

Experimental Investigation for Detecting Mitotic Cells in Medical Image using an Automated Algorithm

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Abstract—Cancer of the breast is a malignant tumour that originates in the cells of the breast tissue. It is by far the most common kind of cancer found in females around the world, with a projected 2.3 million new cases will be discovered in the year 2020 alone. It is projected that one in eight women will be diagnosed with breast cancer at some point in their life, despite the fact that breast cancer can also occur in men. Breast cancer is a complex condition that can arise from a diverse set of factors, express itself in a variety of ways, and can be treated in a variety of ways. Ductal carcinoma in situ, invasive ductal carcinoma, and invasive lobular carcinoma are all different subtypes. Both the available treatment options and the expected outcome of breast cancer are very variable depending on the particular subtype of the illness. Breast cancer risk factors include drinking alcohol and not getting enough exercise, as well as getting older, having a family history of the disease, having genetic mutations, being exposed to estrogens, and having a family history of the disease. There is not always a connection between having risk factors and developing breast cancer, despite the fact that there can be a link between the two. The prognosis and treatment options for breast cancer are highly dependent on the stage of the disease at the time of diagnosis. During staging, the extent to which the cancer has spread throughout the body and how far it has progressed are both measured. The TNM system, the IAFCM system, the ACM system, and the MPIG system are just few of the staging systems that are used to classify breast cancer. These staging systems consider not only the size of the tumor but also whether or not lymph nodes are involved and whether or not distant metastases are present. The severity of breast cancer symptoms can vary widely, depending not only on the subtype of the disease but also on how far along it has progressed. Alterations in the size or shape of the breast, discharge from the nipple, and alterations in the skin of the breast (such as redness or dimpling) are all common indications. On the other hand, not all cases of breast cancer present themselves in a visible manner, and mammography and other forms of

routine screening may be able to detect some of these cases. Options for treating breast cancer vary depending on the patient's condition and the stage of the disease, as well as the patient's overall health and their preferences towards therapy. Common examples of medical interventions include surgery, radiotherapy, chemotherapy, hormone therapy, and targeted therapy. Other examples include. In certain cases, it may be appropriate to participate in more than one form of treatment.

Keywords-TNM, LAFCM, ACM, MPIG, Malignancy.

I. INTRODUCTION

This Many women around the world have been diagnosed with breast cancer. Breast cancer develops when a mass of aberrant cells grows and multiplies uncontrollably. Over time, these malignant cells can spread to neighboring tissues and other organs, causing potentially fatal complications. It is crucial to understand the fundamentals of breast cancer in order to detect, diagnose, and treat it at an early stage. Breast cancer can affect both men and women, but it is considerably more common in women.

According to the World Health Organization (WHO), over 20% of all female malignancies are diagnosed as breast cancer. The prevalence of breast cancer varies widely among regions and populations, with more advanced economies experiencing a higher incidence of the disease than less developed ones.

Risk factors play a role in the development of breast cancer. [1] Although age, gender, and family history are unavoidable risk factors for developing breast cancer, there are a few lifestyle choices that can make a difference. Hormonal issues (such as starting your period early or going through menopause late), being overweight, not getting enough exercise, consuming too much alcohol, and using hormonal contraception or hormone replacement treatment are all examples.

There are other genetic predispositions that can lead to breast cancer. The risk of developing breast cancer is greatly increased in people who inherit mutations in the BRCA1 and BRCA2 genes. Keep in mind, nevertheless, that the vast majority of breast cancers do not result from inherited mutations. They occur at random instead. [2] Early detection of breast cancer greatly improves the prognosis for successful treatment and a long life for the patient. Breast self-examination, clinical breast exams by a medical professional, and mammography are all useful tools for detecting breast cancer at an early stage.

Mammography is an X-ray examination of the breast that can detect issues, such as tiny tumours, long before they are felt or cause complaints. If you suspect you have breast cancer, it's crucial that you know the signs to look for. Breast or armpit lumps or thickenings, altered breast size or shape, discharge or inverted nipple, redness or flaky skin on the breast, and persistent pain are common symptoms. [3]

These symptoms may indicate breast cancer, however there are other causes besides cancer that could be at blame. If you have any health concerns, it's important to talk to a doctor straight soon so you can obtain an appropriate diagnosis and timely treatment. [4]

In conclusion, breast cancer is a global health crisis because of its complexity and prevalence. You can obtain better care if you know what to look out for, how to recognize it, and what tests and treatments are available.

