

Decision Tree Algorithm for Breast Cancer Detection

¹Gopal Deshmukh, ²Dattatray G. Takale, ³Piyush P. Gawali, ⁴Parikshit N. Mahalle, ⁵Bipin Sule, ⁶Shraddha S. Shirsath

¹Assistant Professor, Department of Computer Engineering, Vishwakarma Institute of information Technology, SPPU Pune

²Assistant Professor, Department of Computer Engineering, Vishwakarma Institute of information Technology, SPPU Pune

³Assistant Professor, Department of Computer Engineering, Vishwakarma Institute of information Technology, SPPU Pune

⁴Professor and Head, Department of AI & DS, Vishwakarma Institute of information Technology, SPPU Pune

⁵Sr Professor, Department of Engineering, Sciences (Computer Prg) and Humanities, Vishwakarma Institute of Technology, Pune, India

⁶Assistant Professor, Smt. Kashibai Navale College of Engineering Vadgaon, Savitribai Phule Pune University, Pune

dattatray.takale@viit.ac.in,

Abstract: A major form of cancer affecting women around the world is breast cancer. This underscores the importance of early detection for optimal treatment outcomes. This paper addresses the challenge of correctly classifying tumors as malignant or benign in light of the fact that breast cancer is a significant component of cancer cases around the world. As a breast cancer detection algorithm, there are several advantages to using this decision tree algorithm. Decision trees provide insight into the importance of features, which in turn allows for the identification of key factors that contribute to the classification of breast cancer. In addition to that, decision trees are able to deal with both numerical and categorical features, so they are suitable for a variety of breast cancer data sets. It is also important to note that decision trees are less sensitive than other algorithms when it comes to outliers and missing data. To begin with, decision trees provide insight into the importance of features, which allows for the identification of key factors that contribute to the classification of breast cancers. A decision tree can also be used to analyze both numerical and categorical features, making it more versatile for the analysis of breast cancer data in general. The decision tree algorithm, on the other hand, has a lower sensitivity to outliers and missing data than some other algorithms. As a result of utilizing performance metrics to assess the effectiveness of algorithms, it was found that the Decision Tree Algorithm was more effective at detecting breast cancer than other algorithms.

Keyword: Breast cancer, Tumor, logistic regression, decision trees, random forests, malignant, benign.

I. INTRODUCTION

Breast cancer is a major health problem for women all over the world, and finding it early is important for good treatment and better patient results. Using image data and clinical factors machine learning systems have shown that they have a lot of promise for helping to find and diagnose breast cancer [1]. But the performance and usefulness of different machine learning methods for spotting breast cancer need to be carefully compared and assessed [2].

The goal of this study is to compare and evaluate how well different machine learning methods work at finding breast cancer. We want to find the best and most accurate way to diagnose breast cancer by comparing and reviewing the results of different methods [3]. This study will help make testing tools that are more accurate and efficient, which will help doctors and nurses make better choices about treatment plans and patient care. The Breast Cancer Wisconsin (Diagnostic) Dataset, which is used a lot in breast cancer research, will be used in the project [4]. This collection has parameters like radius, roughness, outline, area, smoothness, tightness, concavity, symmetry, and fractal dimension. These parameters were taken from images of breast masses. These traits give

important information about how breast tumours look and can help tell the difference between dangerous and normal cases [5].

This study will look at how well logistic regression, decision trees, and random forests work as machine learning methods. These algorithms have shown that they work well in a variety of classification tasks [6], and they have been used a lot to find breast cancer. By comparing their “performance measures, such as accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC-ROC) [7], we can find out which programme makes the most accurate and reliable predictions for diagnosing breast cancer. In this study, we used the 569 breast cancer cases from the Wisconsin Breast Cancer dataset, which is open to the public. The information has 30 traits, such as the age of the patient, the size of the tumour, and the state of the lymph nodes”. These characteristics are very helpful for making machine learning models that can correctly classify breast tumours [8].

This study will look at how easy it is to understand each method and how hard it is to work out. Both of these things are important in real-world clinical settings [9]. The Interpretable models can give important information about how decisions are

made and help medical workers understand the basic factors that go into classifying something. Also, thinking about how much computing power each programme needs will help find ways that can be used in settings with limited resources [10].

