IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

ENHANCED BREAST CANCER PREDICTION USING ADVANCED MACHINE LEARNING TECHNIQUES

[1]Gourav Kumar Dhiman, [2]Er. Shivani Rana
[1]Research Fellow, [2]Assistant Professor
[1]M.Tech(Computer Science and Engineering),
[1] Himachal Pradesh Technical University, Hamirpur, India

Abstract : As much as today breast cancer still ranks among some of the diseases that are common among women and are linked to clinical, lifestyle, and other social and/or economic factors. This means that employing machine learning, it is possible to predict breast cancer based on traits which are hidden deeply in data. In the case of a breast cancer detection in its preliminary stages, it will be wise to incorporate classification, clustering techniques, and feature selection among the other machine learning techniques. Reduce mortality and improve domestic and international health care delivery systems. The purpose of the research is therefore to develop a prediction model that will help in predicting the existence of breast cancer at its preliminary stage which is the use of classification and clustering. A great performance analysis of many health indicators, such as accuracy, True Positive Rate, False Positive Rate, Root Mean Square Error, precision, recall, etc., has been conducted.

***Keywords**:* Prediction Method, Breast Cancer, Effectiveness, Efficiency, Machine Learning.

INTRODUCTION

As citizens seek quality health facilities that are affordable, both emerging and developed countries governments are investing huge capital in the health sector. Very high mortality rates are recorded in cases of breast cancer. Breast cancer according to the World Health Organization is above 1. Besides, 5 million people annually are treated with stem cell in different countries of the world. Some tumor's may be further used in the diagnosis of the existence of breast cancer. Malignant tumors are much more dangerous than benign tumor's when it comes to the life of the affected individual. Epidemiological malignancies can only be screened using an active detection method other from the active medical personnel. Cancer diagnosis remains difficult even for practitioners considered to be specialists. However, many countries especially those in the developing world still lack the healthcare facilities to adopt ICT. Due to the global increase of chronic diseases and the proportion they contribute to the annual mortality rate, the identification of chronic diseases at an early stage is challenging; for instance, cancer, renal failure, heart diseases, etc. ICT actively contributes not only to helping patients who need a more efficient way of therapy, but also to help the medical professionals make the right medical decision from the received data from the early stage of the disease.

1. Breast Cancer

Statistics show that cancer is a significant disease threatening people’s lives all over the world. It is the affliction that has caused the death of multitudes and shall continue to do so in the consequent years. Biopsy revealed over two hundred several varieties of cancer, every one of which is called by the kind of cell it primarily impacts. Mohammed, Ghani (2020)1 Breast cancer originates from the breast muscle and usually takes place in the milk ducts or the lobules that release the milk funnel. Boys as well as girls can get the disease, though man are many times rarer than women to receive it.

The management of breast cancer is complex and this is an area of concern even in the advanced world today. It is forecasted that in the participating developing and developed countries, about ten percent of all women will develop breast cancer sometime in their lifetime. Today, breast cancer is regarded as one of the most common types of malignancies – the second most frequent cancer. Breast cancer still ranks among the leading killer diseases among women ranking the second after lung cancer. It has been reported through research that the left breast has higher propensity of developing cancer than the right breast. Family history is one of the determinant of breast cancer, meaning the more the number of close relative’s who had breast cancer the higher the likelihood of a woman developing the disease. Mentioned disease affects only 5-10% of affected women; At present, breast cancer develops primarily due to hereditary predisposition. Should the disease have spread to other body organs, then it is stated to have metastasized from the breast. Breast cancer commonly spreads to the bone, lung or liver most of the time.

1.1 Breast Cancer Lesions

The breasts or mammary glands are situated in the upper half of the anterior part of the human body on both left and right side of the stem and comprise a part of the anterior quadrant of the compartment of the human body from the starting point of the second rib to the termination of the sixth. The glands which start releasing a milky fluid after childbirth.

