Evaluation of SVM and NN Machine Learning Classifiers in Thyroid Tumor Detection system

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Abstract:

Cancer is one of the world's most hazardous diseases, and it is particularly effective in women. As a result, our primary goal must be to cure cancer through scientific inquiry, with early identification of cancer as a secondary goal. Diagnosis can aid in the complete removal of cancer. Cancer is critical for improving survival rates. As a result, a reliable diagnosis and detection procedure is required. Medical practitioners will benefit greatly from automatic detection techniques. There are several approaches for cancer detection that have been proposed. However, this is not a simple task due to various uncertainties in mammography detection. Mammograms are images created by a radiologist using a machine. The doctor examines these mammograms and diagnoses the cancer for future therapy. Because all general hospitals lack specialists, patients have had to wait for their results. As a result, waiting for a breast cancer diagnosis may take some time. This delay may have caused the cancer to spread, lowering the patient's chances of survival. Machine Learning (ML) methods can be utilized to produce tools for doctors which can be used as an efficient system for early cancer detection and diagnosis, considerably improving patient survival rates. This does not imply that a computer can replace an expert or a physician, but rather that a computer can help an expert better grasp a case and produce findings more quickly. K-Nearest Neighbors, Support Vector Machine (SVM), and Neural Network (NN) are examples of machine learning algorithms that help us tackle this challenge by producing solutions with great sensitivity and accuracy. Various metrics such as specificity, sensitivity, and accuracy are used to evaluate cancer images in this study.

Keywords: *Cancer Diagnosis, Convolution Neural Network, Neural Network, Random Forest, Support Vector Machine, Machine Learning.*

1. INTRODUCTION:

Cancer research has progressed steadily during the past few decades [1]. To find cancer types before symptoms appeared, researchers utilized a variety of methods, including early stage screening. They've also developed new methods for anticipating early on the outcomes of cancer therapy. Large amounts of cancer information are collected and made available to the medical scientific community as a result of technology breakthroughs in the field of medicine. However, one of the most exciting and difficult challenges for clinicians is reliable disease outcome prediction. As a result, medical experts are turning more and more to machine learning techniques.

These strategies are able to detect and recognize patterns and links between them, from complicated information, while accurately predicting future results of a cancer type. Given the relevance of customized medicine and the growing popularity of its application, we present an overview of research that uses machine learning approaches for cancer prediction and prognosis. Prognostic and predictive qualities that may be independent of a specific treatment or integrated to guide therapy for persons with cancer, respectively, are taken into consideration in these studies Consequently, we investigate alternative machine learning (ML) methodologies, the data they include, and the performance of every proposed system. There is a definite tendency toward integrating clinical and genomic data. The lack of peer review or testing of their models' prediction ability was a reoccurring problem in several investigations. We know that ML approaches can help us better forecast cancer risk, recurrence, and overall survival. Using ML approaches, the reliability of cancer prediction outcomes has increased by 15% to 20% over the previous few years, according to [3]. Early cancer detection and prognosis have been made possible in several studies that have been published [4–7] and are influenced by various methodologies. It has been shown that miRNA profiling can be used to detect and identify cancers, and these studies detail how this can be done. In terms of early screening, these approaches have limited sensitivity and difficulty distinguishing between benign and malignant cancers. Gene expression signatures have been used to make predictions about cancer outcome in a number of studies [8,9]. Microarrays for cancer outcome prediction have both potential and limitations, as shown in these research. We have made little progress in applying gene signatures in the clinic even though they could vastly enhance our prognosis for cancer patients. For genetic surveillance to be employed in medical practise, more extensive research is required.

It is the leading cause of death for both men and women in the world. Breast cancer is the leading cause of cancer deaths in developing countries, accounting for 23% of all cancer deaths. [10]–[12] One in every three cancer deaths in American women, excluding melanoma, is caused by breast cancer, which is the second leading cause of cancer-related death in the country

behind lung cancer[13]. Breast cancer claimed the lives of approximately 29% of American women in 2016. Cancer claimed the lives of 595,690 Americans in 2016, a rate of 1,600 fatalities per day. [14] Lung, bronchioles, prostate, and colorectum cancers kill more men than any other type of cancer, whereas lung, bronchioles, breast, and colon cancers claim the lives of women. Men are more likely than women to be diagnosed with invasive cancer throughout the course of their lifetime (42 percent versus 38 percent), Due to differences in exposure to the environment, as well as endogenous hormones, and the intricate interplay between these factors. Three-quarters of the six differences in cancer risk between men and women can be attributed to genetic and nutritional influences on height. [15].