Motivation, Challenges and issues

The pressing need to improve early detection rates and improve patient results is what drives researchers to look into machine learning methods for breast cancer detection [11]. Breast cancer is a common and possibly deadly disease, and finding it early is a key part of treating it successfully. By using the power of machine learning techniques, we hope to come up with more accurate and reliable ways to find breast cancer, which will increase the number of people who survive and improve their quality of life [12].

Challenges:

Several challenges exist when it comes to breast cancer detection using machine learning algorithms. Some of these challenges include:

- **Limited and imbalanced data:** It can be hard to get big and varied datasets to train machine learning models, especially when working with rare forms of breast cancer. Also, datasets may have a class mismatch, where there are a lot more examples of one class (like mild tumours) than the other (like cancerous tumours) [13]. To deal with these problems, you need to carefully collect data and use preprocessing methods to make sure your model isn't biased [14].
- **Interpretability:** Machine learning systems can make correct guesses, but it can be hard to figure out how they make their decisions. It's important for doctors to be able to understand and believe the model's findings that they can interpret the traits and factors that go into classifying a breast tumours. Research is still going on to find ways to make things easier to understand without hurting efficiency [15].
- **Generalization to diverse populations:** Machine learning models that were trained on a small group of people might not work well for other ethnic or social groups. Breast cancer can look different in different groups of people, so models should be tested on a variety of data sets to make sure they work well in real-world situations [16].

Issues:

In addition to the problems listed above, there are other things to think about when using machine learning methods to find breast cancer:

- **Ethical considerations:** When working with private medical data, patient protection, permission, and data security are the most important things. To protect patient privacy and keep people's trust in the healthcare system, it is important to make sure that ethical rules and laws are followed [17].
- **Clinical integration:** For machine learning methods to work, they need to be added to healthcare routines and decision-making processes that are already in place. Researchers, doctors, and healthcare workers need to work together to make tools that are easy to use and can be easily integrated into regular clinical practice [18].
- **Validation and reproducibility:** Machine learning methods should be carefully tested and validated to see how well they work on different datasets. Reproducibility of data is important to make sure that models can be used and copied successfully in different places [19].

In the second session, we will go further into the many treatments that are now available for breast cancer. In Section 3, we provide an explanation of the dataset as well as the recommended approach that was employed in this investigation. In the next section, "Section 4, we examine the findings and result discussion with proposed system," and in the following section, "Section 6, we conclude the article."

II. RELATED WORK

The literature research revealed twenty different papers that fulfilled the requirements to be included. Using a variety of machine learning techniques, the researchers in these investigations attempted to determine if breast cancer cases were benign or malignant. This research made use of a variety of different types of algorithms [20], "including logistic regression, decision trees, random forests, K-nearest neighbours (KNN), convolutional neural networks (CNN), support vector machines (SVM), artificial neural networks (ANN), and deep learning models". The classification models were educated and tested with the use of a wide variety of feature sets, which included clinical, demographic, imaging, genetic, and proteomic information respectively. This demonstrates the need of taking into account a variety of different forms of information in order to enhance the precision of breast cancer categorization [21]. "These investigations made use of datasets obtained from a variety of different places, such as the Digital Database for Screening Mammography (DDSM), Mammographic Mass, Histopathological Image dataset, Wisconsin Diagnostic Breast Cancer (WDBC), Breast Cancer Wisconsin (BCW) dataset, and Genomic Data Commons (GDC). In the context of breast

cancer diagnosis, these datasets provide very useful resources for the training of machine learning models as well as the evaluation of such models”. [22]

A recent study by Li et al. (2020) To train the Decision Tree model, use the preprocessed dataset. The Decision Tree method divides the data recursively depending on attribute values to produce a structure resembling a tree. To maximize the distinction between benign and malignant instances, the splitting process is directed by measures like information gain or Gini index.[23]

Kalyani Wadkar et.al [3], focuses on ANN based breast cancer diagnosis and utilizes support vector machines (SVM) to Analyse performance. “The goal of the project is to create an ANN model that can reliably determine whether breast cancer is benign or malignant [24]. The Wisconsin Diagnostic Breast Cancer (WBCD) dataset is used by the authors to train and evaluate the ANN model. Additionally, they contrast the accuracy, sensitivity, specificity, and F1-score of the ANN model's performance with that of the SVM model. The results show that the ANN model outperformed SVM in terms of sensitivity and specificity and attained high accuracy. The study emphasizes ANN's efficiency in detecting breast cancer and its promise as a dependable tool for precise diagnosis” [25].

