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Breast Cancer Detection using Convolution Neural Network

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Abstract

Breast Cancer is amongst the most fatal and highly aggressive form of cancer for females. This is one of the critical diagnosis that can be effective if performed in due time. The majority of the breast cancer related deaths that are happening across the world are mostly due to the late diagnosis of the cancer. The slower diagnostic interventions can allow the breast cancer cells to metastasize which can lead to an increased spread of the cancer cells. This can lead to further complications and can be difficult to prevent the untimely demise of the patient. Therefore, there is a need for an effective and timely diagnosis of the breast cancer for which the CT scan images are utilized. The manual analysis of these images is highly cumbersome and can take a large amount of time which is not the most effective strategy as it can be quite detrimental to the patient. Thus, this research article is tasked with the realization of the breast cancer detection in CT images through the use of image processing methodologies. The presented approach trains a Convolutional Neural Network along with the implementation of Decision making to perform the identification of the Breast cancer in CT images which leads to a drastic improvement in the detection accuracy. The experimental evaluation has been performed using the confusion matrix with satisfactory results for the breast cancer identification accuracy.

Keywords*— *Breast CT images, Convolutional Neural Network, Decision Making.

I INTRODUCTION

Cancer is a group that causes abnormal cell reproduction with the ability to spread to other sections of the body, resulting in a significant medical problem and the leadingcause of mortality globally. Breast Cancer is the most frequently diagnosed cancer in women and a subsequent cause of morbidity and mortality in women, and it is rapidly would become the significant cause of morbidity and mortality in emerging nations. Breast carcinoma cells development is unregulated, and the cell loses form as the malignancy spreads.

Malignancy is amongst the most frequent kinds of canceramong females worldwide. Because there are now no techniques to dissuade breast cancer, prompt identification is critical in its management and has a significant influence in lowering morbidity [1]. The greatest technique to detect breastcancer in its early stages is to evaluate mammography images. Various studies, nevertheless, have revealed that radiologists might overlook detecting a considerable number of irregularities while also maintaining a high incidence of false positives. A characteristic is a crucial component to categorizethe condition in the Breast Cancer Detection Technique.

Extraction of features is a critical step in several image processing domains, including pattern identification and breast cancer screening. Feature selection is the process of processing raw data into a set of characteristics.

Breast cancer is being identified in a growing number of individuals throughout the globe. Breast cancer affects one out of every eight women throughout her lifespan. For frequency and death percentages, data reports from many new cancer institute offices have been compared. Whenever mammary tissue cells continue to reproduce, a clump of aberrant cells known as a tumor forms. Malignancies are classified as cancerous when aberrant tissues migrate to other places of the organ beyond where they originated.

Tumors can be classified as malignant or benign basedon characteristics such as form, perimeter, and volume. There are several therapeutic approaches available now for identifying breast cancer. Mammary tumors can be discovered by self-examination and clinical evaluation. The existing accepted diagnostic tool for monitoring breast cancer is mammography. Echocardiography, Magnetic resonance, CT scanning, PET, and infrared cameras are just some of theimaging technologies [2]. Early identification of breast cancer can enhance overall survival.

Mammary cancer develops when unstable cells in the breast proliferate excessively. Mammary cancer is classified into two types: ductal carcinoma and lobular carcinoma. Ductal cancer develops from the channel to the nipple, whereas lobular cancer develops from the glands that produces human milk. Most occurrences of malignancy are caused by a mix of genetics and external components. Hereditary variables such as family background, early ovulation, age at menopause, and thick mammary glands are possible causes that we should modify or regulate. Becoming overweight or obese, a lack of personal exercise, and consuming alcohol are causes of ecological and behavioral factors associated over which we have influence.

Mammary cancer is currently one of the most serious health issues confronting women. Cancer mortality rates are growing on a worldwide basis. In India, nevertheless, the prevalence of breast carcinoma has grown during the last threedecades. Breast cancer has been recorded in greater rates in younger demographics (in their thirties and forties). Perhaps early identification of cancer can improve life expectancies in these kind of circumstances. Breast cancer is the most common of cancer-related mortality in women worldwide. Routine screening and management of this cancer has been shown to significantly reduce fatality rates from this severe illness.