Breast cancer mortality rates can be reduced and treatment can be expedited if the disease is discovered and detected early. Breast cancer can be detected and diagnosed by imaging, physical examination, and biopsy [16]. Breast cancer can be detected using imaging techniques such as mammography and ultrasound. X-rays are used to make breast pictures in this procedure. Mammograms are the medical term for these photographs. Mammograms are read by radiologists who have received specialized training in looking for signs of breast cancer. Radiologists' explanations can help determine the efficacy of a screening approach [17]. Sonograms and mammograms can be performed on patients with palpable breast cancer that appear normal or non-specific in appearance [18]. Patients must get a biopsy in order to determine whether or not they have breast cancer.

Radiologists may also miss as much as 30% of breast cancers, according to research [19], based on the thickness of the breasts. Masses and micro-calcifications, two significant indications of breast cancer, have been used to grade mammography. Micro-calcification identification is more difficult than detecting masses in a mammogram because of the wide range in size and form that masses might have, as well as their poor image comparison [20]. Mammograms are interpreted by radiologists depending on their expertise, training, and personal preferences. However, even experienced specialists can have an inter-observer variation rate of 65-75 percent. As a result, CAD may assist radiologists in interpreting mammography to detect and identify abnormalities. Research shows that between 65 to 90 percent of the samples of suspected malignancies came out to be harmless, so developing strategies to discriminate between malignant from benign lesions is quite significant. Combining CAD, expert knowledge, and machine learning approaches could significantly enhance detection accuracy. Detection accuracy was less than 80% without CAD, whereas it was over 90% with CAD [21].

The remaining parts of this work are structured as described below. In the second section, a literature assessment of earlier research on cancer detection and diagnosis is presented and discussed. Section 3 discusses about Various bench mark datasets in which cancer data is available. Section 4 discusses about the proposed SVM and NN Methodologies and finally Section 5 evaluates both the classifiers.

2. Literature Survey

Breast cancer detection models are getting better and better because to a variety of machine learning techniques that have been created and tested over the past few decades. The sections that follow provide an overview of some of the related research being done in this area. Jurgen Schmidhuber, Giovanni Giusti, Daniel C. CireSan, and Luca M. Gambardella developed an advanced deep neural network model that helped predict the mitotic sequence in breast cancer [22]. They employed a maximal pooling convolution neural network to detect mitosis. It was possible for the neural networks to classify every digital image, and then post-process the neural output in a simple way.

For a long time, computers tools were seen as critical in the early detection of breast cancer. Grey Level Founder Matrix (GLCM) features were used by Nithya and Santhi to develop a diagnostic approach for digital mammograms [23]. Mammography is one of the most important diagnostic tools used in the early stages of the breast cancer detection process. Using this procedure, pictures obtained from mammograms are sorted into categories denoting whether or not they contain cancer. This model's accuracy was estimated at 96%.

It is possible to create an ensemble algorithm by combining a number of different common approaches. In this paper, the authors were able to come up with an ensemble model that was 97.07% accurate. S. K. Mandal, Animesh Hazra, and A. Gupta conducted a comparative study among different machine learning techniques in a paper titled "Study and Analysis of Breast Cell Detection Using Nave Bayes, SVM, and Ensemble Algorithms," and their successful work helped them achieve an accuracy of 95.1 percent.

Different features retrieved from colon biopsy pictures were used in prior studies in order to diagnose cancer and discriminate between normal and malignant people. For categorization of colon biopsy images, [24], [25] evaluated six textural features and got an overall accuracy of 90.2 percent [24]. Using a probabilistic neural network, [26] extracted multi-scale textural features from the tissue around micro-calcifications to identify breast cancer (MCs). Classification of colon biopsy images using an SVM classifier and a hybrid feature set that combines typical histograms of directed gradients-based features as well as variant statistical examples and Haralick texture features has been proposed by [27] and has obtained 98 percent accuracy. Computerized methods for the automatic vehicle segmentation of at that in an area of interest (ROI) [28] and artificial intelligence based techniques, including the use of fractal dimension [29], have also been used in the past few decades to identify and treat breast colon images. These methods include the probabilistic automatic system and the radial slope index based algorithm [30]. Other techniques include the Convolutional Neural Network (CNN) classifier and the mixed feature based neural network [31].

