



Hybrid GLFIL Enhancement and Encoder Animal Migration Classification for Breast Cancer Detection

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Abstract: Breast cancer has become the second leading cause of death among women worldwide. In India, a woman is diagnosed with breast cancer every four minutes. There has been no known basis behind it, and detection is extremely challenging among medical scientists and researchers due to unknown reasons. In India, the ratio of women being identified with breast cancer in urban areas is 22:1. Symptoms for this disease are micro calcification, lumps, and masses in mammogram images. These sources are mostly used for early detection. Digital mammography is used for breast cancer detection. In this study, we introduce a new hybrid wavelet filter for accurate image enhancement. The main objective of enhancement is to produce quality images for detecting cancer sections in images. Image enhancement is the main step where the quality of the input image is improved to detect cancer masses. In this study, we use a combination of two filters, namely, Gabor and Legendre. The edges are detected using the Canny detector to smoothen the images. High-quality enhanced image is obtained through the Gabor-Legendre filter (GLFIL) process. Further image is used by classification algorithm. Animal migration optimization with neural network is implemented for classifying the image. The output is compared to existing filter techniques. Ultimately, the accuracy achieved by the proposed technique is 98%, which is higher than existing algorithms.

Keywords: Breast cancer; Gabor filter; Legendre filter; GLFIL algorithm; animal migration optimization; neural networks

1 Introduction

According to the World Health Organization (WHO), 2.1 million women worldwide are affected by breast cancer yearly. Among all cancer deaths, breast cancer accounts for 15%. To improve the survival



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rate of a patient with breast cancer, early detection and treatment, such are screening and diagnosis, are advised. Screening comprises mammography called clinical breast exam (CBE). Mammography is the process of taking low energy X-rays to detect breast abnormalities. Mammography helps reduce risk of breast cancer by 20%. WHO concluded that mammography screening is ideal for early diagnosis. Digital mammography images are recommended for ages 40 to 60. Detecting cancer lumps or cells in the mammographic pictures is highly challenging among researchers. Fundamentally, the collected images cannot be used directly for diagnosing. Computer science and its intelligence algorithms are needed to enhance the quality of and classify cancer images.

Mammography has been clinically proven effective for early detection. It reveals abnormal tissues in the breast before patients can feel or notice symptoms [1-3]. The abnormalities in the mammography images are masses, calcifications, lumps, architectural distortions, and so on. Masses come in various shapes, such as oval, elliptical, circular, and nodular lobules. Mass detection is crucial in early detection [4,5]. There can be various challenges in mammographic cancer detection given that not all masses can be labeled as cancerous. In addition, some tissues that are clustered and thick can hide cancer masses. Thus, automatic detection of cancer is extremely complicated for radiologists. Given that analyzing textures in complex images is extremely difficult, studies on image detection using the Gabor filter remain extant, and these studies have obtained significant results.

The extraction feature has become a crucial procedure in image processing [6]. The iris extraction feature using the Gabor filter is explained in Refs. [7,8]. Individual iris identification using special code generation is computed in this process. The Gabor filter is commonly used for image feature extraction process. Legendre wavelet filters work the same as the Gabor technique, but the difference is that Legendre is a polynomial-based extraction process, which makes it better than the Gabor filter.

In our proposed article, the image enhancement process is as follows:

- 1. It combines the advantageous characteristics of the GL filters.
- 2. Through this image enhancement, the proposed model performs more accurately in detecting images than the existing mean and median filters.
- 3. The main contribution of this article is combining two feature extraction processes for better image enhancement outcome.
- 4. After enhancement, we perform edge detection on images for precise detection of lumps and masses. Image segmentation and classification are done by using animal migration optimization and recurrent neural network (RNN) good outcomes.

The remainder of this paper is organized as follows. Section 2 studies and explains the literature work. Section 2 presents and studies the implementation of the proposed work. Section 4 explains the experimental results. Section 5 concludes and defines future enhancement.

