Exploring The Growth Level Of Pancreatic Tumor Using Highly Efficient Cnn Classifier

Ajanthaa Lakkshmanan1 Dr.C.Anbu Ananth2 Dr.S.Tiroumal mouroughane3

1Research Scholar, Dept. of Computer Science and Engineering, Annamalai University, Chidambaram,Tamilnadu,India.
2Associate Professor, Dept. of Computer Science and Engineering, Annamalai University,Chidambaram,Tamilnadu,India.
3Assistant Professor, Dept. of Information Technology, Perunthaiavarkamarajar Institute of Engg.& Tech (PKIET) ,Karaikal, Pondichery, India

Abstract: The pancreatic cancer (PC) has the lowest survival probability and ranks as the fourth prominent reason of cancer death and the rate of death is increased by ever year. The major risk factors for the invasion of pancreatic cancer are smoking, intake of alcohol, diabetes mellitus and earlier pancreatitis also leads to the development of pancreatic cancer. The aim of this suggested method is to detect the PC, which is accomplished by using the image processing technique. In this paper, the CT image is considered as the input image which experiences the process of preprocessing to eliminate the presence of noise in the image and that has been accomplished by adaptive Weiner filter. After the preprocessing, the noise free image is then segmented by using the modified region grow model. SIFT (Scale invariant feature transform) method is used to extract the parameters of the pancreatic cancer and this extracted features are enhanced by PCA (principal component analysis) to optimize the features of the pancreatic CT image. The parameters of the image have been stimulated by relating the CNN (convolutional neural network) classifier. After classification, the classified image has been compared, thus the comparison is done only between the test data and the trained data to categorize the image as PC or non-PC. The entire process is then stimulated in the MATLAB and most recent technique is used for the performance estimation and so high accuracy is achieved.

Keywords: Adaptive MATLAB, Modified region grow model, SIFT, PCA, CNN classifier

1. Introduction

The universe is generally influenced by cancer which is the serious ailment and that results in the stream of death. The permanent damage in the respiration of the healthy cell is the major cause, which leads to severe cell injuries and this ends up with cancer [1]. The detection of cancer at the early stage and the limitation of diffusion with other parameters, help humans to sustain. Among different malignant cancers, pancreatic cancer (PC) is one that frequently endangers the patient’s survival [2]. In recent times, death caused by other cancer is minimized annually but the rate of death caused by the PC remains unchanged. This occurs due to the unavailability of clinical progression for the treatment of PC, when compared to several other cancers [3]. To identify PC, the input CT image undergoes various process like preprocessing, segmentation, feature extraction, feature selection and classifier.

Initially at the preprocessing stage, the noise and edge highlights are minimized along with that, several SOPs (self-organization pattern) [4] are used together with plasma to stimulate the saline solution and to determine the cause of anti-tumor at plasma stimulated saline solution, the major issue of this technique is noise reduction. However, to enhance this technique supervised and un-supervised schemes [5] are utilized, at which the tuned information of the samples are classified into several groups with domain features. Then the rate of proliferation for the tumor image is provided by the 2-[18 F]-fluro-2 deoxy D-glucose positron emission tomography (FDG-PET) [6] and the local densities of tumor cells are provided by CT image which is enhanced. For the visualization of pc, spatial limitation based anatomy is used to design the dual-frequency endoscopic transducer [7] that delivers alignment of vascular imaging at high-resolution with abnormalities. To overcome these issues, adaptive Weiner filter is utilized since it minimizes the noise, which is presented in the image.

After preprocessing, segmentation of the image is performed, where the preprocessed image is further divided into several regions and each one of the region demonstrates various information. The analysis of whole-tumor stiffness is done by two orthotopic PDAC xenograft designs [8]. Also the multi-loss ensemble [9] is used to detect the pancreatic segments in the CT image, in which two stage frame works have been designed to separate the pancreas from rough level. However, in Recurrent saliency transformation network (RSTN) [10] [11], a hierarchical description is introduced to classify the small segments from the pancreatic tumor. For the evaluation of pancreatic cell line surface, modified AuNPs with synthesis based green chemistry is used [12], which analyzes the effect of anticancer cells in the pancreatic cancer. The anticancer movement is improved by the morphology of ZNP and PZNP [13]. To overcome these issues, SIFT method is utilized in this developed paper since it describes the image features.
From the segmented image, the single image is selected to extract the set of data attributes, along with that, SVM [14] and MRI [15] recognition is utilized for the research of image processing. To diagnose the tumor in the early stage, multi-level feature extraction is proposed with two deep learning models [16] like Inception-v3 and DenseNet201. The classification of segmented image is performed by neural networks and in the initial stage, deep neural network (DNN) [17] [18], is utilized. It is a feed-forward network, which transmits the input data to output data, through the hidden layer, however it is unable to transmit the data quickly. To eliminate this issue, encoder and decoder neural network [19] is utilized, which has two neural networks, one for encoding the input data and another for decoding the encoded data, this method requires excessive data to perform. To classify the samples as per their features, artificial neural network (ANN) [20-21] is utilized, in which samples with same features are grouped together. To perform classification, ANN requires long training time and high computation cost. To overcome these issues, convolutional neural network (CNN) is utilized in this paper. The aim of this paper is to detect the pancreatic cancer by using image processing technique to gain the incredible results. The feature of this proposed technique includes texture, border, height, thickness. Thus this identification results in the novel development for specifying the pancreatic tumor, in which the content of input has gone over various progression that are initiated by preprocessing and ends at classification, for achieving diagnosis more efficiently and/or obtaining high accuracy. CNN classifier is used to execute this process with high speed and less time. This classifier helps to compare the training data with test data and produce the result more accurately. This entire process is stimulated in MATLAB and the accuracy, sensitivity and specificity of proposed CNN is compared with the support vector machine (SVM) and artificial neural network (ANN).