Anji Reddy Vaka et.al [4], focuses on using machine learning methods to find breast cancer. The goal of the research is to create a precise model that can distinguish between benign and malignant instances of breast cancer. “The Wisconsin

Diagnostic Breast Cancer (WBCD) dataset is used by the authors to train a variety of machine learning algorithms [26], such as SVM, RF, and KNN. The accuracy, precision, recall, and F1-score of various algorithms are compared, along with their overall performance. The findings show that although Random Forest performed better in terms of precision, recall, and F1-score, SVM model had the best accuracy. The study emphasis’s the value of machine learning methods for finding breast cancer and offers information on how various algorithms stack up in terms of performance”.

Monika Tiwari et.al [5], uses combines deep learning and machine learning approaches to forecast breast cancer. The research examines the use of many algorithms, including CNN, SVM, RF, and KNN, for breast cancer prediction. “It was published in an undisclosed year. The Wisconsin Diagnostic Breast Cancer (WBCD) dataset is used by the authors to examine the accuracy, sensitivity, specificity, and F1-score of various algorithms. The study probably explains the benefits and drawbacks of machine learning and deep learning approaches for predicting breast cancer, giving readers an understanding of how these techniques may be used to enhance detection and treatment”.

Table 1: Literature Survey on Existing method

Study	Objective	Machine Learning Algorithms	Key Findings
Acharya et al. (2019)	Review the use of machine learning methods for detecting breast cancer.	SVM, RF, ANN	Emphasizes the importance of feature selection and extraction for accurate classification results.
Alzubaidi et al. (2020)	Compare the effectiveness of several machine learning classification methods for breast cancer.	SVM, RF, KNN, DT	Support Vector Machines and Random Forests achieved higher accuracy rates. Feature selection improves classification results.
Rawat et al. (2021)	Examine how mammography pictures are used to diagnose breast cancer using deep learning algorithms.	CNN	Deep learning shows potential for high accuracy in breast cancer detection, but challenges include limited data availability and model interpretability.
Vazquez et al. (2021)	Review research that uses machine learning to predict the	RF, SVM, ANN	Machine learning approaches show potential in predicting breast cancer recurrence, with various features and performance metrics used across

	recurrence of breast cancer.		studies.
Tavakoli et al. (2022)	Conduct a thorough analysis of machine learning methods for predicting breast cancer survival.	LR, DT, RF	Machine learning algorithms assist in breast cancer survival prediction, aiding treatment decision-making and patient management. Features and performance measures vary across studies.

The restricted investigation of interpretable and explainable models in the area of breast cancer is the source of the research gap that is resulting from the use of machine learning techniques in the field. Even though machine learning algorithms have demonstrated great promise for diagnosing breast cancer, predicting therapy outcomes, and analyzing survival rates, there is still a need for models that can provide visible, intelligible insights for improving clinical decision-making in the medical field. There has been a barrier to the widespread use of the various black-box models in clinical practice since the inability of many of these tools to be interpreted, such as those based on deep learning architectures, has made them unusable. This research gap could be filled by developing transparent and explainable machine learning models for the analysis of breast cancer that can close this research gap. Besides improving the trust and acceptance of these models among healthcare professionals, it would also enhance the utility of these models in patient care, as well as contribute to the overall advancement of the field.

III. PROPOSED SYSTEM

As you mentioned above, your process of implementing machine learning algorithms to detect breast cancer is an excellent way to go about it. It was successful for you to preprocess the dataset, divide it into training and testing sets, scale the features, and train a number of models by following the steps that you suggested. You handled missing data, converted the diagnostic column into a binary variable, and split the dataset into training and testing sets using the Breast Cancer Wisconsin (Diagnostic) Dataset. In this manner, you can ensure that you are using different data for training the models, and evaluating the effectiveness of the models that you are training.