2 Related Work

Recent studies on image processing are mostly based on disease diagnosis using images. There exist more classification algorithms used in detecting lung cancer nodules in CBIR. Random forest algorithms are suggested in classifying CT scan images in Baboo et al. [9]. The genetic algorithm-based image classification for cancer diagnosis is performed and the results are obtained [10]. Breast cancer [11] detection uses transcriptome in the cells for automatic selection of tumors with expert-based annotations. Similarity calculation [12] method implements cancer cell detection in a mammogram-based feature extraction process.

Extreme learning algorithms are proposed in breast cancer detection regarding digital mammography [13]. Fuzzy-based pulse couple neural network with support vector machine is conjugated with feature extraction using a wavelet filter [14]. The expert system is implemented for detecting breast cancer using neuro fuzzy techniques [15]. An ensemble-based Bayesian network is used for mammographic image classification [16], and its output is compared to a multilayer neural network classifier. The Bayesian network has been proven effective in image classification.

The ensemble classification with neural network is used in malignant classification and detects cancer cells [17]. Image retrieval process in Jiang et al. [18] uses content information for mass detection in mammograms. The abnormalities are detected in mammograms using the ensemble learning technique [19]. Dimensionality reduction in breast cancer classifier using mammogram is described in Ebrahimpour et al. [20]. Here, a screening process has been performed using digital mammographic data followed by three more steps, namely, extraction, selection, and classification. Currently, in machine learning algorithms, artificial intelligence is used in the classification of images [21–25]. Breast cancer detection is done using deep convolution neural network (CNN) with semi supervised graph algorithm. The accuracy is achieved with 82% [26–29]. Deep CNN with a computer-aided diagnosing technique is developed for breast cancer detection using mammography.

3 Proposed GLFIL Methodology

Image enhancement improves the quality of the original image through technology. Original images require enhancement to be classified accurately. The proposed work is classified as three steps, (i) preprocessing (enhancement, edge detection, and segmentation) and (ii) segmentation (iii) classification. First, the pre-processing stage aims to remove noise from the digital images by using mean and median filters, and the GLFIL algorithm is used for better image enhancement. The procedure of the proposed work is as follows:

- 1. Image Enhancement: The GLFIL algorithm is used for image quality enhancement during mammograms. This process is used to obtain clear image segments for further classification.
- 2. Edge detection: This process uses a Canny edge detector. It is applied to smoothen the blurry edges of scaled images. The Gaussian filter is used in this process.
- Segmentation: It plays on important role in image processing stages. In this proposed work, for image segmentation, foreground and background subtractions are used for accurate breast image detection. Thereafter, unwanted images are removed from the input image dataset.
- 4. Classification: For breast cancer classification and detection, a novel RNN with auto encoder (AE)based classification is used for feature extraction by assimilating animal migration optimization (AMO) for tuning the parameters of the RNN model. Then, Softmax classifier is used with the novel RNN algorithm.
- 5. Comparative study: To analyze the best enhancement technique-based classification, the classified results with the GLFIL-enhanced image classification are compared to our previous work called mean and medial filter-enhanced image classification. The results conclude that we can obtain the best classified results of mammogram images while applying the GLFIL compared with our previous mean and median filter enhancement techniques.

Given that this work is focused on enhancement, the Gabor and Legendre filters were analyzed before combining them as one. Occasionally, the Gabor filter is used with a band pass filter in noise removal. A filtering process is the main idea behind using the Gabor filter, which is considered of suitable value by local variances. The main advantage of using the Gabor filter is that it uses frequency metrics and spatial image coordinates. The Gabor function can be created by using inputs, such as orientation angle, frequency, or and variances in x, y directions. The orientation angle and frequency metrics with localized value are used to filter each block. Eq. (1) from Danlami et al. [1] used a real Gabor function for the Gabor filter.

$$G(x, y, \theta, f) = \exp\left\{-\frac{1}{2}\left[\frac{x_{\theta}^2}{\sigma_x^2} + \frac{y_{\theta}^2}{\sigma_y^2}\right]\right\} \cos(2\pi f x_{\theta})$$
(1)

$$x_{\theta} = x \cos \theta + y \sin \theta \tag{2}$$

$$y_{\theta} = -x \sin \theta + y \cos \theta \tag{3}$$

where the local orientation angle is = θ , frequency is = f, standard deviation is = σ_x , and σ_y with Gaussian function.