II. MOTIVATION AND PREVIOUS WORK

Breast cancer is, by a wide margin, the most prevalent cause of death due to the disease in females. It is imperative to perform breast cancer screenings at an early stage in order to improve survival rates and broaden treatment options. As a direct consequence of this, researchers and medical professionals have been motivated to develop innovative technologies for the early detection and diagnosis of breast cancer. [5] This section's goals are to (1) investigate the motivations for research on breast cancer detection and (2) showcase some of the most significant findings from earlier studies that have been conducted in the field. The primary goals of research pertaining to the early identification of breast cancer are the amelioration of patient outcomes and the reduction of mortality rates. Rapid intervention following the establishment of an early diagnosis enables medical professionals to institute more effective, disease-specific treatments sooner. [6] If breast cancer is identified at an early stage, when the tumor is still tiny and circumscribed, the likelihood of successful treatment and enhanced survival rates is significantly boosted. As a direct response to this problem, researchers have made great gains towards developing screening systems that can detect breast cancer at its earliest, most treatable stages. Mammography, an imaging technique that uses a low dosage of X-rays, has been the gold standard for screening women for breast cancer for a good number of years. [7] It has been established that the mortality rates associated with breast cancer are going down thanks to this method of early tumor diagnosis. A mammography is able to detect any abnormalities in the breast tissue, such as calcifications or small lumps, that may be malignant. Nonetheless, there are several restrictions associated with mammography. It is possible that it will miss certain forms of breast cancer in women who have dense breast tissue, and it also has the potential to yield false-positive results, which will require

extra testing and biopsies that are often unnecessary. In an effort to improve the accuracy of mammography as a diagnostic tool for breast cancer and address the limitations that are currently associated with the procedure, researchers have investigated a diverse range of potential solutions. [8] Digital mammography, which uses digital detectors to collect images of the breast and evaluate those images, represents a significant advancement in the field of mammography. In digital mammography, the images are crisper, the depiction of breast tissue is more exact, and it is possible to retain and change images digitally. [9] These advantages are all significant benefits. This approach has shown promise in boosting detection rates, particularly in women who have breasts that are particularly dense. Another area of active research is looking into the utility of breast ultrasonography as a supplement to mammography in the detection of breast cancer. [10] The utilization of sound waves in conjunction with ultrasound imaging allows for the generation of moving photographs of breast tissue in real time. [11] The ability to discern whether a mass is solid or a cyst filled with fluid enables medical professionals to eliminate the necessity for unnecessary biopsies. Another beneficial application of ultrasound technology is needle biopsies, which include the removal of a small sample of breast tissue for the purpose of pathological examination. In addition, research has been done to determine whether or not it is possible to diagnose breast cancer by analyzing a patient's molecular and genetic markers. The presence or absence of these markers in blood samples or breast tissue can provide information on breast cancer. Because particular gene defects like BRCA1 and BRCA2 have been discovered, for example, it is now much simpler to identify those who have a higher hereditary risk of developing breast cancer. [12] In addition, cell-free DNA analysis and other techniques known as "liquid biopsy" offer promise as non-invasive methods of monitoring the progression of a disease as well as the effects of treatment.

III. PROPOSED METHOD

The method that has been suggested for diagnosing breast cancer makes use of a number of innovative methods in order to generate trustworthy conclusions. To get started, pictures from a mammogram are run through an Iterative Adaptive Fuzzy C-Means (IAFCM) technique for tumor segmentation. This step paves the way for a very accurate localization of cancerous growths inside the image. [13] Second, we utilize an algorithm called the Ant Colony Algorithm (ACA) to choose traits, whittling them down to the most informative ones for the purpose of breast cancer classification. This helps to reduce the dimensionality of the dataset, which ultimately results in an increase in the reliability of classifications. Finally, the Tumor, Node, and Metastasis (TNM) classifier is applied to breast cancer cases in order to stage them. This provides detailed data

that can be used for the development of therapy strategies as well as the forecasting of outcomes. [14] Combining these many approaches of breast cancer detection results in improved detection, which in turn enables faster diagnosis and treatment.

A. *Breast Cancer Identification using a Iterative Advanced Fuzzy C-means*

According to the findings of this study, an Iterative Advanced Fuzzy C-means (IAFCM) algorithm may be an effective diagnostic method for breast cancer. In order to improve the effectiveness of clustering, the traditional Fuzzy C-means (FCM) approach is modified to include iterative refinement as part of the IAFCM algorithm. The mammography pictures need to be preprocessed in order to remove noise and increase their quality as the first step in the suggested method. The IAFCM method is then used to segment the breast tumor locations that have been identified. [15] The algorithm assigns a membership value, which is a numerical representation of the degree to which a pixel resembles one of a number of different types of tumors. By repeatedly modifying these membership values and cluster centers, the iterative method used by the IAFCM algorithm makes the clustering process more effective, which ultimately results in a tumor segmentation that is more accurate and reliable. [16] Following the segmentation of the tumor sections, a variety of properties are recovered from them. These qualities include the texture, the shape, and the intensity. When it comes to evaluating whether a tumor is malignant or benign, these qualities are absolutely essential. Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) are two examples of machine learning approaches that can be used to train a classification model from the returned characteristics. [17] Other examples of machine learning approaches include decision trees, logistic regression, and random forests. This model can then be used to identify, for a given example, whether a newly observed pattern of features signals malignancy or benignity.