Texture, morphology, SIFT, EFDs and combinations of other features have been used by

researchers in the past to extract features. [32-36]. The currently available methods have some drawbacks, and graph-based methods are prohibitively expensive compared to their alternatives. In contrast, the other texture-based CAD approaches fail to offer the necessary baseline knowledge of morphological traits. Although complexity-based sample complexity and wavelet entropy features can be used to retrieve information concealed in the bulk, segments, and sub of colon biopsy images, it is not possible to extract all of this information from a single image. This is because the information is spread out across multiple layers of the image. Machine learning algorithms based on various feature extraction methodologies have flaws, but classifications aren't fine-tuned. By reducing the amount of error that happens, the parameters of deep learning convolutional neural network models that apply transfer learning methodologies can be adjusted. In order to deal with the issue, we've used the following deep learning transfer approaches. We retrieved innovative features of Breast Cancer Images based on the limits of current features. Early identification of cancer has opened up a whole new study area that has proven the possibility to lessen human system deficiencies through the use of machine help. Based on F-measure, sensitivity (specificity), accuracy (accuracy), and precision (precision), this survey includes numerous parts on state-of-the-art methods for the detection of skin lesion detection, breast cancer detection, lung cancer detection, liver cancer detection, leukaemia detection, and brain tumour detection. A diagrammatic summary of this research is presented in Figure 1.

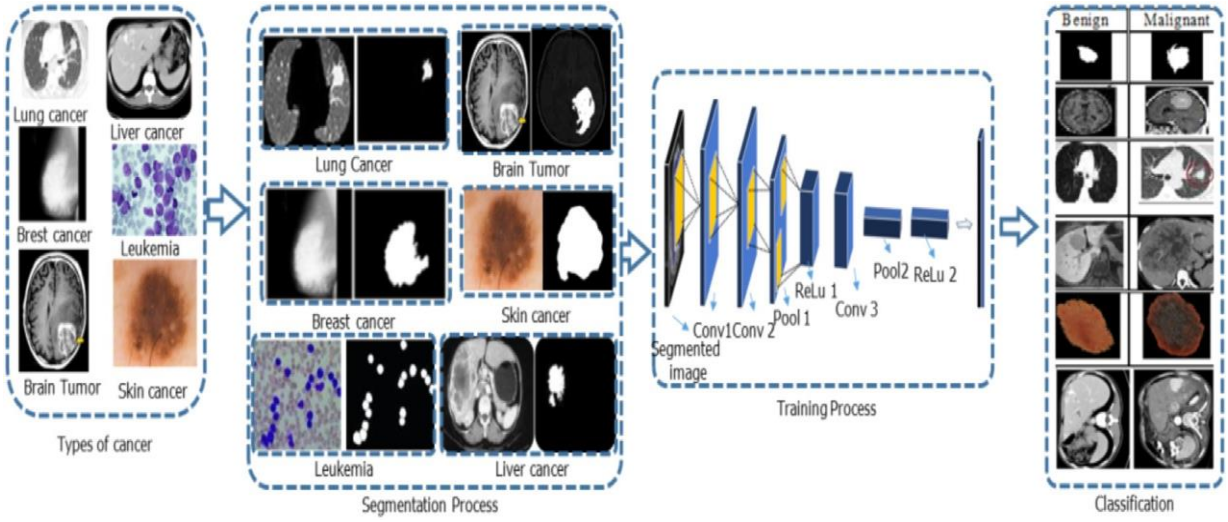


Figure 1. Generic Machine Learning Assisted System for Cancer Detection

3. Benchmark datasets

Machine learning algorithms based on various feature extraction methodologies have flaws, but classifications aren't fine-tuned. By reducing the amount of error that happens, the parameters of deep learning convolutional neural network models that apply transfer learning methodologies

can be adjusted. Their origin, training sets, testing set and performance measures in relation to cancer detection and segmentation are also highlighted in the section below.

3.1 BRATS 2015 dataset

The Perelman School of Medicine at the University of Pennsylvania developed this dataset, which contains 192 undertrained sets and has a total of 274 total sets. High and low grade glioma tumors are included in the training photos. [34] The ground truth has been marked with 5 labels such as 1, 2, 3, and 4 for necrosis; 0 for everything else.

3.2 BRATS2016 dataset

The training dataset used by the 19 teams competing in the BRATS 2016 and 2015 competitions is the same. We've included a similar practice dataset for you to compare against. More than 200 previously unpublished datasets from the BRATS12, BRATS13 and TCIA databases have been shared. Total sets 431 include 285 undertrained and 146 testing instances for both training and testing purposes. The images' dimensions are 155 x 240 x 240.