The hybridized filter with GLFIL. Its computation is based on the polynomial order. In addition, the Legendre filter is a linear filter similar to the Gabor filter, which is used in texture analysis. However, the Legendre filter is developed on the basis of its polynomial order. Initially, the Legendre filter is assumed as a first-order polynomial. The moment the Legendre is referred to as (m, n), the order with the function f(x, y) in the image is defined in $([-1, 1])^2$,

$$\lambda_{m,n} = \frac{(2m+1)(2n+1)}{4} \int_{-1}^{+1} \int_{-1}^{+1} f(x,y) p_m(x) p_n(y) dx dy, \tag{4}$$

where, m, n = 0,1,2, ...

 $p_m(x)$ is considered m, which is the polynomial in Legendre Eq. (5),

$$p_m(x) = \frac{1}{2^n m!} \frac{d^m}{dx^m} (x^2 - 1)^m.$$
(5)

The change in the mean value of the brightness is considered a significant issue. Here, a technique called adaptive unsharp masking is applied to enhance the image contrast. However, it fails to predict the low contrast edges in the images. Enhancing the original mammographic image without overlooking information became extremely challenging, complicating the detection of small classifications in the original images. thus, few researchers are attempting to improve the information loss. Ultimately, the proposed research works focuses on early detection of cancer symptoms in mammograms through enhancement.

Hybrid filter technique using GLFIL in the proposed image enhancement technique performs exceptionally by analyzing the frequency of an image with its specific direction and image orientation. Scientists suggest that the human visual system is similar to this frequency orientation system. The major concern over this frequency and orientation method is that it does not a have rationale supporting evidence. Thus, we use the Legendre polynomial-based frequency computation in our proposed article with filter orientations. Ultimately, it provides better image classification outcome using mammographic input images.

The mammogram features are enhanced using the GLFIL method, which is immune to noise removal compared with previous enhancement filters. Given that enhancing the original digital image is the core point in all image-processing techniques. The GLFIL approach produces mammographic image enhancement with exact naturalness and with no noise for high-accuracy classification. This classification helps us detect breast cancer images accurately with less false positive results and helps medical practitioners to diagnose abnormalities promptly and efficiently. The architecture of our proposed work is shown in Fig. 1.



Figure 1: Proposed architecture for GLFIL enhancement techniques

Fig. 1 presents that the mammogram image is pre-processed to increase the quality of the digitally stored image. Then, further quality is used to the process, such as enhancement, edge detection, segmentation, and image classification. Each section is discussed as follows.

3.1 Text Layout Image Pre-Processing

Image pre-processing is performed to improve the quality of the input image. This enhanced image is sent for further processing, which includes deleting irrelevant data and removing noises in the front and rear sides of the mammographic images. Mammograms are X-ray images with complicated interruptions. To enhance the quality, the first process is pre-processing enhancement. Thus, we proposed a new algorithm called the GLFIL. Then, the enhanced image is ready for further processing involving image segmentation and classification. The removal of noises and high frequency components are proposed in the GLFIL technique.

To reduce the Gaussian noise, spatial filter can be used to block the high frequencies. Thus, in image smoothing, fine-scaled image details and edges may be blurred as a result of this spatial filter. Gaussian

smoothing, median filtering, and mean or average filtering are the conventional spatial filtering methods used for noise removal. GLFIL is compared to previous filtering techniques called mean and median filters.

3.1.1 Mean Value Base Filter

Mean filter is a simple procedure similar to the sliding window technique with spatial filter. Here the middle pixel metric value is replaced by the average value of all pixel in the windows. Generally, a square shape of any kind of window is used. Using arithmetic mean filter, short-tailed noise and uniform noise are removed. Resultantly, the image will be blurred. A pixel average within a local image region is called an arithmetic mean filter.

