points m (x) and (y) are the attributes..

Gain Ratio – It is "information gain ratio," which lowers judgment bias by increasing the signal-to-noise By separating the information gain by the attribute entropy, it is determined (the intrinsic information). Eq. provides the formula for the gain ratio (3).

$$GR = \frac{IG(X)}{IntrinsicInfo(X)} \tag{3}$$

where X denotes the attribute.

Information Gain – The value of an attribute can be evaluated by comparing it to the class's information gain. Entropy information has a role in the answer. The degree of unpredictability or chaos in a system is measured by its entropy. Uncertainty reduction results in an increase in the amount of information available. Eq. defines the equation for information gain (4).

$$IG(X,Y) = H(X) - H(X|Y) \tag{4}$$

where X is the attribute, and Y is class.

ReliefF – Allows for filter-based feature weighting in noisy and incomplete data. ReliefF samples an instance repeatedly to determine the value of each attribute. It also considers the value of a particular attribute for k of its nearest instances of the same and other classes when evaluating its worth.

Symmetrical Uncertainty – This adjustment of information gain lowers the bias toward the multivalued features by using symmetrical uncertainty coefficient. An attribute's value is assessed by comparing its symmetrical uncertainty to the class. Equation (Eq.) shows the symmetrical uncertainty equation (5).

$$SU(X,Y) = 2\frac{IG(X,Y)}{H(X)+H(Y)} \in [0,1] \quad (5)$$

where X is the attribute, and Y is class.

D. *Classification*

The one-dimensional CNN is used to classify the selected features (1D-CNN). To do this, the 1D-CNN classifier is fed the data from each feature that has been chosen. There are no fixed values for the weights, and they are tied to each input. The subsequent hidden layer's hidden nodes execute the function of multiplying the input value by the weight vector of all of the input nodes related to that value. The back propagation process is improved by using random weight values. The optimization is carried out in this manner. The output of this layer is subsequently transferred to the following layer using the activation operation. The classifier's output is heavily influenced by these weights. Following are the algorithmic processes used in the classification of 1D-CNNs.

Step 1: Equations (6) and (7) can be used to express the selected feature values and their equivalent weights:

$$F_i = \{F_1, F_2, F_3 \dots F_n\} \quad (6)$$

$$W_i = \{W_1, W_2, W_3 \dots W_n\} \quad (7)$$

A feature's input value (F i) and its weight value (W i) are used to specify the n corresponding weights, i.e., a feature has a weight value of n.

Step 2: Decide on a set of weight vectors and multiply the inputs by them, then add them together:

$$M = \sum_{i-1}^{n} F_i W_i \quad (8)$$

where M signifies the summed value.

Step 3: *Regulate the activation function (AF).*

$$A_{fi} = C_i\left(\sum_{i=1}^{n} F_i W_i\right) \quad (9)$$

$$C_i = e^{-F_1^2} \quad (10)$$

An A fi activation function and a C i exponential are shown below. This proposed system makes use of an AF type known as Gaussian functions.

Step 4: Appraise *the next hidden layer's* production *using*

$$Y_i = B_i + \sum C_i W_i \quad (11)$$

Step 5: Each of the 1D-layers CNN's undergoes the aforementioned three processes. Finally, compute the values of the output layer neurons by summing the weights of all the input signals in the output unit:

$$R_i = B_i + O_i W_i \quad (12)$$

Here, the value of O i is denoted by its position on the stack prior to R i, and W i shows the weights of the hidden layer.

Step 6: In this stage, the network output is compared to the desired value. The error signal is the difference between these two numbers. The following is a mathematical representation of this value:

$$\mathrm{E_r} = \mathrm{D_i} - \mathrm{R_i} \quad (13)$$

where E r denotes an error, and D i signifies the desired output. where

Step 7: The output unit's value is compared to the goal value in this example. We've located the source of the problem. As a result of this fault, an error value I is generated, which is also used to convey this error at the output back to the other network units.

$$\delta_i = E_r[f(R_i)] \quad (14)$$

IV. Results and Discussion

An Intel® CoreTM i7 6700 3.40 GHz CPU was used with a single core to run all experiments using the WEKA toolkit to build the suggested algorithm in Java.

A. Performances Measure

Classification accuracy rate were used to evaluate the suggested method's performance.