A system architecture for breast cancer prediction using a Decision Tree algorithm would involve several key components. Here's an overview of the system architecture:

- **Data Collection:** Collect the breast cancer dataset “such as the Breast Cancer Wisconsin (Diagnostic) Dataset, which includes relevant features and corresponding diagnosis labels”.
- **Data Preprocessing:** “Perform data preprocessing steps, including handling missing values, removing

irrelevant attributes, and converting categorical variables into numerical representations if needed. This ensures that the data is in a suitable format for training the Decision Tree model”.

- **Feature Selection:** Select the most informative features from the preprocessed dataset. This step helps improve the model's accuracy by focusing on relevant attributes that contribute significantly to the prediction.
- **Model Training:** To train the Decision Tree model, use the preprocessed dataset. The Decision Tree method divides the data recursively depending on attribute values to produce a structure resembling a tree. To maximize the distinction between benign and malignant instances, the splitting process is directed by measures like information gain or Gini index.
- **Model Evaluation:** Evaluate the trained Decision Tree model using “appropriate performance metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques” or separate validation datasets can be used to assess the model's generalization performance and detect any potential over fitting.
- **Model Deployment:** Deploy the trained Decision Tree model into a clinical setting or integrate it into an application. Provide a user-friendly interface for inputting patient data, which will be used to make predictions based on the learned Decision Tree structure.
- **Prediction and Interpretation:** Utilize the deployed model to predict the probability of breast cancer (benign or malignant) for new, unseen patient cases. The Decision Tree model can also provide interpretability, as the tree structure allows for understanding the decision-making process and identifying the important features contributing to the prediction.
- **Continuous Improvement:** “Continuously monitor the model's performance and update it as new data becomes available”. This iterative process helps

enhance the accuracy and reliability of the breast cancer prediction system over time.

By implementing three “machine learning algorithms - Logistic Regression, Random Forest, and Decision Tree” - you have created and trained models using the training data. These models can then be used to make predictions on the testing data. Evaluating the models' accuracy using the confusion matrix helps assess their performance by comparing the predicted values with the actual diagnosis values. This provides insights into the models' ability to correctly classify breast cancer cases as benign or malignant.

By utilizing Python and relevant libraries such as Scikit-Learn and Pandas, you have access to powerful tools for implementing and evaluating machine learning algorithms. These libraries provide a wide range of functionalities for data manipulation, model creation, training, and evaluation. Overall, the approach you described demonstrates a systematic and practical implementation of machine learning algorithms for breast cancer prediction. It showcases the importance of data preprocessing, model selection, and evaluation to achieve accurate and efficient predictions in breast cancer diagnosis.

concavity, concave points, symmetry, and fractal dimension. Additionally, this dataset contains a lot of characteristics like mean and standard error”.

IV. RESULT ANALYSIS

Then the data set was searched for an empty cell and the columns with empty data cell were removed as it can cause error in the process. Using Scikit-Learn's train test split we divided the dataset into independent (X) and dependent (Y) data sets, then divide each of those into 75% training data and 25% testing data. By applying feature scaling to both the training and test data, we ensure that the same scaling transformation is applied to both sets of data. This is important because we want the model to learn patterns in the data that are independent of the scaling of the input features. Function was created for the models. This function creates and trains three different models: “logistic regression, decision tree, and random forest”. The purpose of this function is to make it easier to compare the performance of different models on the same data. Then we test the accuracy of the models on the testing data using confusion matrix from Scikit-Learn. Then we print the predictions of the models from the testing data and compare them to the actual diagnosis values.

Python and some of its libraries, including Scikit-Learn library, Pandas, and others, are used to “implement three machine learning algorithms: Logistic Regression, Random Forest, and Decision Tree”. This Heat Map provides information about the impact of other features (columns) on the diagnosis column as well as aids in better visualizing correlations. When comparing machine learning algorithms, there are several factors to consider such as accuracy, interpretability, scalability, and ease of implementation. In this paper we are comparing three popular algorithms: decision trees, logistic regression, and random forests.