 $m \times n$ is the size of the rectangular sub image, assume that S_{xy} are the coordinates representation centered to the point (x, y). The defined area using S_{xy} is a arithmetic mean filtering process. This is used to calculate the average value of the corrupted imagesg (x, y). At any particular point (x, y), the restored image value will be equal to the arithmetic mean of pixels in the region shown by S. The filter process is presented in Eq. (6)

$$\hat{f}(x,y) = \frac{1}{mn} \sum_{(s,t) \in S_{xy}} g(s,t).$$
 (6)

3.1.2 Median Value Base Filtering

Median filtering is a statistic-based nonlinear signal processing method. The digital image noise in the input image will be replaced by the median of the image in the adjacent digital sequence. Masks of pixels are ranked on the basis of the gray levels of the image, and the noisy value is substituted by group median value. The output of the median filtering is termed in function as o(x, y) mdi{ f $(x - i, y - j), i, j \in D$ }, where the original picture is termed as f (x,y), and the output filtered image is termed as o(x,y), D is defined as 2-D mask, and $n \times n$ is the size of the mask. Cross, circular, square, linear-shaped masks are used. Owing to the non-linear structure of median filtering, images will have random noises. It is a complex algorithm for mathematical analysis. Median filter noise variance can be approximated for the image to have zero mean as,

$$\sigma_{med}^2 = \frac{1}{4nf^2(n)} \approx \frac{\sigma_i^2}{n + \frac{\pi}{2} - 1} \cdot \frac{\pi}{2}.$$
(7)

where, σ_i^2 – is the input noise power, n – is the median filtering mask size, and f (\bar{n}) – is the noise density function. Average filtering noise variance is calculated as,

$$\sigma_0^2 = \frac{1}{n} \sigma_i^2. \tag{8}$$

In comparison, the median filter reduces random noise better than average filtering performances. Concurrently, the median filter gives less effective results in impulse noise of narrow pulse with less than n/2 pulse width. The average filtering algorithm is combined with a median filtering algorithm to enhance the performance on noise density, mask size is varied adaptively. Benign, malignant noise removal on mini mammographic (MIAS) images are shown in Fig. 2.

3.1.3 Gabor–Legendre Filtering (GLFIL)-Proposed Image Enhancement Techniques for Mammogram Images

A polynomial approximation of frequency and orientation representation is used to design the GL filter. This filter encompasses various frequencies with polynomial computations. Legendre filter technique calculates the amplitude, phase value, and transient response in images. This filter repository comprises hybrid Gabor–Legendre (GL) filters which create the different values of scales and rotations. The signals are combined with the filters to form a GL space. This GL space is used in mammogram enhancement. Digital images have different object relations in activating specific spatial locations. Thus, the activations are extracted from the GL space to create a sparse representation of the object. The GLFIL improves its attention due to its characteristics of polynomial approximations of the frequency and orientation representation of mammogram images can be approximated. The algorithm for the GLFIL is,



Figure 2: Original vs. GLFIL-enhanced mammograms

Algorithm of the GLFIL

```
Initialization: v-orientation, m = row dimension, n = column dimension
 1. Initialize GLFIL = zeros(m, n), m1 = m2 = 1, k1 = k2 = 1, n = 1
 2. for j = 1:v
 3. For x = 1:m do
 4.
              For y = 1:n do
5. Calculate GLFIL using Eq. (7)

GLFIL(x, y, \theta, f) = \sqrt{\left(m_1 + \frac{1}{2}\right)\left(m_2 + \frac{1}{2}\right)} 2^{\left(\frac{k_1 + k_2}{2}\right)} \times p_{m1}\left(2^{k_1} \times \frac{x_{\theta}}{\sigma_{x^2}} - f_1\right) p_{m2}\left(2^{k_2} \times \frac{y_{\theta}}{\sigma_{y^2}} - f_2\right) \cos 2\pi (fx_{\theta} + fy_{\theta})
             x_{\theta} = x\cos\theta + v\sin\theta
            y_{\theta} = -xsin\theta + ycos\theta.
                                                                                                                                                                                                                           (9)
where \theta is the local orientation, f is the frequency, and \sigma_x, \sigma_y are the standard deviations
 6.
              End
 7. End
 8.
              Return GLFIL(x,y)
```