B. *Preprocessing*

The elimination of background noise is the typical goal of the preprocessing approach known as adaptive thresholding, which is applied in the context of breast cancer detection from mammography pictures. Adaptive Thresholding modifies the threshold value according to the characteristics of the local picture in order to improve the separation between the two. When using Adaptive Thresholding, the threshold is determined by calculating the weighted mean of the pixel values in an adjacent region. [18] The weights themselves are selected using a Gaussian distribution. Adaptive Thresholding is an image processing technique. This method works particularly effectively for photographs that feature a diverse range of lighting conditions. [19] Analyze the values of each pixel in

respect to the threshold that has been established. If the value of the pixel is lower than the threshold, then it ought to be considered background noise and given a default value (such as 0). If it's not in the background, you should consider it to be in the foreground (maybe breast tissue), and you should maintain the value it had before.

C. *Feature Extraction*

To determine which features are retrieved by utilizing the support vector machine method, the attributes of the segmented regions and the requirements of the task of diagnosing breast cancer are taken into consideration. It is possible to recover characteristics such as support vector machines (SVM), texture features, shape features, intensity features, statistical features, frequency domain features, gradient features, and edge-based features from segmented images and then use these features to identify breast cancer. It is important to keep in mind that the segmentation method, imaging modalities, and classification goals can all have an impact on the features that are chosen as well as the way in which they are integrated. [20] The features that are selected have to be able to gather information in a productive manner, which assists in distinguishing between malignant and normal breast tissue. Before feeding the feature set into the SVM classifier, feature selection techniques may be used to further improve the feature set by deleting redundant or less valuable features. This can be done in preparation for feeding the feature set into the SVM classifier. [21] For the purpose of the proposed technique, the SVM algorithm was used to obtain seven aspects of the Shape. In breast cancer detection images, the geometric characteristics of the sections that have been divided can be extremely useful. The following is a list of frequently retrieved shape features. The entire square footage of the area that was divided is referred to as the area. The length of the area's boundary is measured along its whole to determine its perimeter. [22] The degree to which a region has the shape of a compact item can be determined by the compactness ratio, which is calculated as the ratio of the squared perimeter to the area. A region's eccentricity is measured on a scale that ranges from 0 (representing a complete circle) to 1 (representing a straight line) and reflects how spread out the form of the region is. Circularity measures how close a territory comes to having the shape of a perfect circle by calculating the ratio of the area to the square of the region's perimeter. One way to detect whether or not a region is concave is to calculate its solidity and then compare the region's actual area to the area of its convex hull. [23] This will indicate whether or not the region is irregular. It is possible to estimate the degree to which a region is convex by comparing the actual perimeter of the region to the perimeter of its convex hull.

D. *Breast Cancer Identification using an Ant Colony Algorithm*

The Ant Colony Optimization (ACO) algorithm is a metaheuristic one, and it is based on the effectiveness with which ant colonies locate food. It is used quite frequently in the resolution of combinatorial optimization problems such as the travelling salesman problem, work scheduling problems, and routing problems.