The next session of this research paper is dedicated to the survey of the past work. In section 3 the proposed model is elaborated in detail and then the obtained output results are evaluated in section 4. In section 5 this research paper is concluded with some flash light on future scope.

II LITERATURE SURVEY

Than Than Htay [3] introduced first degree statistical characteristics, Gray Level Co-occurrence Matrix (GLCM), with k-NN classification for preliminary stage breast cancer detection technique. The k-Nearest Neighbor (KNN) classification is a straightforward classifier that performs well on classification techniques. Since it provides very precise forecasts, the k-NN technique may be compared to other classifiers. As a result, for the breast cancer recognition system, which demands highest sensitivity, researchers utilize the k-NN algorithm. They utilize the MIAS images using "Portable Gray Map" (PGM) formatting variants in their research. The testing findings suggest that the approach has a categorization accuracy of the highest order.

Masud Rana Basunia [4] states that the fully automated forecasting of breast cancer is considerable to alleviate the potential against extending this illness. The secret to treating breast cancer is prompt diagnosis. This research suggests a classification approach, layering classifier, for breast cancer detection, which enhanced accuracy. The increased accuracy suggests that malignant tumors can be recognized optimally. The authors chose the top twenty characteristics for predicting breast cancer. The key disadvantage of this strategy is the absence of effective input data for the objective of detecting breast cancer.

Yi Wang [5] presents a novel 3D CNN for computer- assisted cancer diagnosis in ABUS volumes. Researchers think they are often the first to use deep learning technologies to solve this problem. A novel threshold mapping is designed for the system to produce voxel-level thresholds to distinguish cancer voxels versus healthy tissues areas, resulting in reduced false - positive results. Furthermore, a substantially deep monitoring is used to significantly improve sensitivities by successfully using multi-layer discriminative information. Comprehensive assessments of this strategy have been conducted, which have proven valuable in assessing the approach's effectiveness.

Kavya N [6] offers a technique for detecting breast cancer employing thermal imaging. The present investigation on mammography and thermal imaging identifies the scans as malignant or benign. The overall classification accuracy is dependent on adequate extraction of features and the clarity of input pictures. The Computer Aided Detection approach for breast cancer detection used effective image processing technologies to analyze electronic health records. It is critical to protect the personal health information from unwanted access, and storage administration is a critical duty. The CPS gathers information and distributes it to certain systems. CPS consists of cutting-edge application software, high- performance networks, and infrastructure. The expense of migrating information to the cloud is reduced.

Nur Syahmi Ismail [7] describes that deep learning procedure utilizing VGG16 and ResNet50 network have indeed been incorporated for healthy and unhealthy breast cancer identification. The categorization algorithms were assessed based on three performance metrics: precision, recall, and accuracy rate. The VGG16 technique delivered the best classification performance results. The biggest disadvantage is that aberrant pictures might be labeled as normal and cancerous tumors. That will be very helpful in carrying out the ensuing surgery for the patients.

Hao-Chun Lu [8] states that Data adaptation is an appropriate approach for expanding the volume of information also found to significantly improve the effectiveness of categorization and therefore the strength of discriminatory procedures while transfer learning has had an added benefit of relatively short training phase. These two methods have always been utilized to boost performance of the models. To improve the quality of the pictures, we used the CLAHE to modify our mammograms. This approach avoids the possibility of noise augmentation, which is typical when employing Adaptive histogram Equalization that over- amplifies picture sharpness. By restricting the gradient of the cumulative distribution, the CLAHE lowers augmentation noises.

Shubham Sharma [9] expresses that even the most commonly encountered form of cancer is breast cancer. A woman selected at random has a 12% probability of being confirmed with the condition. As a result, early identification of breast cancer could also save many lives. The presented method in this work is a systematic examination of several machine learning methods for breast cancer diagnosis. The Wisconsin Diagnosis Breast Cancer data set was used to monitor the effectiveness of machine learning algorithmic methodologies. Each methodology was shown to have a high level of accuracy in determining whether a tumor was malignant. The researchers discovered that kNN is by far the most successful in detecting breast cancer since it outperformed some other schemes in terms of reliability, sensitivity, and F1 score.