9. End

In the GLFIL algorithm, the first step is to initialize the function of array for GL arguments with orientation, row dimension, and column dimension. Second, initialize the GLFIL arrays with zeros. Third, validate the number of arguments. If it has four arguments with the number of frequencies and orientations, then it is true. Next, to create a Legendre filter, declare GL Array as u,v in the cells. In Steps 6 and 7, loop with x,y arguments with respect to local orientation and frequency. In Step 8, return the GL array with respect to the x,y.

Fig. 2 shows the better enhanced mammogram images using the GLFIL. Comparative to the standard mean and median algorithms, GLFIL gives better enhanced images for further classification and segmentation.

3.2 Edge Detection

In our proposed work, Canny edge detection is used to detect the edge. Numerous mathematical algorithms have been used to detect edges for point identification in a digital image where sharp brightness changes appear. Curved line segments called edges are organized to represent the points with sharp brightness changes.

Normally, Canny edge detection is used in various vision objects to derive the structural information. Fundamentally, it reduces the number of data to be processed. The requirements of applying edge detection on diverse vision systems are similar to Canny edge detection. The general conditions of edge detection are represented as follows.

The process of the Canny edge detection algorithm is as follows:

The Canny edge detection algorithm process has five steps.

a) Filtering: The image is smoothened for noise removal by applying the Gaussian filter. Gaussian blur or Gaussian smoothing is defined as the blurring produced from the Gaussian function. Image with noise is smoothened by passing the Gaussian filter G with input image I(i, j). It is denoted as,

$$F(i,j) = G * I(i,j).$$
⁽¹⁰⁾

b) Gradient calculation: The intensity gradient of the image is computed using Canny algorithm. In an edge of an image, there are various directions, blurred images, diagonal, vertical, and horizontal edges, that are detected using four filters of the Canny algorithm. The edge detection operators, such as Sobel, Prewitt, and Roberts with vertical direction (G_j) , and horizontal direction (G_i) are used to derive the values. Thus, the edge gradient is denoted as,

$$G = \sqrt{G_i^2 + G_j^2}.$$
(11)

c) Suppressing process: Non-maximum-based suppression process is used to thin the edge for better edge-detection results. From the gradient result, the blurred edges are extracted after the gradient calculation. All gradient values are suppressed except for the local maxima values using a non-maximum suppression. The sharpest change locations of the intensity value are specified using this method.

d) Doubling limit: It is used to calculate the potential edges. If the high threshold value is smaller than its gradient value, then the edge pixel is called a strong edge pixel, and if a high threshold value is greater than its gradient value then it is called as a weak edge pixel. Although a local maxima and non-maxima exist, noise problem remains. Thus, two thresholds T_{low} and T_{high} are selected instead of one to avoid this problem.

e) Hysteresis tracking of edges: All other weak edges that are not connected to strong edges are suppressed for final edge detection. To track the edge connections in the weak edge pixel, blob analysis is performed with eight connected manners of neighborhood pixels. To detect a pixel m(i, j) with gradient magnitude G as the edge, the following conditions are used. If $G < T_{low}$, then the edge is discarded, if $G > T_{high}$, then the edge is maintained, if $T_{low} < G <$ and T_{high} and in a 3×3 region, and any of its surrounding neighbors has a gradient magnitude greater than T_{high} , then edge is maintained.