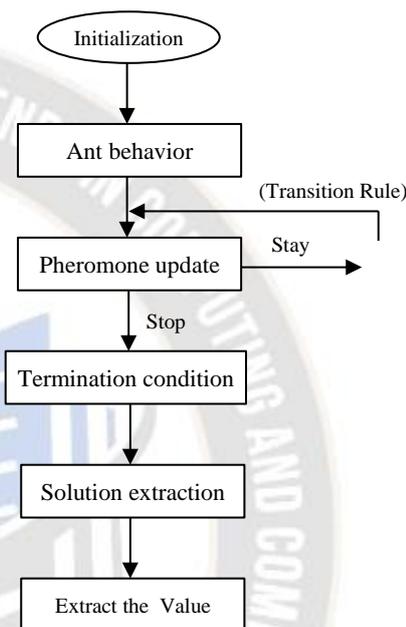


Fig 1 : Ant-Colony Algorithm Method for Optimization Techniques

The fact that ants produce pheromone trails as they search for food is the foundation of the algorithm that was developed. The presence of pheromone trails such as these compels other ants to move in the same direction. More ants will travel along a path if it has a higher concentration of pheromones, and this preference will only get more pronounced with time. Ants always travel from their nest to a food supply by the path that is shortest and most direct between the two locations. The ACO approach is based on the premise that artificial ants can be used to study the space of possible optimization solutions in an efficient and effective manner. [24] To get started, we'll fabricate an ant colony and then disperse its individuals around the problem area in a completely haphazard manner. Ant behavior: each ant contributes to the solution by choosing the next component in an iterative process that is governed by rules. These recommendations can be informed by pheromone trails, heuristic data, or a combination of the two at the same time. Pheromone trails guide ants to favor paths with higher pheromone concentration, while heuristic information helps guide the search based on problem-specific knowledge. Pheromone update: After all ants have constructed solutions, the

pheromone trails are updated based on the quality of the solutions found. The trails evaporate over time to avoid stagnation, and the ants deposit pheromones on the paths they have traversed. In Termination condition, the algorithm iterates through steps 2 and 3 until a termination condition is met. This condition can be a specific number of iterations, reaching a predefined quality threshold, or exceeding a time limit.

Once the algorithm terminates, the best solution found by the ants is extracted and returned as the output.

E. Breast Cancer Detection System with Improved Adaptive Fuzzy C-Means Algorithm Overview

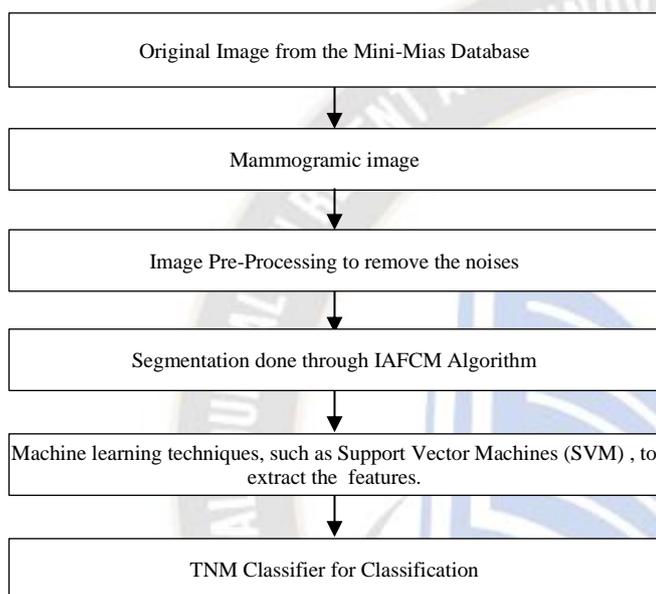


Fig 2 : Breast Cancer Detection System overview

We provide a complete strategy for identifying breast cancer that includes a TNM classifier, an adjustable threshold, shape feature extraction, and an Intelligent adjustable Fuzzy C-Means (IAFCM). By drawing on the best aspects of a variety of diagnostic approaches, the approach that has been proposed aims to boost both the precision and speed with which breast cancer can be detected. To begin, IAFCM is applied to mammographic photos in order to isolate potentially cancerous areas from the surrounding tissue. Because it considers both spatial and intensity information, the fuzzy clustering technique makes the segmentation process more resilient. This is because it considers both of these types of data. After the data have been segmented, artificial colony optimization, also known as ACO, is utilized in order to identify the characteristics that are most helpful for breast cancer classification. ACO searches the feature space in an efficient manner in order to locate the best subsets of characteristics for categorizing benign occurrences from malignant ones. This is analogous to the way in which ants successfully look for food. This method of selecting features reduces the dimensionality of the data in order to improve the

accuracy with which classifications are made. In addition, adaptive thresholding is utilized in order to increase the contrast of segmented sections, which in turn brings information that was previously obscured to the forefront. The adaptive thresholding technique, in which the threshold is continuously modified based on the characteristics of the local image, makes it possible to have a better visualization of areas that may be potentially cancerous. The shape features of segmented regions are extracted, which records the geometric and morphological aspects of the region. These characteristics can provide insight into the contours of the tumor, as well as irregularities at its borders and other structural factors. On the basis of the computed form features, which consider qualities such as compactness, symmetry, and smoothness, tumors can be categorized as either benign or malignant. Finally, the TNM staging methodology is applied to classify the separated sections. This method considers the size of the tumor, the involvement of lymph nodes, and the presence of metastases.