3.3 BRATS 2018 dataset

Board-certified neuroradiologists have manually rectified all of the ground truth in addition to the more frequent 3 T multimodal MRI scans that doctors have received. The data sets have been revised. 285 sets were used for training and 191 sets were used for testing, totaling 476 sets.

3.4 LIDC-IDRI

The Lung Image Database Consortium maintains a searchable open-source database with nodule outlines and subjective nodule characteristic assessments (LIDC-IDRI). There are 244,617 images in the database, which was designed to aid in the research of lung nodules.

3.5 WBCD dataset

699 records from human breast tissue Fine Needle Aspirates (FNAs) are stored in the Wisconsin Cancer Dataset (UCI Machine Learning Repository). It's possible to identify a record by one of nine features. The database contains 444 (65.0 percent) benign specimens and 239 (35.0 percent) malignant samples.There are 201 records in one class & 85 entries in the other. It is possible to have as many as nine different qualities for a single record.

3.6 FFDM dataset

739 images are stored in a Full-Field Digital Mammography system that uses 12-bit quantization and 100 × 100 m pixel dimensions. Mass lesions were found in 287 patients, with 148 of them being malignant and 139 of them being benign.

3.7 MIAS MiniMammographic Database:

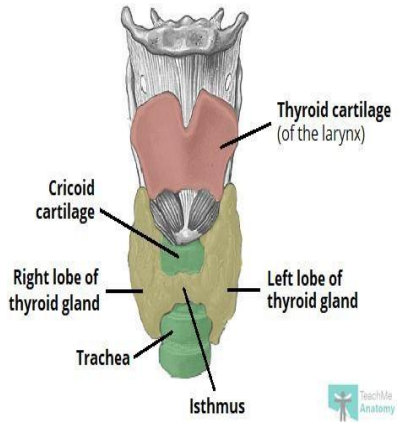
There are 322 films in the database, each with a resolution of 1024 × 1024. The University of Essex's Pilot European Image Analysis Archive (PEIPA) houses mammographic pictures.

3.8 Digital database for screening mammography (DDSM):

A major collection for mammographic pictures was produced as part of a collaborative effort involving the University of South Florida's computer science and engineering department, Sandia National Laboratories, and Massachusetts Hospital.

4. Methodology:

For the human body to produce thyroid hormones, it needs the thyroid nodule. Much of the body's internal functionality is regulated by this hormone. Human metabolism will be controlled and ageing will be prevented by this supplement. These are the parts of the thyroid in humans: the right and left lobes, and the trachea. The thyroid gland is housed in the trachea of the human body. Figure 2 depicts a person's thyroid gland and various parts of it in a healthy state.



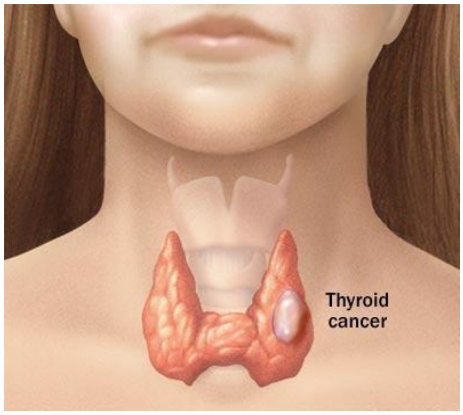


Figure 2.1. Thyroid Gland **Figure 2.2.Thyroid gland having cancer region(Source: Mayo Foundation for Education and Research)**

The thyroid gland produces aberrant cells, either internally or externally, as a result of a variety of genetic factors. As the cancer spreads, it affects the surrounding cells in a rapid manner, as well as disrupts the functionality of those cells. Figure 2.2 depicts a cancerous thyroid nodule. Ultrasonic imaging is performed in this study to identify any aberrant thyroid tissue. Various image processing techniques in computer processing techniques are used to further process the scanned image after it has been entirely scanned by the thyroid gland's ultrasonic scanner. When scanning thyroid pictures, researchers apply soft computing approaches to classify the problematic spots. Figure 3 depicts the suggested thyroid cancer classification and

detection system utilising NN classifiers, which divides the source thyroid picture into normal and abnormal cases, respectively.