1.1.1 Calcifications

Calcifications of various types are a predominant feature while mammography is conducted, thus representing a key concern. Calcification is a pathological process in the formation of calcium deposits in the breast tissues. Again calcification is not a sign that you should worry that you have Breast cancer, more so when it's not associated with any pain. But calcification is at times a necessity that indicates that a malignancy is in its early stages when it is curable.

1.1.2 Mass

A mass is an area of interference that involves the region of suspicion and is described by a radiologist form and limit or its margin. Ray and colleagues stated that breast cancer commonly presents as a mass or finally as a calcification.

1.1.3 Screening Mammography

Mammography screening is using x-rays on breast with a view of identifying whether a woman has had a sign of breast cancer.

1.1.4 Diagnostic Mammography

Transitional: Still, the performance of diagnostic mammography is done if ever there are irregularities in the breast. Below are the investigative procedures involved in making the diagnosis; diagnosis involves carrying out a mammogram and at the first instance the radiologist will assess the size and location of the breast abnormality.

1.1.5 Digital Mammography

Digital picture has penetrated in the society in the current generation especially in the last decade. Some of the present day medical imaging technologies include digital mammography, MRI, and CT among others. The methods of image formation that are included in this category are those that involve image construction in digital form right from the start. Bearing this protocoled in mind, digital mammography is growing within the United States and screenshots are fashionable.

1.1.6 Mammogram Database

For evaluation, several mammography databases are available for women with the breast cancer. Out of all the databases, MIAS database and DDSM database are apparently the most used.

1.2 Breast Cancer Modeling Approaches

Breast cancer is ranked as one of the primary causes of death among women and it is a common ailment thereby constituting a primary cause of death among females globally. Systemic breast cancer alone is responsible for 30% cancer occurrences among women and 15 % of all cancer death rates next to lung cancer. Typically, characteristics of cells which are found in the human body alter or transform, and the cells start to act in a weird way in this type of cancer. As the illness rapidly transmits from one individual to another, getting breast cancer at an early date helps to minimize people's death from the sickness. When it comes to model development for different chronic diseases for correct early detection two most popular approaches are used. Benbrahim (2020)2

1.2.1 Descriptive Modeling

Unlabeled data is used to conclude, thus the name "unsupervised learning." Among the many unsupervised learning techniques available, clustering is by far the most widely used because of its potential use in discovering previously unseen patterns in data.

1.2.2 Predictive Modeling

Also called "supervised learning," this technique is typically put to use in the context of making forecasts utilizing analyses like classification and regression. When building a classification model from scratch, supervised learning is typically the method of choice because of the ease with which a variety of features and classes can be added and labeled to a given dataset. To complete the Classification job, the dataset is first partitioned into a training dataset and a testing dataset. Mostafa (2018)[3] the different features of a dataset are utilized in the training dataset to construct a prediction model, while the test dataset is used to verify the accuracy of the model.

2. Machine Learning Algorithms

To determine whether a tumor is benign or malignant, doctors frequently train a classification model based on machine learning calculations including the breast cancer dataset, which requires the loading and extraction of features from the dataset. Noncancerous, or benign, conditions pose no threat to health. Uncontrolled cell growth is the root cause of cancer, which can metastasize or invade neighboring tissues very rapidly. Kumar, Nikhil (2017)[4]

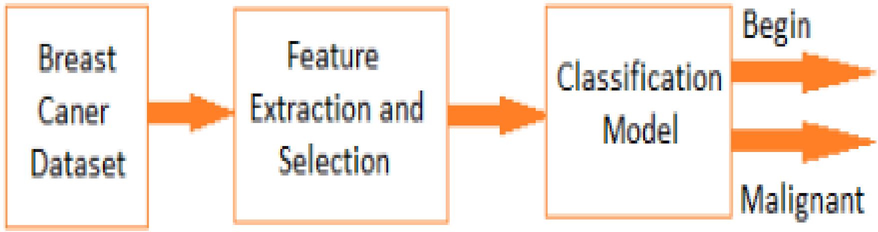

Figure 1: Breast Cancer Classification Model

2.1 k-Nearest Neighbor (kNN)

By relying on a concept called "feature similarity," the k Nearest Neighbors algorithm can predict the estimates of the most recent data samples, and it can also give a value to a newly discovered data point based on how closely it resembles the points in the training set.