3.3 Image Segmentation

The process of dividing the image pixels into multiple regions on the basis of the pixel character is called image segmentation. This process also separates the front and rear images. Further segmentation clusters the

similar image pixels with the same color and shape. During segmentation, each pixel of an image is labeled on the basis of the sharing of the same label pixels characteristics.

Separation Rear Front Images

Foreground-background separation is a segmentation task, where the image is split into foreground and background. In semi-interactive settings, the user denotes some pixels as "foreground," and others as "background," on the basis of the algorithm to classify the rest of the pixels of the image for segmentation.

Steps in segmenting images,

a) Image filter using threshold: Thresholding of an image is the key concept it binarization. In binarization, the pixels with that having less gray level than the stated threshold value are grouped as foreground or background, and the remaining pixels are groups as another class. In thresholding, the selection of threshold (Th) is to extract the object. The *Th* computes as the block's mean gray value. This is represented in Eq. (12)

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) > Th \\ 0 & \text{if } f(x,y) <= Th \end{cases}$$
(12)

where, f(x, y)- gray scale pixel values and g(x, y)-binarized image

b) Image shaping and thinning: The process of deleting unwanted image pixels from an image and modifying the image pattern by one pixel less thick is called thinning. Other side parallel computation by processing binary image at n iteration has a pixel element value which depends on the current pixel value and its neighbor pixel of (n–l) iterations. Its process as pixels with non-zero value is used to represent objects, and pixels with zero-value are used to represent images background.

c) Removing muscles: The sliding window algorithm (SWA) reads the mammographic image and removes pectoral muscles in the images. This removal process is crucial because the region of interest is similar to the value of intensity of the pectoral muscles. Separating this this process is difficult. Fig. 3. reveals the sliding window representation of the mammogram images.



Figure 3: Sliding window mammogram images

The overall segmentation process of the sampled images is shown in Fig. 4.

Classification is essential in image processing. This process predicts specified data points class in a segmented image. Classification is a supervised learning, which means the input data are specified as the

equivalent targets. In this proposed work, the enhanced image with the GLFIL image is classified for breast cancer detection. The classification is performed using RNN with an auto encoder-based animal migration algorithm.



Figure 4: a) original image b) segmented image c) binarized image and d) thinned image

3.4 Image Classification Steps

Fig. 5 shows the flowchart for the AR-AMO-RNN, which is designed for the classification of medical images of the MIAS dataset. Input layer, the network takes medical image as input and low-level feature vectors are extracted from the input image. The feature extraction is trained automatically in the hidden layer of the network with the help of AMO and RNN. To classify the image data, auto encoder (AE) and Softmax classifier are used on the extracted feature.

The structure and quality of RNN networks is based on the hidden layer performance. Normally, the input vector is passed through the hidden layer and animal migration optimization is used to optimize the parameters in the hidden layer. The final output layer is called the classification layer, which is added into the supervised training segment to learn the final prediction of detecting the breast cancer of the MIAS dataset.

3.5 Auto Encoding with Neural Network

The more powerful human gestures are handled using neural networks, such as RNN. This study explains the process of training the neural network on the basis of previous information. The input

images from the GILFIL output are auto encoded with RNN. Feature extraction and dimensionality reduction are carried out by encoding process. Decoding hidden layer reconstructs the features and expands the dimensions.



Figure 5: Flow chart for image classification

3.6 Animal Migration Optimization

The swarm intelligence-based optimization algorithm is implemented for classifying the images. The behavior of the animals during the migration is developed as a metaheuristic approach. Fundamentally, the two processes are carried out by animals during the migration. The first is migrating process; second step is updating the details. The process of moving to a new location is called migration. Position updating is calculated using s probabilistic method.

There exist three main steps to be followed in the algorithm as follows. First, collision among neighbors must be avoided. Second, the direction of moving must be the same among neighbors. Third, close distance with neighbors must be maintained. With help of the Softmax classifier process, the cancer-detected images are classified and optimization is performed.