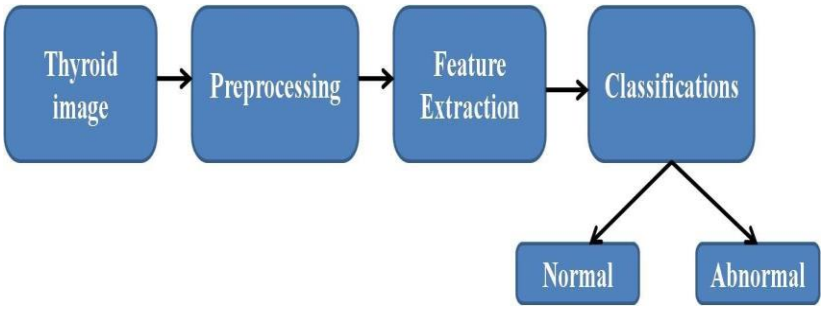


Figure3 Proposed thyroid cancer detection and classification system

4.1Preprocessing

It is used to fix the width and height of an ultrasound image of the thyroid to 128*128 pixels. It also converts all of the color pixels in the ultrasound thyroid image into grayscale pixels in order to speed up the execution of the computer system.

4.2 Feature Extraction

The following energy-based features are employed in this study to classify ultrasound thyroid pictures for the detection of cancerous regions. From the Grey Level Founder Matrix (GLCM) matrix that may be constructed in each thyroid picture with regard to 45 ° angle pixel orientation, these features can be extracted I and 'j' denote the rows and columns of the GLCM matrix, respectively. Pd is the number of pixels in the I and 'j' connectivity points.

$$Contrast = \sum_{i,j=a}^{N} Pd(i-j)^2 \rightarrow (1)$$

$$\text{Homogeneity} = \sum_{i,j=1}^{N} \frac{Pd}{1+|i-j|} \rightarrow (2)$$

$$Entropy = \sum_{i,j=1}^{N} Pd(-\ln Pd) \rightarrow (3)$$

$$\text{Mean: } \mu i = \sum_{i,j=1}^{N} i(Pd) \rightarrow (4)$$

$$\mu j = \sum_{i,j=1}^{N} j(Pd) \rightarrow (5)$$

4.3 Classifications:

The ultrasound wand thyroid pictures were classified using the extracted feature set using the classification method in this study. As a result, this article makes use of a Recurrent Networks (NN) classification system to distinguish between aberrant and normal thyroid pictures. Classifiers based on NN classification are trained using the features retrieved from this work's data. Classification techniques based on radial neural networks and feed forwards back propagation networks are two different approaches to the suggested NN classification algorithm. Other classification methods cannot take advantage of the feedback property that fed forward back propagation network classifiers possess. Binary response is provided by neural network classification algorithm, which shows normal thyroid image with no abnormal patterns on it, while pathological thyroid image with many abnormal pixels on it is shown by high binary response.

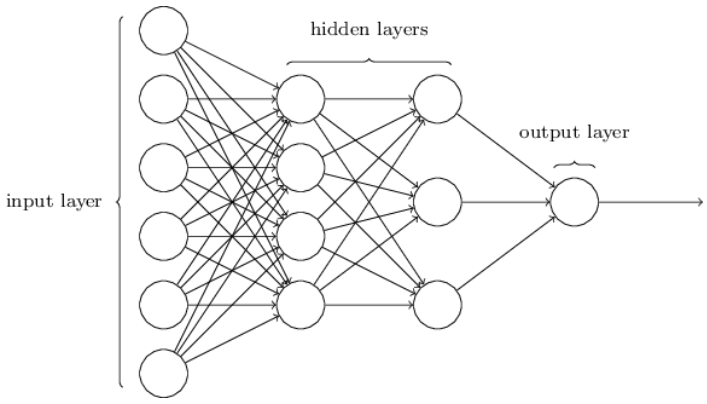


Figure 4, the input, hidden, and output layers used to construct the NN classification architecture are shown generically.

4.4 THYROID TUMOR DETECTION USING SVM

Thyroid pictures are being used to develop a method for detecting tumours utilizing image registration and enhancement techniques. Figure 3.5 depicts the full process of identifying tumour regions in ultrasonic thyroid imaging. There are two modes of operation for the SVM classifier, one for training patterns and one for testing. It is demonstrated in Figure 5 that normal as well as abnormal ultrasonic images of the thyroid may be used to generate a training pattern, and Figure 6 demonstrates how thyroid images can be categorized according to this training pattern.