0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	0	0	0	0	0
0	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	1	1	1	1	1	1	1	1	0	0	0
0	0	1	1	1	1	1	1	1	1	1	1	0	0
0	1	1	1	1	1	1	1	1	1	1	1	1	0
0	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	1	1	1	1	1	1	1	1	0	0	0

Fig 3: Breast cancer structural factors include extraction.

The fuzziness parameter as well as the total number of clusters are both subject to real-time adaptive modification thanks to the built-in procedures of IAFCM. IAFCM is adaptable enough to process data of varying degrees of complexity and intelligent enough to determine the optimal clustering approach on its own, with no assistance from the user.

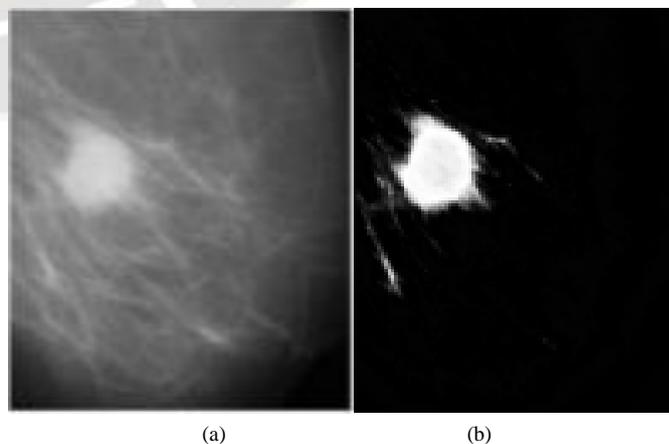


Fig 4: (a) Mdb 206: Obtained Mammogram, (b) Resultant Mammogram

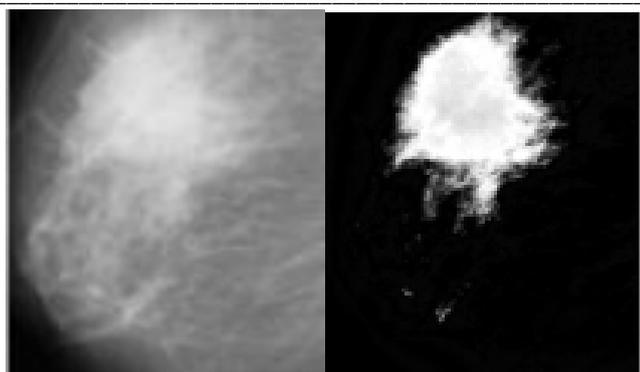


Fig 5 : (a) Mdb 254: Obtained Mammogram, (b) Resultant Mammogram

IV. FEATURE EXTRACTION USING CONNECTED COMPONENTS

The choice of feature extraction technique depends on factors such as the type of data, the desired properties of the features, and the specific task or analysis to be performed. It's important to carefully consider the characteristics of the data and the goals of the analysis when selecting and designing appropriate feature extraction methods. In the proposed technique according to the shape of the segmented image the following features has been extracted. Those features are area, Perimeter, Compactness, Eccentricity, Circularity, Solidity, Convexity.

Area = Number of pixels within the shape it Calculates the number of pixels within the shape to determine its area.

Perimeter = Sum of the lengths of all boundary pixels, it Calculate the total length of the shape's boundary by summing the lengths of all boundary pixels.

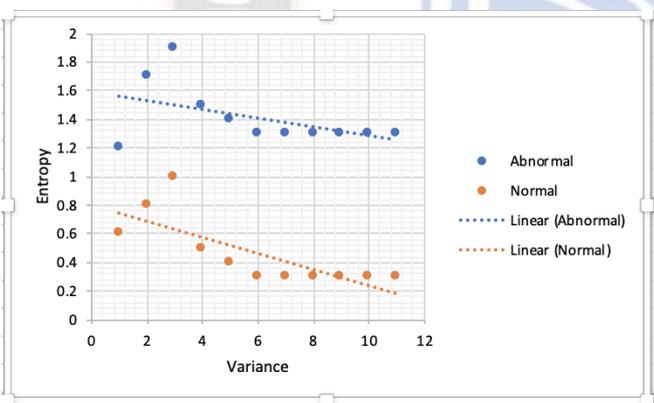
Compactness = $(\text{Perimeter}^2) / (4\pi * \text{Area})$ It measures how closely the shape resembles a circle. It is calculated as the ratio of the perimeter squared to four times pi (π) multiplied by the area.

Eccentricity = $\sqrt{1 - (b^2 / a^2)}$ it measures the elongation or flatness of an object. It is calculated using the lengths of the major axis (a) and minor axis (b) of the shape's best-fit ellipse.