Veena Suresh [10] explained how Deep Neural Networks are used to address the Inverse Electromagnetic Problem. The dataset created using the instantaneous approach is utilized to train the neural network. The neural network's source is the dispersed electric field, and its output is the transmittance readings of the normal, cancerous, and surrounding tissues voxels. Microwave scanning can be used to examine the illness on a regular basis. It must be identified more accuratelysince the dielectric characteristics of breast cells are equivalent. Deep Neural Network is employed in this case to solve the inverse issue of determining the multidimensional transmittance from the dispersed field and hence finding malignant voxels. The network is trained using dispersed data from different architectures of tumors with constant dielectric characteristics. It is utilized here to recreate distinct architectures of breast cancer malignancy and discriminate amongst normal, cancerous, and skin voxels.

B. Sundarambal [11] elaborates that perhaps the Preliminary diagnosis of disease should also reduce the number of fatalities in women. Despite the fact that the overall incidence is likely to rise year after year, organizations have made steps to lower the death rate. Because routine monitoring identifies breast cancer at a preliminary phase, prescreening with thermography in this study allows for more cost-effective and straightforward assessment. This allows suspected individuals to seek additional diagnostic only when warranted, avoiding unnecessarily costly and uncomfortable routine mammograms at an early stage. Although mammography is widely used for screening mammography, the study indicates that perhaps the false positive rate is significant. To counteract the higher false positive rate, supplemental screening with biopsy is performed for additional verification of cancer existence. Thus, these results suggest that regular mammography pre- and post-screening be included to enhance women's health status.

De Cai [12] proposes using a customized RCNN for mitotic identification. Although as far as researchers understand, the approaches surpassed all previously reported findings. The scalability effectiveness of the suggested technique is further investigated using cross-validation outcomes from prominent datasets without and with colour normalization. Color normalization significantly improves the outcomes of cross-validation in these other datasets. The mitotic identification method has been successfully tested, with highly exciting results.

Mengfan Li [13] described a method depending on the design of such a deep learning algorithm for cancer cell malignant and benign segmentation based on three- dimensional breast ultrasound records, with an emphasis on the effects of making adjustments the convolutional neural network architecture to combine multiple details on classifier performance. It is demonstrated that utilizing a convolutional neural network for multi-information combination is an appropriate fusion strategy that eradicates the measures of unnaturally developing fusion methodologies and enhances classification performance and quality by incorporating the attributes of distinct details and the adaptability of utilizing the CNN architecture. This strategy shows some promise for handling three-dimensional data categorization and data aggregation challenges.

Uswatun Khasana [14] discusses that the investigation of breast classification utilizing the watershed transform algorithm does have many inconsistencies if the cancer area is covered or compressed by a neighborhood that is colored more or less the same moment the segmentation procedure. Based on these findings, the vast cancer region has outstanding reliability. As a result, the authors conclude that now the watershed transform technique approach may be utilized to execute breast localization on mammary ultrasound pictures.

III PROPOSED METHODOLOGY

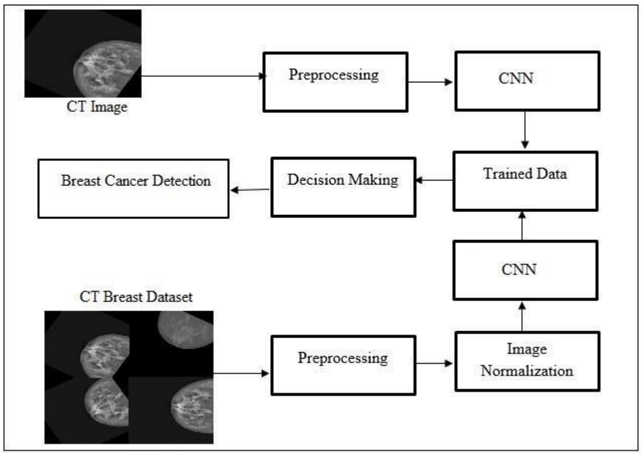

Figure 1: Proposed model for Breast cancer Detection The implemented methodology for the detection of the breast cancer is broadly narrated in this section with the below mentioned steps. And in the above figure 1 the proposed model is depicted which is designed through the use of theConvolutional neural network.