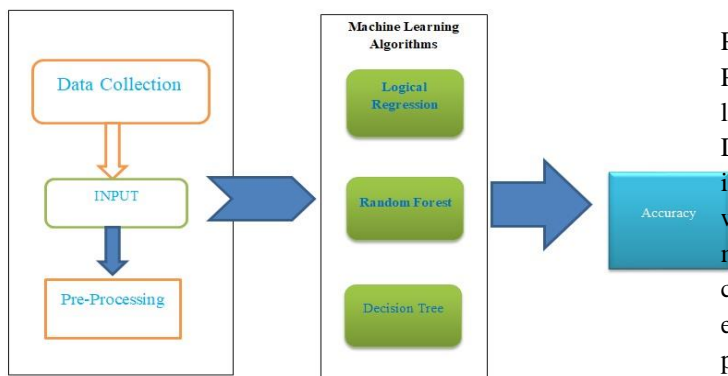


Figure 1: System Architecture

A number of technological advances have enabled us to be able to forecast the risk of breast cancer in a way that is more accurate and precise in the future. The prediction of breast cancer incidence will be done using machine learning. Our computer will be trained to recognize whether the tumours are benign or malignant by employing multivariate regression as the main technique for analysis. “For the purposes of this study the Breast Cancer Wisconsin (Diagnostic) Dataset from the UCI Machine Learning Repository (Wolberg, 1995) was utilized. There are 569 instances and 30 attributes in the dataset, including 357 benign cases and 212 malignant cases (as shown in figure 1), as well as different metrics such as the mean, standard error, and worst value (i.e., the highest value) of ten features from digital images of breast tissue, including radius, texture, perimeter, area, smoothness, compactness,

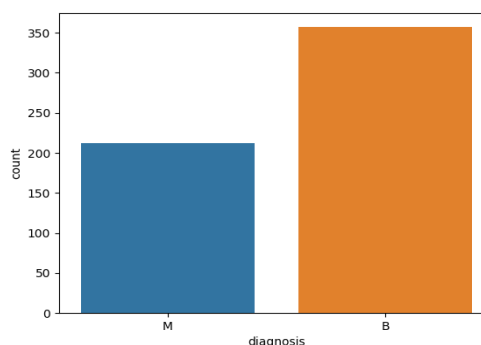


Figure 2: Diagnosis with System

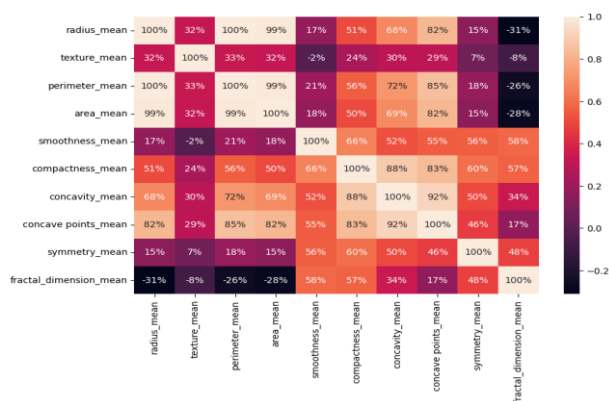


Figure 3: Confusion Matric

In this particular research project, the existence of breast cancer was hypothesized with the use of three different “machine learning algorithms: the Decision Tree Classifier, the Logistic Regression, and the Random Forest”. It was determined by comparing the degrees of accuracy achieved by each algorithm [27] to see which one was the most appropriate for the endeavor. Because it has the greatest prediction accuracy, the Random forest method is the best one for making forecasts [on the "Breast Cancer Wisconsin (Diagnostic) Data Set"]. Therefore, it is possible to predict breast cancer with an almost perfect level of accuracy by utilizing our Decision Tree Classifier method in conjunction with the characteristics obtained from this dataset. The results of the experiments are shown in Table 2.

Table 2: Accuracy Analysis Using Different Algorithms

Model	Logistic regression	Random forest	Decision tree
Training accuracy	97	98	99
Testing accuracy	94	96	97