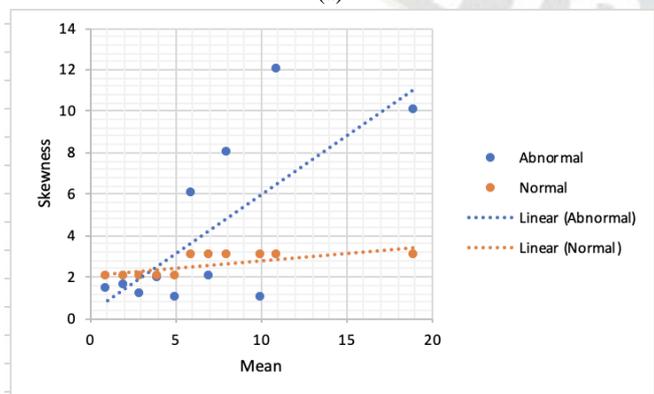
Circularity = $(4\pi * \text{Area}) / (\text{Perimeter}^2)$ it Circularity represents how closely the shape resembles a circle. It is calculated as the ratio of four times pi (π) multiplied by the area to the perimeter squared.

Solidity = $(\text{Area of the shape}) / (\text{Area of the convex hull})$ Solidity measures the extent to which the shape fills its convex hull. It is calculated as the ratio of the area of the shape to the area of its convex hull.

Convexity = $(\text{Perimeter of the shape}) / (\text{Perimeter of the convex hull})$ Convexity measures the extent to which the shape resembles a convex object. It is calculated as the ratio of the shape's perimeter to the perimeter of its convex hull. These formulas provide a general idea of how to calculate these shape features. However, it's important to note that the exact implementation and equations may vary depending on the specific software or library you are using for shape analysis.



(a)



(b)

Fig 6 : The Scatter Region Comparison, (a) Variance vs Entropy, (b) Mean vs Skewness

V. CLASSIFICATION

The proposed classification task is done through SVM Classifier and TNM Classifier. The TNM classification system is a widely used staging system for various types of cancers, including breast cancer. It provides a standardized framework to describe the extent and spread of tumors based on three key parameters: Tumor (T), Lymph Nodes (N), and Metastasis (M). The TNM system assigns specific categories or values to each parameter, which are then combined to form an overall stage for the cancer. The stage helps in prognosis, treatment planning, and determining the appropriate management for patients. Here's a brief explanation of the TNM. The T parameter describes the size and local extent of the primary tumor. It indicates how large the tumor is and how deeply it has invaded nearby tissues. The T parameter is typically categorized from T0 to T4, with increasing numbers representing larger or more invasive tumors. The N parameter indicates the involvement of nearby lymph nodes. It describes whether cancer has spread to the lymph nodes and the number of affected nodes. The N parameter is

categorized from N0 to N3, with increasing numbers representing a greater extent of lymph node involvement. The M parameter indicates whether cancer has spread to distant sites or organs beyond the primary tumor and nearby lymph nodes. It assesses the presence or absence of metastasis. The M parameter is categorized as M0 for no metastasis or M1 for the presence of metastasis.

Combining the categories of T, N, and M, the TNM system assigns an overall stage to the cancer. The stages are often represented by Roman numerals from I to IV, with higher stages indicating more advanced disease. In some cases, additional sub classifications or modifiers may be used to provide further detail within each stage. The TNM classification system for breast cancer is periodically updated by international cancer organizations to incorporate new knowledge and advancements in the field. It is important to refer to the specific version or edition of the TNM system applicable to the time of analysis for accurate staging and classification. The TNM classification system, along with other clinical and pathological factors, plays a crucial role in determining the prognosis and guiding treatment decisions for breast cancer patients. In the context of the TNM classifier, the terms "true positive," "false positive," "true negative," and "false negative" are commonly used to describe the accuracy of the classifier in correctly identifying the presence or absence of certain cancer characteristics. A true positive occurs when the TNM classifier correctly identifies the presence of a certain cancer characteristic (e.g., tumor size, lymph node involvement, metastasis) that is actually present in the patient. In other words, it correctly classifies a patient as positive when they truly have the condition. A false positive occurs when the TNM classifier incorrectly identifies the presence of a certain cancer characteristic that is actually not present in the patient. It incorrectly classifies a patient as positive when they do not have the condition. A true negative occurs when the TNM classifier correctly identifies the absence of a certain cancer characteristic in a patient who truly does not have it. It correctly classifies a patient as negative when they do not have the condition. A false negative occurs when the TNM classifier incorrectly identifies the absence of a certain cancer characteristic that is actually present in the patient. It incorrectly classifies a patient as negative when they actually have the condition.