2.2 Support Vector Machine (SVM)

The field of cancer malignant development determination and guess uses Support Vector Machine, which is one of the characterization methodologies used extensively in Supervised Machine Learning. To perform its task, a Support Vector Machine selects "help vectors," which are simple samples from each class, and uses these examples to develop a linear function that separates the classes as thoroughly as possible. For this reason, it is often held that the formulation of plans involving the mapping of an input vector to a high-dimensional space is achieved utilizing a Support Vector Machine, the goal of which is to locate the most prominent reasonably hyperplane that partitions the data set into classes. Chaurasia (2014)[5.]

2.3 Logistic Regression (LR)

The classification process of Logistic Regression is an important part of machine learning. The concept is related to the family of linear classifiers and is functionally similar to polynomial and statistical regression. If you need a fast and easy method to assist you to interpret your results, consider using logistic regression. Although it is primarily a route for binary classification, it may be extended to multi-class problems as well. This is usually not the same as statistical regression, which is concerned with predicting stable characteristics. The chance of a response being placed in a given category is modeled using logistic regression.

2.4 Naive Bayes (NB)

Naive Bayes is a type of classification strategy that uses Bayes' Theorem as its theoretical foundation while also assuming that all predictor variables are uncorrelated. Simply put, a Naive Bayes classifier assumes that the proximity of features inside a class is unimportant relative to the proximity of any other features within the same class. Even though these traits depend on each other or the presence of opposite properties, those properties freely add to the likelihood of a class, which is why it is called "Naive." Naive Bayes (NB) is a simplistic method of estimate since it assumes that all relevant estimation factors are independent of one another. Aruna (2011)[6]

3. LITERATURE REVIEW

3.1 Araneus Anna Rajani &ThamaraiSelvi (2019)[7] have detailed a pattern recognition technique for identifying breast cancers. A classification accuracy of 88.75% was attained by using DWT to extract features and an SVM classifier to categorize breast tissue.

3.2 Verma &Zhang (2017)[8] have created a method to analyze mammograms for microcalcification patterns and categorize them. Histogram, average grey level, energy, entropy, number of pixels, standard deviation, skew, average boundary grey level, difference, contrast, and 14 modified versions of these measures were retrieved from the pictures. To further streamline the classification process and zero down on the most useful features, they employed a feature selection technique known as a neural-genetic algorithm. From a total of fourteen characteristics, a neural-genetic algorithm chooses five as the most important: modified skew, border average grey level, standard deviation, skew, and modified standard deviation. The microcalcification patterns are categorized using a neural network classifier, which results in an 85.0% accuracy rate.

3.3 Satya P Singh et al. (2016)[9] method for diagnosing breast cancer employing polar complex exponential transform and adaptive differential evolution wavelet neural network has been demonstrated. Features of textures are extracted from the magnitude and phase fingerprints of polar complex exponential transform. The MIAS database is used to evaluate this study.

3.4 Bhanumathi & Suresh (2015)[10] have reported a 94.94% accuracy rate when applying their suggested approach to identifying whether tiny calcifications in a mammogram are benign or malignant. There are three phases involved in the classification process: pre-processing, feature extraction, and classification. After an image has been preprocessed, characteristics such as the trace transform and singular value decomposition are retrieved and fed into a support vector machine classifier.