Step 1: Dataset collection and Preprocessing– Datasetfor the breast cancer is collected for the Computed Tomography (CT) images through the following URLs: http://www.eng.usf.edu/cvprg/Mammography/Database.html and https://data.mendeley.com/datasets/ywsbh3ndr8/2. TheseURL contains the CT images for digital mammographynamely MIAS(Mammographic Image Analysis Society),DDSM (Digital Database for Screening Mammography), andINbreast. These datasets have been augmented through theuse of adaptive histogram equalization that is contrast limitedand then resized to a size of 150 X 150 in png format imagesand eventually all the images integrated together to obtaintotal images of 13,710 cancerous and 10,866 non-cancerousimages. These images are used for the training and testingpurpose as narrated in the below mentioned steps.

*Step 2: Image Normalization through Gray scaling –*Here in this step each of the dataset images is considered to convert into the absolute grayscale format. In this process each pixel's RGB channel values are averaged to set them back to the channel to obtain the absolute gray scale image. This process is depicted in the algorithm 1.

ALGORITHM 1: ABSOLUTE GRAY SCALING FORNORMALIZATION

// Input: Dataset Image D_{IMG}

// Output: Gray scale image G_{IMG}absoluteGrayScaler(D_{IMG})

Start

IMG_{OB}=rgbChannel(D_{IMG})

Width, Height = sizeOf(IMG_{OB}) pix[][]=load(IMG_{OB})

for i = 0 to Width ***for*** j=0 to Height

Color[ ]= pix[i][j]

```
            R= Color[0]
                G= Color[1]
              B= Color[2]
          X=(R+G+B)/3
       AVG=int(X)
       Color[ 0]=AVG, Color[1]= AVG, Color[ 2]= AVG
        pix[i][j]=Color[ ]
    end for
    end for
G_IMG = pix[][]
Stop
```

After the dataset images are resized and normalized for the absolute gray scale channel, then these images are segregated to test and train images. A total of 24,576 images are used to train and test the breast cancer detection model through Convolution neural network. For the purpose of deployment the proposed model uses python programminglanguage by using the deep learning libraries like keras and tensorflow, which are imported for the required classes.

Initially the test and train dataset paths are set and then a batch size of 64 is set. A batch size is representing a total number of images that are being used to train by the model ata given instance. After setting a batch size a 500 epochs are set, which in turn representing the number of times the neural network is being employed for the input images for the training purpose.

An ImageDataGenerator object is created to set the investigation ratio of the training images to 1:255 as rescaling factor. By setting this factor $1/255^{th}$ of a pixel value is also set to be analyzed while training the images in the process of detection of the breast cancer. This ImageDataGenerator object is used to allocate the train and test directory paths along with their size factor of 150 X 150. After this process a batch size is set to the object along with color mode as gray scale and class mode as categorical. The class mode is set as categorical to categorize the learning process as cancerous andnon- cancerous classes.

Step 3: Training with Convolutional Neural network -

A sequential class is used to set the type of the neural network object to call it as a model. In the first layer of the convolution neural network a 32 kernels of size 3 X3 are set with activation function 'Relu' and input dimension of 150 X 150 with color channel code as 1 because of grayscale images. A second layer of convolution neural network with 64 kernels of size 3 X3 are set with activation function 'Relu' followed by a max pooling layer is added with the kernel size 2 X2 to segregate the trained neuron with the drop rate of 25%.

In the third layer of convolution neural network 128 kernels of size 3 X3 are set with activation function 'Relu' followed by a max pooling layer with the kernel size 2 X2. The same thing is applied to the fourth layer to end with a dropout rate of 25%.

Next for the fifth layer of convolution neural network

256 kernels of size 3 X3 are set with activation function 'Relu' followed by a max pooling layer with the kernel

size 2 X2. The sixth layer is repeated as fifth layer again with a dropout rate of 25% in the end.

After the six layers the neural network object has flattened using the function flattens. Then the trained neurons are collected with the bucket size of 1024 with activation function 'Relu' using a Dense layer. On these collected neurons 50% dropout rate is applied to retain the best trained neurons. The obtained neurons are classified into 2 classes using another dense layer by applying a 'softmax' activation function.