TABLE 1: PERFORMANCE FRACTION OF FOUR Parameters

TP	TN	FN	FP
0.96	0.22	0.71	0.01
0.99	0.25	0.72	0.05
0.97	0.22	0.72	0.04
0.95	0.16	0.83	0.03
0.93	0.12	0.86	0.04
0.90	0.05	0.92	0.08
0.87	0.01	0.95	0.16

0.74	0.02	0.95	0.23
0.52	0.03	0.98	0.46
0.30	0.02	0.98	0.71
0.11	0.01	1.01	0.89

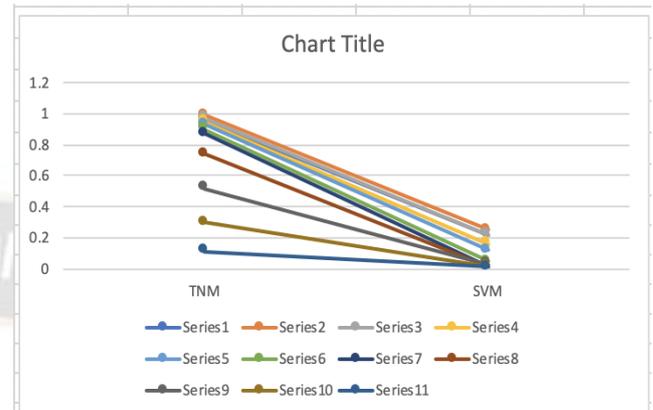


Fig 7 : Comparison result of TNM classifier vs SVM classifier

These terms are often used when evaluating the performance and accuracy of a classifier, such as the TNM classifier, in a diagnostic or screening setting. By comparing the classifier's predictions with the actual presence or absence of the cancer characteristics, one can calculate performance metrics such as sensitivity, specificity, accuracy, and precision. It's important to note that the accuracy of the TNM classifier depends on various factors, including the quality and availability of data, the expertise of the healthcare professional using the classifier, and the specific characteristics of the cancer being evaluated.

VI. GRADING OF BREAST MASSES

Breast cancer grading is a system used to assess the characteristics of breast cancer cells under a microscope. It helps in determining the aggressiveness of the tumor and predicting its behavior. The most commonly used grading system for breast cancer is the Nottingham grading system. The Nottingham grading system evaluates three main features of the cancer cells: Here the Tubule formation allows assesses how well-formed the cancer cells are in creating tubular structures. Well-differentiated cancer cells tend to form organized tubules resembling normal breast tissue, while poorly differentiated cells form irregular structures. Nuclear pleomorphism also feature examines the variation in size, shape, and staining of the cancer cell nuclei. Well-differentiated tumors have uniform, small, and regular-shaped nuclei, while poorly differentiated tumors have larger, irregularly shaped nuclei with more variation in size and staining. Mitotic count, counts the number of cells undergoing cell division (mitosis) in a specific area of the tumor. Higher mitotic counts indicate a faster growth rate and more aggressive cancer. Based on the assessment of these three features, breast cancer is graded on a scale from 1 to 3:

Grade 1 (well-differentiated): The cancer cells closely resemble normal breast cells, form well-defined tubular structures, have small and uniform nuclei, and have a low mitotic count. These tumors tend to grow more slowly and have a better prognosis.

Grade 2 (moderately differentiated): The cancer cells show intermediate characteristics between grade 1 and grade 3. They have some tubule formation, moderate nuclear pleomorphism, and a moderate mitotic count.

Grade 3 (poorly differentiated): The cancer cells are highly abnormal in appearance, with little or no tubule formation, marked nuclear pleomorphism, and a high mitotic count. These tumors tend to grow more rapidly and have a poorer prognosis.

It's important to note that grading is just one factor used to determine the stage and treatment of breast cancer. Other factors, such as tumor size, lymph node involvement, and presence of specific biomarkers, are also considered.