3.5 Eltoukhy & Faye (2014)[11] have described a method for detecting breast cancer using the wavelet and curvelet transforms and compared the transforms' resulting classification accuracies. An area of interest (ROI) measuring 128 by 128 pixels is extracted from the source image and processed for noise reduction. Decomposing the ROI pictures with the aid of transforms yields wavelet and curvelet coefficients, and the mean value of vectors is determined for each class. Second, the threshold idea is used to determine the absolute differences between the classes and extract unique characteristics. The detection accuracy is calculated using a support vector machine (SVM) classifier and 25 cross-validations. They found that by employing the wavelet transform, the success rate was 89.51% for normal/abnormal and 89.58% for benign/malignant.

3.6 Nizar et al.(2013)[12] To better diagnose breast cancer, radiologists can use an algorithm developed for computer-aided detection of microcalcification. These methods consist of two phases. In the first step, we apply a variety of one-dimensional wavelet transforms on the image to determine which wavelet provides the best results. Second, the results of the first step are subjected to a two-dimensional wavelet transform. Images of microcalcification can be found by first filtering the picture and then re-reconstructing it with the approximation coefficient set to zero.

3.7 Dheeba et al. (2012)[13] have developed a method for early diagnosis of breast tissue microcalcification clusters. The microcalcification clusters in the ROI are used to derive textural characteristics according to the laws of nature. Swarm optimization neural networks are employed as a novel classification technique. Clinical photos captured in real-time are used along with the MIAS database to assess this study. A ROC curve is generated by the system, with an A (z) value of 0.9761 for the MIAS database and 0.9138 for real-time clinical pictures.

3.8 Fraschini (2011)[14] has suggested using the CAD approach to categorize breast cancer tumors. The wavelet transform is used to decompose images, dimensionality reduction techniques are employed to minimize the number of features, and an artificial neural network classifier is used to determine classifications.

4. RESEARCH METHODOLOGY

To determine whether a malignancy will be benign or malignant, the research study employed four different classification algorithms: SVM (Support Vector Machine), J48, Naive Bayes, and Random Forest are some of the techniques. These specific classifiers were chosen since they are among the best 10 examined classification algorithms in the fields of AI. The prediction model was developed with the help of the 10 fold cross validation approach and the data used in it was gathered from Wisconsin Diagnostic Breast Cancer (WDBC) dataset. In total, there are 569 instances of this data set, of which the number of benign instances is 357 and the number of malignant instances is 212. A patient identifier is also recorded as well as thirty characteristics related to the diagnosis and a single tumor type which is Benign or Malignant.

4.1 Naive Bayes

It's a machine-learning method typically employed to solve categorization issues. It follows Thomas Bayes's proposed probability theorem. It is easier to use than competing methods while still providing solid results, and it speeds up the process of creating a classification model for use in making predictions. This method is Naive because it assumes the existence of a single feature without regard to the presence of any others; it is Bayesian because it accounts for the joint occurrence of many qualities. Thomas Bayes, a famous statistician, and philosopher are honored with the naming of this theorem in his honor. Formally, we may express this theorem as:

$$P(A|B) = P(B|A)*P(A)/P(B) \quad \text{......}(1)$$

4.2 J48

It is a classifier with a tree-like structure, where each node can be either a leaf node displaying the value and class of the target attribute, or a decision node specifying that testing must be conducted on an attribute with a single value. When creating a decision tree, J48's ability to handle both categorical and continuous characteristics is invaluable. It's capable of processing missing values as well. It takes advantage of the information entropy to construct the decision tree from the labeled training data. It is predicated on the idea that dividing the data into subsets maximizes the utility of each feature for decision-making. In this case, the qualities that provide the most useful information for making a choice are chosen first, and the algorithm is subsequently applied to smaller and smaller groups. To streamline the tree and fine-tune the classification, pessimistic pruning can be used for J48. To facilitate subsequent categorization, this classifier employs a greedy divide-and-conquer strategy to iteratively induce decision trees that incorporate properties of a dataset. Information gain and entropy are represented by equations 2 and 3, respectively.

$$Entro(D) = -\sum^{m} p_i log_2(p_i) \quad \text{......}(2)$$

Here, 'p_i' is the probability that the dataset has an arbitrary attribute.

$$Gain(A) = Entropy(D) - Entropy_A(D) \quad \text{......}(3)$$

Here, $Entrop(D)$ has the anticipated data required to perform classification on the basis of certain attribute "A" that has a set of values, each of which bear a meaning.