After all the above process now neural network model is compiled using an Adam Optimizer with the precision of 0.0001 and a decay value of 10^{-6}. Now the neural network object is activated to perform the training using the fit generation function for the given batch size, number of epochs and with test, train data generator objects to obtain the trained data in a special format of file called .h5. This whole process of training is depicted with architecture of Convolution neural network as mentioned in figure 2.

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 256 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 256 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 2	Softmax
Adam Optimizer	

Figure 2: Convolution Neural network architecture

Step 4: Breast cancer detection through testing and Decision making - As a CT image of the breast is fed to the system to detect the breast cancer, initially this image is resized to the dimension of 150 X 150 and then it converted into grayscale as mentioned in step 2.

After this again a neural network model is created according to the Convolution neural network architecture as mentioned in the previous step. Along with this the trained data (stored in .h5 file) are also loaded to the neural network model.

After this process the openCV object is used to normalize and resize the image to squeeze it in bytes to feed to the neural network model. Once this is done, then a prediction score is obtained from the predict function of the neural network model. A dictionary is created for the classification classes and the prediction score index is used to fetch the respective label name from this dictionary as cancerous or non- cancerous.

Based on the input test image average summation score of the entire pixel's RGB Color channel a threshold value is obtained. This threshold value is used to mark the cancerous part to display in a special window through an interactive GUIcreated using the Tkinter library of python programming language.

IV RESULT AND DISCUSSIONS

The formulated methodology for the intention of attaining Breast cancer identification on CT images employing deep learning has indeed been realized through the use of Python programming language. The Spyder IDE has been utilized to complete the development process. The developer machine is equipped with 8GB of RAM, 1TB of storage, and an Intel Core i5 CPU.

The effectiveness of the strategy was evaluated by examining the offered technique. The performance assessment is essential to determine how the constituents were integrated. The Precision and Recall perspective was used to evaluate the approach.

The experiment was carried out using a dataset that was created by combining three separate datasets, namely MIAS, DDSM, and INbreast. These datasets have been augmented through the use of adaptive histogram equalization that is contrast limited and then resized to a particular size and eventually all the images integrated together. The images from this dataset are collected and then provided for the testing of the system that is performed as follows.

Performance Evaluation through Precision and Recall

The Precision and Recall assessment focuses on determining the system's usefulness in identifying breast cancer. The aggregated dataset is fed into Convolutional Neural Networks. Diverse modules, comprising preprocessing, image normalization, convolutional neural networks, and decision making, were used to establish the detection approach. In order to deliver correct suggestions, these modules must be run successfully, and the output from one component to another must be suitable. Precision, recall, accuracy, and F Measure metrics are utilized to assess the efficacy of the consultation.

Precision and recall are two extremely useful metrics for assessing the correctness of the system's implementation. The precision measure denotes the system's complete accuracy, whilst the recall metric denotes the system's relative accuracy.

For assessment purposes, accuracy is defined as the ratio of correct Breast cancer detections to total number of input pictures. The recall measure is calculated by dividing the number of positive breast cancer detections by the total number of incorrect breast cancer detections.

So, precision, recall, accuracy and F Measure can be defined as

Precision=A/ (A+B) ----------------------(2)

Recall=D/ (A+B)----------------------(3)

Accuracy = (A+D)/ (A+B+C+D) (4)

F Measure = 2*(Precision*Recall)/ (Precision + Recall)Where,

A = the number of accurate Breast Cancer detections(True Positive).

B= the number of inaccurate Breast Cancer detections(False Positive).

C = the number of accurate Breast Cancer not detected(False Negative).

D = the number of inaccurate Breast Cancer not detected(True Negative).

Breast cancer detection competency was assessed using accuracy and recall criteria. The findings of a thorough research of the approach for a number of tries with an increasing number of images given with each repeat are described in table 1 below. Figure 3 depicts the results of breast cancer detection in the context of a chart.