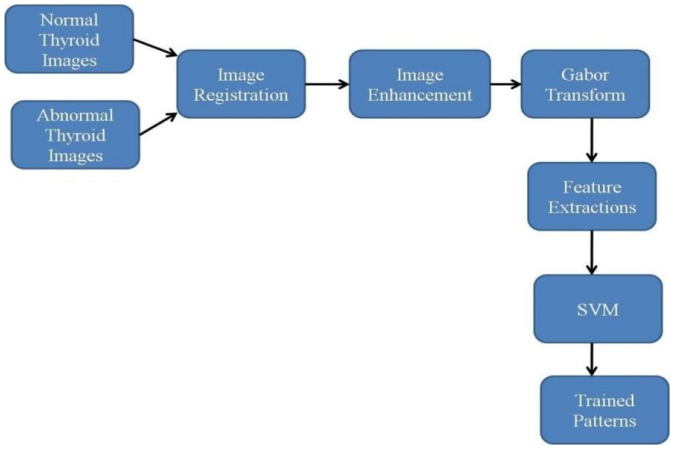


Figure 5 Thyroid Tumor detection using image registration and SVM

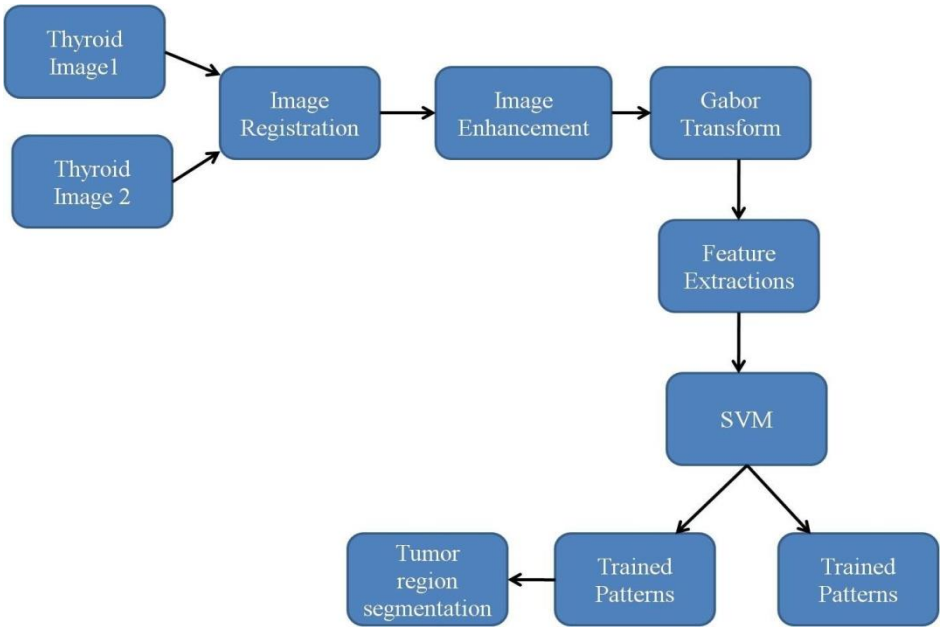


Figure 6 Thyroid Tumor detection using image registration and SVM

4.5 ImageRegistration

Images are aligned in relation to a reference image when they are aligned This image registration procedure necessitates the use of both source and reference images. The face recognition of ultra sonic thyroid pictures is accomplished by the geometric transformation method described in this chapter. In order to change pixel coordinates from the sources and reference acoustic thyroid pictures, a geometric transformation method is used. Ultrasonic thyroid images that have been aligned with reference images are registered as final images. The pixel values for the source ultrasonic picture of the thyroid are denoted by Xi and Yi, whereas the pixel values for the comparison ultrasonic image of the thyroid are denoted by ui and vi. According to the formula shown here, the final image of the

thyroid was created by combining the source and reference pictures.

$$\epsilon = \text{argmin}\left[\sum_{i=1}^{M}(xi, yi)\right] + \sum_{j=1}^{N}(ui, vi)\right] \rightarrow (6)$$

The width (M) and height (N) of the final registered ultrasonic image of the thyroid are denoted by the letters M and N, respectively.

4.6 ImageEnhancement

There are areas of low contrast in the registered picture of the thyroid due to the synchronization of the reference image with the source image. As a result, the contrast level of the various regions of the register thyroid image must be improved before the tumor region can be recognized and segmented. To improve the contrast of the registered thyroid picture, this study employs histogram equalization. Enhanced images have a greater number of pixels that are brighter than those in the original images. The following equation depicts histogram equalization.

$$E = \text{Round}\left[\frac{PDF(x)-CDF(x)}{M*N!}\right] * (L-1) \rightarrow (7)$$

PDF (x) represents the probability density of the pixel and CDF (x) represents the cumulative distribution function of the pixel. A thyroid image's pixel count, L, is used to represent the total amount of pixels in an image.