4.3 SUPPORT VECTOR MACHINE (SVM)

In cases of pattern recognition, classification, and regression analysis, they are well known in the family of related supervised learning called support vector machines. It is a form of learning that employs the use of statistics theory in teaching. In this case,-line is the hyperplane through which the algorithm aims at maximizing the distance between the two different datasets. It achieves this through the use of a set of tools that is known as support vectors in conjunction with the margins of the training tuples with the aim of minimizing the classification error. The official statement of this is:

P(x) = w.x+b = 0..(4)

Here, P(x) is the collection of points, w and x are the support vectors, and b is the coefficient used to build the hyperplane connecting the two sets.

4.4 RANDOM FOREST

Ensemble learning includes the classification method known as random forest, in which several predictor trees are combined in such a way that each tree predictor uses a randomly chosen vector value uniformly distributed over all forest trees. Each tree in a random forest uses a decision tree as its base classifier, and all of the trees in the forest use a voting procedure to determine which class has the most votes. To create a random forest, we randomly choose a subset of input variables at each node. The following are the two parameters used in random forest to obtain the generalization error:

- Classifiers individual accuracy
- Dependency between individual classifier

5. EXPERIMENT AND RESULTS

The effectiveness and efficiency of the classifiers employed in this work have been documented in detail. Results were achieved using the open-source WEKA tool, which supports several machine learning algorithms, and the 10-fold cross-validation approach to ensure the highest level of precision.

5.1 Effectiveness

Accuracy (%), successfully categorized occurrences, erroneously classed instances, and the time needed to develop the prediction model are all used to assess the classifiers' efficacy. Preciseness can be measured by:

Accuracy = (TP+TN) / (TP+TN+FP+FN)..(5)

where:

TP (True Positive): The number of correct positive predictions.
FP (False Positive): The number of incorrect positive predictions.
TN (True Negative): The number of correct negative predictions.

FN (False Negative): The number of incorrect negative predictions. Table- 1 displays effectiveness calculations made on parameters like correctly classified instances, incorrectly classified instances, time to build model, and accuracy, revealing that SMO (Sequential Minimal Optimizer) as in WEKA SVM is available as SMO, which performs better than the other classifiers in terms of accuracy.

Table 1: Results for Effectiveness of Algorithms

Evaluation parameters	**SVM**	**J48**	**Naive Bayes**	**Random Forest**
Correctly classified instances	557	530	527	522
Incorrectly classified instances	12	39	42	47
Time to build a model (sec)	0.84	0.14	0.04	0.02
Accuracy (%)	97.89	93.14	92.61	91.73

The study takes into account both training and simulation mistakes to get a more accurate picture of the classifiers' overall performance, as given in table 2, which also show that SVM has the lowest error rate of 0.14% compared to the other classifiers.

Table 2: Training and Simulation output

Evaluation parameters	**SVM**	**J48**	**Naive Bayes**	**RandomForest**
Kappa Statistic(numeric)	0.95	0.85	0.84	0.82
Mean Absolute Error(numeric)	0.02	0.07	0.07	0.082
Root Mean Square Error in (%)	0.14	0.25	0.26	0.28
Relative Absolute Error in (%)	4.5	15.83	15.65	17.66
Root Relative Square Error in (%)	30.03	53.23	54.75	59.44

Table 2 presents the details of the various parameters used in training and simulation which include Kappa statistics, mean absolute error, root mean square error, relative absolute error, and root-relative square error. Thus, the observed kappa statistic is 0 which indicates that the inter-rater agreement is extremely high. 95, and a mean absolute error of 0. 02 , and a root mean square error of 0. The relative absolute error is calculated to be 14%, and 4. 5 per cent, and root relative square error of 30. 03%, However, based on the said criteria mentioned above, SVM has displayed better results than the one mentioned above.