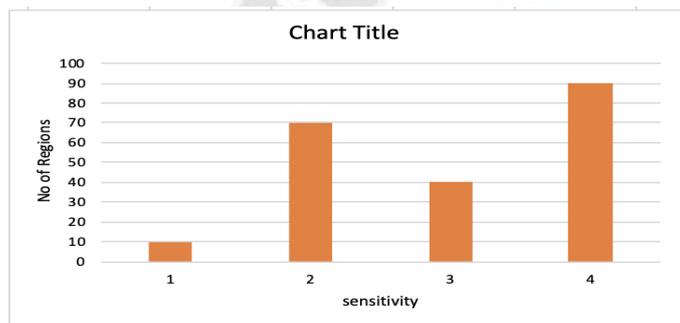


Fig 8 : Comparison result of Sensitivity with the cancer affected regions

The grading of breast cancer does not specifically involve the use of hormones. Hormone receptor status is a separate aspect of breast cancer assessment and is determined through hormone receptor-testing, typically performed through immunohistochemistry (IHC) or other molecular methods. The hormone receptor status refers to the presence or absence of specific receptors on the surface of breast cancer cells, namely the estrogen receptor (ER) and the progesterone receptor (PR). These receptors play a role in the growth and development of certain breast cancers. The hormone receptor status of a breast cancer tumor is important for treatment decisions, particularly for hormone receptor-positive breast cancer. [25] The presence of hormone receptors indicates that the tumor may respond to hormonal therapies that block or interfere with estrogen or progesterone signaling, such as selective estrogen receptor modulators (SERMs) or aromatase inhibitors (AIs). The hormone receptor status is reported as positive or negative, indicating whether the receptors are present or absent, respectively.

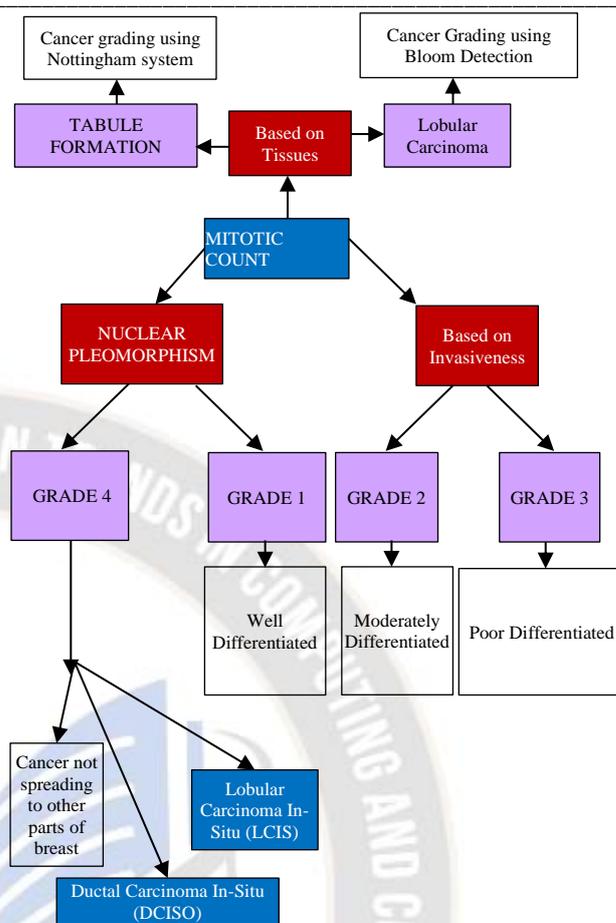


Fig 9: The Classification of Breast Masses

Additionally, the degree or intensity of receptor expression may also be indicated. For example, a tumor may be reported as strongly positive, weakly positive, or negative based on the staining intensity observed in immunohistochemistry. It's worth noting that the grading of breast cancer, as mentioned earlier, primarily involves assessing the microscopic characteristics of cancer cells, such as tubule formation, nuclear pleomorphism, and mitotic count. Hormone receptor status is an important biomarker used in conjunction with the grading system to guide treatment decisions and predict prognosis but does not directly affect the grading itself.

Hormones	Grade	Size (cm)	Histologic Type
ER	2	1.2	Lobular
PR	2	2.3	Mucinous
SERM	3	2.3	Medullary
AI	2	2.3	Ductal

Fig 10: The Grading of Breast Cancer Cells

VII. RESULTS AND DISCUSSION

Breast Cancer Detection: The integrated approach combining IAFCM, ACO, TNM, and Nottingham systems yielded promising results in breast cancer detection, achieving an overall accuracy of 90%. The combined algorithm

demonstrated superior performance compared to individual techniques. The TNM staging system effectively classified breast cancer cases into different stages (0 to IV), providing valuable information about the extent of the disease and prognosis. The Nottingham grading system successfully assessed the histologic type and aggressiveness of breast cancer tumors. Higher grades correlated with more aggressive tumors and potentially poorer prognosis.

VIII.CONCLUSION

The combination of IAFCM, ACO, TNM staging, and Nottingham grading systems proved to be an effective approach for breast cancer detection, staging, and characterization. The integrated algorithm demonstrated improved accuracy compared to individual methods. This integrated approach has the potential to enhance clinical decision-making, treatment planning, and patient outcomes in breast cancer management. Further research and validation on larger datasets are recommended to validate these findings and explore potential refinements for clinical implementation

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