4.7 NN Classifications:

The thyroid tumour detection system's performance is hampered by the lack of feedback provided by the SVM classification approach. This chapter uses a NN classification strategy to discover and categorise thyroid tumour locations in order to increase tumour segmentation accuracy in images. In this research, Feed Back Backpropagation Neural NN is utilized for categorizing the thyroid pictures into regular or abnormal. This NN has three layers: an input layer, an output layer, and a layer that is concealed from view. There really are number of nodes included within every layer to maximize the classification performance of the suggested system. In this study, 6 number of hidden units and each hidden units consists of 30 biological neurons after multiple tests with varying number of neurons. The representation of the input layer is equal to the length of the feature vectors obtained in this study. Two neurons make up the output layer, which represents two distinct categories: normal and pathological. It is possible to train and test the designed NN. In the training phase of this NN architecture, the features taken from both normal and pathological thyroid pictures are used to generate the trained pattern. In testing step of this built NN structure, the features are calculated from source thyroid picture and these features are input into the NN with training

patterns.

5. RESULTS AND DISCUSSION

The proposed methods are simulated using the MATLAB R2018 edition. The following variables, as shown in the equations, are used to evaluate the thyroid cancer categorization system's performance.

$$Sensitivity\ (Se) = TP/(TP + FN) \quad \text{----(8)}$$

$$Specificit(Sp) = TN/(TN + FP) \quad \text{----(9)}$$

$$Accurac(Acc) = (TP + TN)/(TP + FN + TN + FP) \quad \text{----(10)}$$

However, these characteristics are determined by how many cancer and non-cancer pixels are correctly and incorrectly identified in thyroid ultrasound pictures.

Table 1 shows the evaluation of performance with respect to sensitivity, specificity and accuracy using SVM Classifier

Cancer Images	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
10	97.5	94.5	95.2
20	96.6	93.8	92.9
30	95.6	92.5	91.6
40	94.6	91.7	90.4
50	93.5	90.5	89.5
60	92.4	89.4	88.7
70	91.5	88.6	87.6
80	90.8	87.2	86.3
90	89.5	86.5	85.1
100	88.4	85.3	84.7
Average	**93.04**	**90.0**	**89.2**

The suggested SVM classifier for detecting thyroid tumours is shown in simulation in Table 1. Its sensitivity is 93.04 percent, its specificity is 90 percent, its accuracy is 89.2 percent. Figure 7 depicts a graphical plot of the segmentation of thyroid cancer using SVM classifier in terms of sensitivity, specificity, and accuracy.

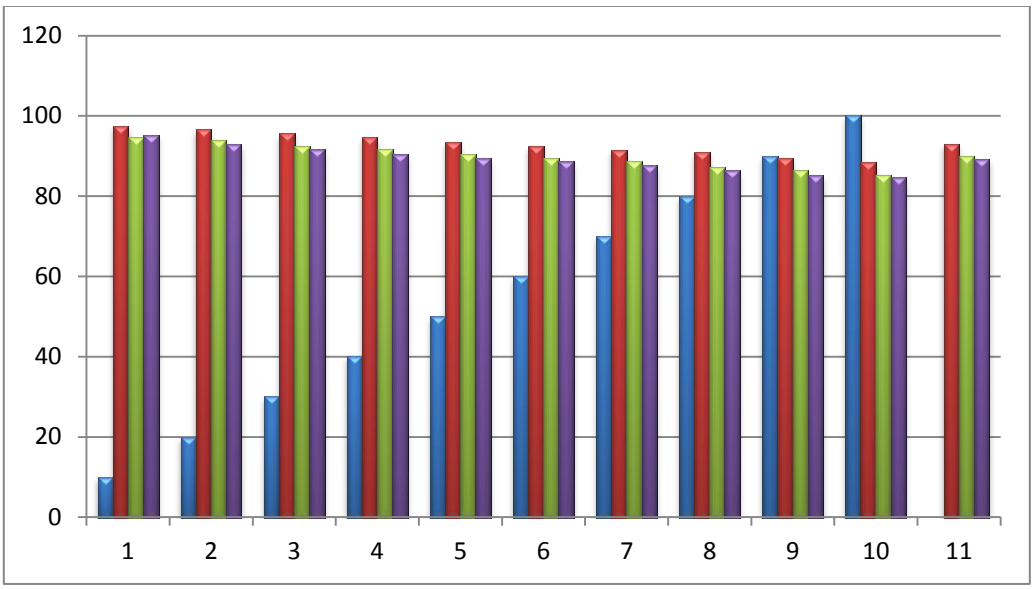


Figure 7 SVM classifier for thyroid cancer segmentation is depicted in terms of sensitivity, specificity and accuracy.