Divide the entire number of true positives and false negatives by the total amount of instances to arrive at classification accuracy. Eq. represents the equation in its entirety (15).

$$\mathrm{ACC} = \frac{\mathrm{TN+TP}}{\mathrm{TN+TP+FN+FP}} \quad (15)$$

The number of the letters TN,TP,FN, and FP, respectively. In addition, the 10-fold cross-validation method is utilized for all accuracy calculations.

The predictive performance AUC is the area under the ROC curve. An AUC of 0 indicates that the predictive model erroneously classifies all cases, whereas an AUC of 1 indicates that the predictive model correctly classifies all cases.

The positive predictive is known as precision. By dividing the total amount of real positives and false positives by the number of true positives, it is determined. Eq. defines the equation for precision (16).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{16}$$

The actual positive or hit rate is known as recall. By dividing the total number of true positives and false negatives, it is determined. Eq. (17) defines the equation for recall.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{17}$$

F-Measure is the harmonic mean of recall. It is distinct in Eq. (18).

$$\text{F} - \text{Measure} = 2.\frac{\text{Precision.Recall}}{\text{Precision+Recall}} \tag{18}$$

Table 1: Performance of Proposed Method Without Ensemble Filter Based Feature Selection

Classification	$\boldsymbol{Precision}$	$\boldsymbol{Recall}$	Accuracy	$\boldsymbol{F-Measure}$
LSTM	81.0	69.8	69.8	66.6
RNN	70.5	70.3	70.3	70.2
ANN	81.5	81.1	81.1	81.1
Recursive Neural Network	74.4	70.8	70.7	69.4
Bi-LSTM	75.5	75.7	75.4	75.5
CNN	83.1	82.4	82.4	82.4
1D-CNN	84.9	84.9	84.9	84.9

Table 1 represents the Performance of proposed method without ensemble filter based feature selection. In this analysis, there are different method are used to analysis. There are totally different classifiers as LSTM, RNN, ANN, Recursive Neural Network, Bi-LSTM, CNN and 1D-CNN. The proposed 1D-CNN model reaches the better performance of accuracy 84.9% respectively.

Table 2: Performance of Proposed Method With Ensemble Filter Based Feature Selection

Classification	$\boldsymbol{Precision}$	$\boldsymbol{Recall}$	Accuracy	$\boldsymbol{F-Measure}$
LSTM	87.5	81.5	84.4	84.5
RNN	89.2	95.2	92.2	92.2
ANN	93.3	85.3	89.3	89.3
Recursive Neural Network	87.4	87.4	87.3	87.4
Bi-LSTM	84.4	77.7	77.6	77.6
CNN	88.8	78.5	83.6	83.4
Proposed Ensemble filter with 1D-CNN	98.2	96.4	98.5	97.2

Table 2 represents the Performance of proposed method with ensemble filter based feature selection. In this analysis, there are different method are used to analysis. There are totally different classifiers as LSTM, RNN, ANN, Recursive Neural Network, Bi-LSTM, CNN and 1D-CNN. The proposed 1D-CNN model reaches the better performance of accuracy 98.5% respectively.

V. CONCLUSION

A health care system based on ML and the IoT is proposed in this paper. Patients and doctors will benefit from a more interactive experience thanks to the new system. In this study, a breast cancer diagnostic method is built. 1D-CNN was utilised to detect breast cancer in the system's deep learning predictive model. In order to correctly classify persons as malignant or benign, an ensemble filter-based algorithm is employed. From the Wisconsin Diagnostic Breast Cancer dataset, an ensemble filtering technique generated new feature subsets. 70 percent of the dataset was used for training and 30 % was used for testing. Model performance was also assessed using performance measurement methodologies. Malignant and benign people can be accurately identified by analysing the experimental data. Prediction of malignant and benign tumours has improved, which could be attributable to a variety of BC characteristics. Results from this study indicate a potential for using the proposed diagnosis method to properly anticipate BC, as well as its potential for easy integration into the healthcare system. In addition, we know that features that are not significant to the diagnosis process slow down the system and increase calculation time. A new feature selection method was employed to identify the relevant subset of characteristics that improves the classification performance diagnosis system as another component of the suggested study's original approach. It is expected that future diagnostic systems for BC diagnosis will incorporate various feature selection algorithms, optimization, and deep neural network classification approaches.

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