Table 3: Confusion Matrix of the Classifiers

Classifier	**a**	**b**	**Class**
Naïve Bayes	190	22	a= M
	20	337	b= B
J48	195	17	a= M
	22	335	b= B
SVM	201	11	a= M
	1	356	b= B
RF	189	23	a= M
	24	333	b= B

The following classifiers' confusion matrix is given in table 3. It is convenient to quickly obtain information on which class a classifier assigns to the studied object. Here on the matrix, the columns refer to the real class while the rows refer to the expected class. CCD class a here refers to Malignant and class b refers to Benign breast cancer patients, and the prediction in Table 3 is made for these two classes. Performed outcomes are True Positives (TP), False Positives (FP), True Negatives (TN), and False Neutrals (FN) Four of the parameters employed in the confusion matrix for the classifiers are the FN. The Naive Bayes classifier you have is 190 and false negatives of 22, false positives of 20, and false negatives of 337; the J48 classifier is 195, and false negatives of 17, false positives of 22, and false negatives of 335; the SVM classifier is 201 and false negatives of 11 and false positive of 1 and false negatives of 356; and the Random Forest classifier has 189 true positives, 23 false negatives, 24 false positives.

5.2 Efficiency

Upon the building of the prediction model one may evaluate the chosen classifiers used in the given research. The following metrics are taken into account to evaluate a classifier's performance: The next parameters are taken into account as the measures of classifier performance:

The nature of classifier performance can be described using ranges of traditional parameters including TPR, FPR, recall, accuracy and

F-Measure. The results of the post hoc on the following parameters comparisons are summery stated in the following table - 4 as follows –

Sensitivity = TP/ (TP+FN)..(6)

Specificity = TN/ (FP+TN)..(7)

Recall = TP/ (TP+FN) ....(8)

Precision = TP/ (TP+FN)...(9)

F-Measure = 2(P*R)/P+R ....(10)

Here P= Precision, R= Recall, F= False

Table 4: Comparative Analysis of Classifiers to check the Efficiency

Evaluation parameters	**SVM**	**J48**	**NaiveBayes**	**Random Forest**	**Class**
TPR	0.94	0.92	0.89	0.89	M
	0.99	0.93	0.94	0.93	B
FPR	0.003	0.06	0.056	0.06	M
	0.052	0.08	0.10	0.10	B
Recall	0.94	0.92	0.89	0.89	M
	0.99	0.93	0.94	0.93	B
Precision	0.99	0.89	0.90	0.88	M
	0.97	0.95	0.93	0.93	B
F-Measure	0.97	0.90	0.90	0.88	M
	0.98	0.94	0.94	0.93	B

The True Positive Rate, False Positive Rate, Recall, Precision and F-measure concerning the criteria for the classification of the algorithms are described in the Table 4. Comparing all the efficiency measures of the given table, it can be greater spotted that SVM has the highest results among all the classification methods. This relates to 0 percent recovery of the TPR. 96%, FPR of 0. 02%, recall of 0. 96%, precision of 0. This work resulted in accuracy of 0, specificity of 0, recall of 0 and F-Measure of 0 percent though the average accuracy was 98 percent. 97%.

6. CONCLUSION

This was after building the predictive model over the Wisconsin Diagnostic Breast Cancer Dataset over the popular classifiers, namely support vector machines (SVM), J48, Naïve Bayes, and Random Forest. The results display the number of correctly classified instances and the overall efficiency of all the classifiers in terms of many criteria, which, in turn, may help to choose the proper classifiers for the specific dataset. Concerning the other classifiers for distinguishing the type of breast cancer as either benign or malignant, K-SVM has been established to have a higher acrylic of 97%. With the overall being at zero percent, for the 89 percent for the learners that answered most of the questions correctly. 14%. In view of the outcomes achieved it can be concluded that classificational algorithms have great potential in the field of healthcare and, in particular, for the early diagnosis of some diseases, including breast cancer. Accordingly, in the evaluation of the mentioned above alternatives, the SVM has been distinguished as the most precise algorithm for the purpose of distinguishing the malignant tumors from benign ones.