Table 2 shows the evaluation of performance with respect to sensitivity, specificity and accuracy using NN Classifier

Cancer Images	**Sensitivity (%)**	**Specificity (%)**	**Accuracy (%)**
10	94.5	95.6	95.4
20	94.9	95.6	95.6
30	95.6	96.2	95.8
40	96.3	96.4	96.4
50	96.5	96.6	96.8
60	97.1	97.1	97.4
70	97.6	97.3	97.8
80	98.4	97.5	98.4
90	98.8	98.9	98.6
100	98.9	99.6	98.9
Average	**96.86**	**97.08**	**97.11**

MATLAB's simulating tool yielded the results shown in Table 2. An average segmentation accuracy of 97.11 percent is achieved using this proposed technique for thyroid tumour detection (96.86 percent specificity, 97.08 percent specificity).

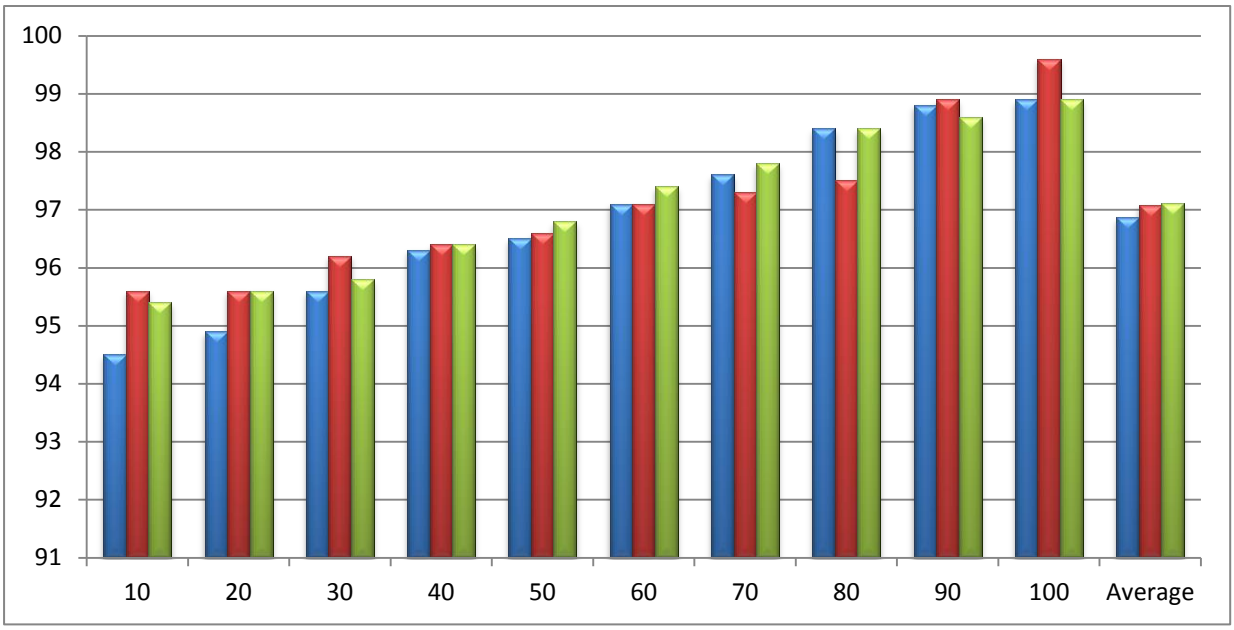


Figure 8 NN classifier for thyroid cancer segmentation in terms of sensitivity, specificity and accuracy.

6. Conclusion:

For the human body to produce thyroid hormones, it needs the thyroid nodule. These features are used to classify ultrasonic thyroid images for the detection of cancerous regions. The ultrasound wand thyroid pictures were classified using the extracted feature set using the classification method in this study. This chapter uses a Neural Networks (NN) classification to distinguish aberrant thyroid images from normal thyroid images. To classify the retrieved features, they are used. The suggested NN classifier is implemented and tested on a variety of thyroid pictures and achieves a sensitivity rate of 96.86 percent, a specificity rate of 97.08 percent, and an average accuracy of 97.11 percent. The results presented in this chapter show that the NN classification technique outperforms the SVM classification strategy in terms of tumor detection accuracy.

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