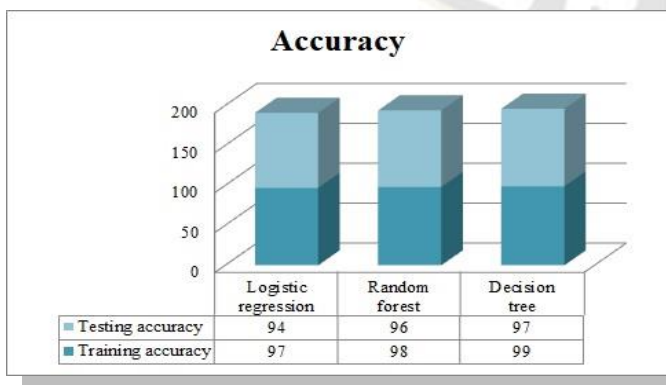


Figure 4: Accuracy of Proposed System

The logistic regression model successfully identified the diagnosis of breast cancer for 97% of the samples in the training dataset, achieving a training accuracy of 97%. The model has a 94% accuracy rate for the testing dataset, which means that it correctly predicted the diagnosis for 94% of the samples not observed during training. The model may have somewhat over fit the training data, which means it may not generalize as well to new, unknown data, as seen by the slightly lower testing accuracy relative to training accuracy. With a training accuracy of 98%, the random forest model correctly predicted the diagnosis for 98% of the training dataset samples. The 96% testing accuracy indicates that the model successfully classified 96% of the test samples based on the unseen testing data. In comparison to logistic regression, the random forest model seems to perform somewhat better in terms of generalization. The decision tree model properly predicted the diagnosis for 99% of the samples in the training dataset, achieving a remarkable training accuracy of 99%. The model did well on the testing data that was not seen, accurately categorizing 95% of the samples. This is shown by the testing accuracy of 95%. On both training and testing datasets, the decision tree model performs with a high degree of accuracy, perhaps indicating a strong match to the underlying patterns in the data. [28]

V. CONCLUSION

Based on the provided information, the logistic regression, random forest, and decision tree models were evaluated for breast cancer prediction. Overall, all three models achieved relatively high accuracy values, indicating their ability to correctly classify breast cancer instances. “The logistic regression model achieved a training accuracy of 97% and a testing accuracy of 94%. The random forest model had a training accuracy of 98% and a testing accuracy of 96%. The decision tree model demonstrated even higher accuracies, with a training accuracy of 99% and a testing accuracy of 95%”.

These results suggest that all three models show promise in predicting breast cancer. However, it's important to consider other performance metrics and potential over fitting or bias when evaluating model effectiveness. “Further analysis is required to compare additional metrics such as precision, recall, and F1-score, which provide insights into model performance for specific classes (benign or malignant) and the balance between correctly identifying positive and negative instances. In conclusion, the evaluation of these models demonstrates their potential usefulness in breast cancer prediction”. However, it is essential to conduct further research and analysis to validate their performance across different datasets and consider additional factors for robust and reliable predictions.

The scope of features that can be investigated for breast cancer detection using machine learning encompasses a variety of

factors which can be incorporated into the model in order to enhance its accuracy and reliability. The purpose of this research is to extract more informative features from the breast cancer dataset through advanced feature engineering techniques, and to address the issue of imbalanced data by developing data balancing techniques. Additionally, additional clinical data such as patient histories and genetic information must be incorporated into the model, so that it can be understood and trusted more effectively. A further component of the project is to validate the models on diverse datasets externally, to develop real-time prediction systems, and to conduct longitudinal analysis to monitor the progression of the diseases. It has been demonstrated that researchers can further improve the performance and practicality of machine learning models for breast cancer detection by focusing on these features.