7. Future Work

There are several potential directions for future research on "Enhanced Breast Cancer Prediction Using Advanced Machine Learning Techniques":

7.1 Model Improvement and Optimization

Improve and make the current type MOs more efficient and add newest forms of ML algorithms and structures of DL to make models more precise and robust.

7.2 Incorporating Multi-Modal Data

There are various interesting possibilities for future work which can include the integration of other sources of information, genomic data, mammogram images and patients' medical history in an attempt to build models with higher accuracy.

7.3 Real-Time Implementation

carefully chosen theoretical models for RT-diagnosis and the related applications needed that are useful in the clinical environments, feasible for use, and easily integrated into the domains involved in the actual caring for patients.

7.4 Explain ability and Interpretability

When it comes to the crucial aspects of using machine learning, it is important to consider the degrees of the algorithms' explain ability to allow clinicians to extend specific solution and prediction underlying.

7.5 Validation and Generalization

Perform more rigorous validation studies on different and larger datasets obtained from other population samples to determine the generalizability and reliability of these models in different clinical contexts with different patient populations.

7.6 Collaboration with Healthcare Provider

Arrange the meetings and discussions with other healthcare professionals with the aim to implement the models and to investigate them as the supplementary to the existing diagnostic approaches.

7.7 Ethical and Legal Considerations

Alongside this, the main ethic dilemmas connected with privacy and jurisdiction concerning the use of artificial intelligence in delivering medical diagnosing should to be correctly addressing to the standard regulatory authorities and users
.

7.8 Longitudinal Studies

The new strategies should then engage the patients, through the predictive models developed with the aim of estimating the outcomes of the system's long term efficiency, plus the impact which was made by early, healthy detected illnesses on the total mortality rates present in population.

Thus, with such future directions, this research can expand the opportunities for creating new AI-based tools to increase diagnostic accuracy for breast cancer and other diseases, as well as work more efficiently with an emphasis on ethical aspects.

REFERENCES

[1] Mohammed, M. A., Abd Ghani, M. K., & Arun Kumar, N. (2020). Decision support system for nasopharyngeal carcinoma discrimination from endoscopic images using artificial neural network. *The Journal of Supercomputing, 76*, 1086–1104.
[2] Benbrahim, H., Hachimi, H., & Amine, A. (2020). Comparative study of machine learning algorithms using the breast cancer dataset. In *Springer*.
[3] Mostafa, S. A., Mustapha, A., Khaleefah, S. H., Ahmad, M. S., & Mohammed, M. A. (2018, February). Evaluating the performance of three classification methods in diagnosis of Parkinson's disease. In *Proceedings of the International Conference on Soft Computing and Data Mining* (pp. 43–52). Cham, Switzerland.
[4] Kumar, U. K., Nikhil, M. B. S., & Sumangali, K. (2017, August). Prediction of breast cancer using voting classifier technique. In *Proceedings of the 2017 IEEE International Conference on Smart Technologies and Management for Computing, Communication, Controls, Energy and Materials (ICSTM)* (pp. 108–114). Chennai, India.
[5] Chaurasia, V., & Pal, S. (2014). Data mining techniques: To predict and resolve breast cancer survivability. *International Journal of Computer Science*.
[6] Aruna, S., Rajagopalan, S., & Nandakishore, L. (2011). Knowledge-based analysis of various statistical tools in detecting breast cancer. *Computer Science Information Technology*.
[7] Rajani, A. A., & ThamaraiSelvi, S. (2019). Early detection of breast cancer using SVM classifier technique. *International Journal on Computer Science and Engineering, 1*(3), 127-130.
[8] Verma, B., & Zhang, P. (2017). A novel neural-genetic algorithm to find the most significant combination of features in digital mammograms. *Applied Soft Computing, 7*(2), 612-625.
[9] Singh, S. P., Urooj, S., Lay, A., & Ekuakille, A. (2016). Breast cancer detection using PCPCET and ADEWNN: A geometric invariant approach to medical X-ray image sensors. *IEEE Sensors Journal, 16*(12), 4847-4855.
[10] Bhanumathi, R., & Suresh, G. R. (2015). Combining trace transform and SVD for classification of micro calcifications in digital mammograms. *IEEE Sponsored 2nd International Conference on Electronics and Communication System* (pp. 1381-1386).
[11] Eltoukhy, M. M., & Faye, I. (2014). An optimized feature selection method for breast cancer diagnosis in digital mammogram using multiresolution representation. *An International Journal on Applied Mathematics & Information Sciences, 8*(6), 2921-2928.
[12] Nizar, B. H., Khaled, T., & Bouhlel, B. H. (2013). Mammographic microcalcifications detection using discrete wavelet transform. *International Journal of Computer Applications, 64*(21), 17-22.