4 Results and Discussions

The dataset for this work is taken from the MIAS breast cancer database. The dataset is freely available online. However, these images have some risk factors. Various cancer cases are available in the datasets. These datasets are classified as early tumor and malignant tumor. The tumor class is computed for nine available features in the dataset. It comprises 322 digital high-resolution breast images.

To compare the image enhancement techniques, the metrics called signal to noise ratio (SNR) and PSNR have been used. The value of the SNR results the comparison noises in signal of background pixels with the particular signal in image. Further, if the SNR value is predicted as higher than the background noise is less in the image.

Peak signal to noise ratio (PSNR) is the value between the maximum power of the signal and the noise of the signal. PSNR has its units as decibels in the logarithmic scale. Even though PSNR value is low, its

(14)

construction is closer to the original compared with other images. The following Tab. 1 shows the comparison of the SNR and PSNR for all the four methods.

Error in mean square (EMS))
$$= \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} K(x_{j,k} - y_{j,k}),$$
 (13)

Peak signal vs. noise ratio (PSNR) = $20 * \log (255^2 / MSE)$,

Ration of signal to noise $(SNR) = 10*\log 10$ (double (original image)/double (enhanced image)). (15)

Enhancement Algorithms	SNR	PSNR
Mean	87.9953	7.6476
Median	85.2663	4.7313
GLFIL (Proposed)	89.2770	0.764483

 Table 1: Noise calculation

Fig. 6 constructed from Tab. 2 unveils that when the SNR increases the PSNR is reduced. Therefore, our proposed GLFIL has high SNR value and low PSNR value. Thus, the GLFIL reduces noise better compared with the mean and median filters.



Figure 6: Comparison of noise ratio

The proposed framework of the GLFIL-enhanced classification AE-AMO-RNN algorithm is compared to our previous work called mean and median-based enhancement classification of the same AE-AMO-RNN algorithm. The performance of the results demonstrates metrics are like accuracy, f-measure, recall, and precision for analyzing the performance of the GLFIL-enhanced AE-AMO-RNN proposed framework.

The correlation comparison in various enhancement method-based classifications between GLFIL-based AE-AMO-RNN and existing methods, such as mean filter-based enhancement-based classification and median filter-based classification are shown in Fig. 7. It indicates GLFIL produces higher precision rate compared with existing techniques. Exact identification of breast cancer with a high precision rate of 95%, recall rate of 97%, F measure rate of 92%, and accuracy of 98% are obtained. When compared to the precision value of existing methods, such as mean filter-based classification, it provides a good precision rate of 86%, recall rate of 89%, F-measure rate of 76%, and 91% accuracy. Next existing

median filter-based classification provides precision rates of 90%, recall rate of 88%, F-measure rate of 83%, and 93% accuracy. However, this filter has lower accuracy than the proposed method. Hence, GLFIL is effective in removing noise, provides better image enhancement quality, and meaningful for short-term disease prediction.



Figure 7: Precision performance comparison of various enhancement methods based on classification

Methods		Metrics			
	Precision data (%)	Recall data (%)	F-measure data (%)	Accuracy data (%)	
Mean—AE-AMO-RNN	86	89	76	91	
Median—AE-AMO-RNN	90	88	83	93	
GLFIL—AE-AMO-RNN	95	97	92	98	

Table 2: Performance comparison metrics vs. Enhancement methods with classification

5 Conclusion

Breast cancer is considered dangerous and is the second highest cause of death among women. Thus, breast cancer detection is an extremely important field in image processing. Our proposed GLFIL algorithm is a combination of Gabor and Legendre filters for image enhancement. This algorithm works with a polynomial computation of Euler transformation using Gaussian computations. Thus, quality of the input images is adjusted with orientation and polynomial computation. The output of this article is based on the quality of image enhancement. When image quality is improved, noise in the images during tumor detection is reduced. Through this, further detecting the appropriate tumor image is done efficiently. GLFIL proves its importance in obtaining perfect features. Ultimately, different machine learning algorithms can also be used to detect abnormalities in images. In the future, different filtering techniques with a heuristic approach can be used for high-accuracy detection.

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