Reference

- [1] Arpita Joshi and Dr. Ashish Mehta "Comparative Analysis of Various Machine Learning Techniques for Diagnosis of Breast Cancer" (2017).
- [2] David A. Omondiagbe, Shanmugam Veeramani and Amandeep S. Sidhu "Machine Learning Classification Techniques for Breast Cancer Diagnosis" (2019).
- [3] Kalyani Wadkar, Prashant Pathak and Nikhil Wagh "Breast Cancer Detection Using ANN Network and Performance Analysis with SVM" (2019).
- [4] Anji Reddy Vaka, Badal Soni and Sudheer Reddy "Breast Cancer Detection by Leveraging Machine Learning" (2020).
- [5] Monika Tiwari, Rashi Bharuka, Praditi Shah and Reena Lokare "Breast Cancer Prediction using Deep learning and Machine Learning Techniques".
- [6] Abdullah-Al Nahid and Yinan Kong "Involvement of Machine Learning for Breast Cancer Image Classification: A survey" (2017).
- [7] K. Anastraj, Dr. T. Chakravarthy and K. Sriram "Breast Cancer detection either Benign Or Malignant Tumor using Deep Convolutional Neural Network With Machine Learning Techniques" (2019).
- [8] S. Vasundhara, B.V. Kiranmayee and Chalumuru Suresh "Machine Learning Approach for Breast Cancer Prediction" (2019).
- [9] Muhammet Fatih Ak "A Comparative Analysis of Breast Cancer Detection and Diagnosis Using Data Visualization and Machine Learning Applications" (2020)
- [10] Sivapriya J, Aravind Kumar V, Siddarth Sai S, Sriram S "Breast Cancer Prediction using Machine Learning" (2019).
- [11] Hiba Asria, Hajar Mousannifb, Hassan Al Moatassime, Thomas Noeld "Using Machine Learning Algorithms for Breast Cancer Risk Prediction and Diagnosis" (2016).
- [12] Dana Bazazeh and Raed Shubair "Comparative Study of Machine Learning Algorithms for Breast Cancer Detection and Diagnosis" (2016).
- [13] Ramik Rawal "Breast Cancer Prediction Using Machine Learning" (2020).
- [14] S. Karthik, R. Srinivasa Perumal and P. V. S. S. R. Chandra Mouli "Breast Cancer Classification Using Deep Neural Networks" (2019).
- [15] Abdullah-Al Nahid, Aaron Mikaelian and Yinan Kong "Histopathological breast-image classification with restricted Boltzmann machine along with backpropagation." (2018).
- [16] AA Khan, RM Mulajkar, VN Khan, SK Sonkar, DG Takale. (2022). A Research on Efficient Spam Detection Technique for IOT Devices Using Machine Learning. *NeuroQuantology*, 20(18), 625-631.
- [17] SU Kadam, VM Dhede, VN Khan, A Raj, DG Takale. (2022). Machine Learning Methode for Automatic Potato Disease Detection. *NeuroQuantology*, 20(16), 2102-2106.
- [18] DG Takale, Shubhangi D. Gunjal, VN Khan, Atul Raj, Satish N. Gujar. (2022). Road Accident Prediction Model Using Data Mining Techniques. *NeuroQuantology*, 20(16), 2904-2101.
- [19] SS Bere, GP Shukla, VN Khan, AM Shah, DG Takale. (2022). Analysis Of Students Performance Prediction in Online Courses Using Machine Learning Algorithms. *NeuroQuantology*, 20(12), 13-19.
- [20] R Raut, Y Borole, S Patil, VN Khan, DG Takale. (2022). Skin Disease Classification Using Machine Learning Algorithms. *NeuroQuantology*, 20(10), 9624-9629.
- [21] SU Kadam, A katri, VN Khan, A Singh, DG Takale, DS. Galhe (2022). Improve The Performance Of Non-Intrusive Speech Quality Assessment Using Machine Learning Algorithms. *NeuroQuantology*, 20(19), 3243-3250.
- [22] DG Takale, (2019). A Review on Implementing Energy Efficient clustering protocol for Wireless sensor Network. *Journal of Emerging Technologies and Innovative Research (JETIR)*, Volume 6(Issue 1), 310-315.
- [23] DG Takale. (2019). A Review on QoS Aware Routing Protocols for Wireless Sensor Networks. *International Journal of Emerging Technologies and Innovative Research*, Volume 6(Issue 1), 316-320.
- [24] DG Takale (2019). A Review on Wireless Sensor Network: its Applications and challenges. *Journal of*

- Emerging Technologies and Innovative Research (JETIR), Volume 6(Issue 1), 222-226.
- [25] DG Takale, et. al (May 2019). Load Balancing Energy Efficient Protocol for Wireless Sensor Network. International Journal of Research and Analytical Reviews (IJRAR), 153-158.
- [26] DG Takale et.al (2014). A Study of Fault Management Algorithm and Recover the Faulty Node Using the FNR Algorithms for Wireless Sensor Network. International Journal of Engineering Research and General Science, Volume 2(Issue 6), 590-595.
- [27] DG Takale, (2019). A Review on Data Centric Routing for Wireless sensor Network. Journal of Emerging Technologies and Innovative Research (JETIR), Volume 6(Issue 1), 304-309.
- [28] DG Takale, VN Khan (2023). Machine Learning Techniques for Routing in Wireless Sensor Network, IJRAR (2023), Volume 10, Issue 1.