[13] Dheeba, J., & Thamari Selvi, S. (2012). A swarm optimized neural network system for classification of micro calcification in mammograms. *Journal of Medical Systems, 36*(5), 3051-3061.
[14] Fraschini, M. (2011). Mammographic masses classification: Novel and simple signal analysis method. *Electronics Letters, 47*(1), 14-15.
[15] Abdar, M., Książek, W., Acharya, U. R., & Pławiak, P. (2020). A new machine learning technique for an accurate diagnosis of coronary artery disease. *Computer Methods and Programs in Biomedicine, 185*, 105124.
[16] Bouzid, Y., & Lassoued, R. (2021). Enhanced breast cancer diagnosis using optimized machine learning techniques. *Neural Computing and Applications, 33*(4), 1151-1165.
[17] Chicco, D., & Jurman, G. (2020). Machine learning can predict survival of patients with heart failure from serum creatinine and ejection fraction alone. *BMC Medical Informatics and Decision Making, 20*(1), 16.
[18] Feng, L., Ma, L., & Feng, Z. (2018). Improved prediction of breast cancer using synthetic minority over-sampling technique and ensemble learning. *International Journal of Distributed Sensor Networks, 14*(7), 1550147718786471.
[19] Gao, J., Jiang, B., & Qi, J. (2021). Prediction of breast cancer recurrence and metastasis using multi-omics data and machine learning. *Frontiers in Oncology, 11*, 620021.
[20] Huang, S., Cai, N., Pacheco, P. P., Narrandes, S., Wang, Y., & Xu, W. (2018). Applications of support vector machine (SVM) learning in cancer genomics. *Cancer Genomics-Proteomics, 15*(1), 41-51.
[21] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems* (pp. 4765-4774).
[22] Nguyen, T. T., Nguyen, T. M., & Tran, T. (2020). Predicting the diagnosis of Alzheimer's disease using feature selection and machine learning techniques. *International Journal of Advanced Computer Science and Applications, 11*(4), 458-465.
[23] Pławiak, P. (2018). Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system. *Expert Systems with Applications, 92*, 334-349.
[24] Venkatesan, P., & Anitha, D. (2019). An improved feature selection method for breast cancer diagnosis using hybrid techniques. *International Journal of Data Mining & Knowledge Management Process, 9*(5), 1-8.
[25] Wang, G., Sun, J., Ma, J., & Xu, K. (2017). Feature selection for SVM based on optimizing the classification margin and feature distribution. *Expert Systems with Applications, 86*, 50-59.
[26] Zhang, Z., & Li, X. (2019). Automated machine learning for cancer prediction with novel feature selection and classification approaches. *Biomedical Signal Processing and Control, 52*, 70-76.