S. no.	No. of of accurate Breast Cancer detections (A)	No. of inaccurate Breast Cancer detections (B)	Relevant Detections not Detected for Breast Cancer (C)	Irrelevant Breast Cancer not Detected (D)	Precision	Recall	F Measure	Accuracy
1	5	0	0	1	100	100	100	100
2	10	0	0	3	100	100	100	100
3	14	0	1	2	100	93.333	96.5517241	94.117647
4	18	0	2	12	100	90	94.7368421	93.75
5	23	1	2	15	95.833333	92	93.877551	92.682927

Table 1: Precision and Recall Performance

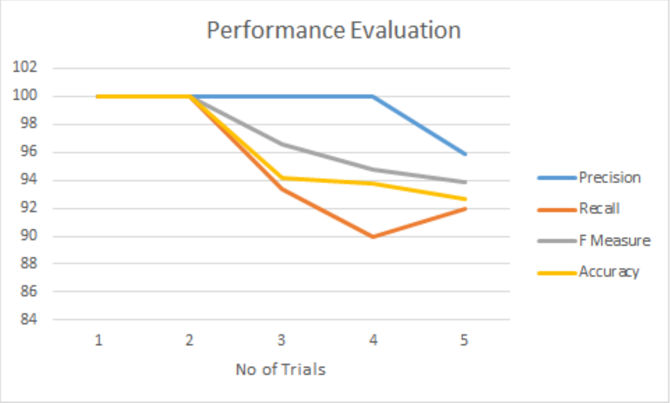

Figure 3: Graphical Representation of the Precision and Recall Values.

The precision, recall, and accuracy scores examined for breast cancer diagnosis revealed the suggested system's usefulness in great detail. The proposed method was successfully contrasted to the KNN based method described in [15]. Our technique delivers precision of 99.16 percent, recall of 95.06 percent, F measure of 97.03 and accuracy of 96.11 percent. The comparability of the KNN based breast cancer detection technique with the provided methodology is shownin table 2 below in a tabular manner.

Performance Metric	Our approach (CNN)	KNN Based approach [15]
Precision	99.16	98.27
Recall	95.06	90.47
Accuracy	96.11	95.9
F - Measure	97.03	94.2

Table 2: Precision, Recall and Accuracy comparison

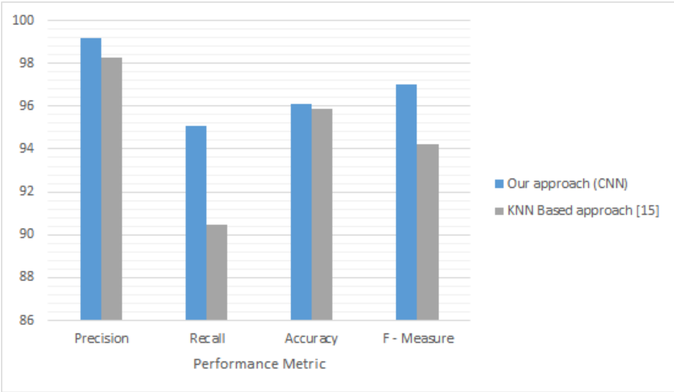

Figure 4: Comparison with KNN based approach depicted in [15]

As illustrated in Figure 4, the deep learning strategy proposed in this research paper consistently outperforms the KNN based approach proposed in [15]. This is because Convolutional Neural Networks have been used to significantly improve the accuracy of breast cancer diagnosis. These findings are extremely satisfactory because the given system achieves the accuracy indicated by the performance scores.

V CONCLUSION AND FUTURE SCOPE

The proposed conceptual framework for the intention of Breast Cancer detection that used the Breast CT images has been concluded through the use of the Convolutional Neural Networks. Initially, the dataset is divided into two sections: one for training and one for testing. These images are effectively collected and utilized for normalizing through the image gray scaling technique after proper preparation. Before being fed into the Convolutional Neural networks, the images are scaled to 150 X 150 size. The CNN approach detects breast cancer by using preprocessed and normalized images as input. The CNN method has previously been trained on the dataset images, which have also been preprocessed and normalized. The CNN is trained on such images for 500 epochs to produce a model file in .h5 format, which will then be utilized to indicate the existence of cancer. To obtain accurate Breast cancer detection, the result of this implementation and diagnosis is categorized using the Decision making module. The effectiveness of the prescribed technique was demonstrated by experimental evaluation utilizing accuracy and recall criteria the resultant values of which outperform the conventional approaches.

The technique may be transformed into an API for easy inclusion in future research areas. It may be used as a cloud- based service to assist healthcare practitioners in detecting the existence of cancer.

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