I. PROPOSED METHODOLOGY

The aim of this proposed method is to determine the exact identification of pancreatic cancer, as it hangs over the size and location of the tumor. To require the precision vastly, this proposed scheme owns five different steps. This method is initiated by saving the CT images of the pancreatic cancer. The unnecessary signals, which have been obtained in the CT images are eliminated with the help of Weiner filter. The use of this filter results in de-noised and re-sized image. After the elimination of these additional signals, segmentation is executed. In this process the segmentation is performed by modified region grow model that classify the preprocessed image into several segments. However the threshold is obtained at corresponding images that authorizes the approximation of threshold. SIFT approach is used in the process of feature extraction; the inadequacy that takes place during this method has been eliminated by this approach. Consequently this extraction is innovated extremely by utilizing PCA (Principal component analysis) which may provide admirable data and gather several data rapidly and productively. This approach is the advanced method, which is used in image processing presentations and has the aptitude to choose the great function from the eliminated highlights. Finally, CNN classifier is used in classification process and its performance is enhanced when compared with other filters. By this novel methods and algorithms, the CT images have passed over several steps and deliver the enhanced data for the improvement of tumor diagnosis.

(a) PREPROCESSING

The suspicious area, which is presented at the CT image has been detected by pre-processing and enhancement methods. The noise and edge highlights are minimized in this pre-processing method. In view of this esteem,
Adaptive wiener filter is utilized, which is a kind of linear optimum discrete time filter. The error that occurs with the proper utilizations are minimized by this filter which is known to be the cost function and this is the major aim of this filter. Most frequently used cost function is mean square error (MSE). The wiener filters are utilized in several functions like image processing, signal processing, control system and digital communication. The Weiner filter is represented as,

$$W(x, y) = \frac{H’(x,y)}{|H(x,y)|^2 + SNR}$$  \hspace{1cm} (1)

Where, $H(x,y)$ as degradation function, $H’(x,y)$ as complex conjugate and SNR as signal to noise ratio. The minimization of MSE is done by designing the wiener filter with the linear combination of data, desired signal and estimated signal. This is also used to minimize the speckle and Gaussian noise and also the smoothing is performed by this filter. The filtered image with zero-mean white Gaussian noise is considered and the occurred issue is represented as,

$$y(i,j) = x(i,j) + n(i,j)$$  \hspace{1cm} (2)

Where, noisy quantity is represented as $y(i,j)$, noise free image as $x(i,j)$, additive Gaussian noise as $n(i,j)$. The aim is to eliminate the $(i,j)$ noise and to require $\hat{x}(i,j)$ linear estimation of $x(i,j)$ that decrease the MSE.

$$MSE(\hat{x}) = \frac{1}{N} \sum_{j=1}^{N} \left( \hat{x}(i,j) - x(i,j) \right)^2$$  \hspace{1cm} (3)

Where, amount of elements present in $(x(i,j)$ is represented as $N$.

The unpretentious scalar arrangement of wiener filter is given as,

$$\hat{x}(i,j) = \frac{\sigma^2_x(i,j)}{\sigma^2_x(i,j) + \sigma^2_n(i,j)} y(i,j) + \mu_x(i,j)$$  \hspace{1cm} (4)

Where, the signal variance and mean are represented as, $\sigma^2_x$, $\mu$ and generally the mean value is assumed to be zero. The Equ(4), can be used only if the $\mu_x(i,j)$, $\sigma_x^2(i,j)$, $\sigma_n^2(i,j)$ are determined. These are evaluated uniformly by average window size $(2r+1) \times (2r+1)$,

$$\mu_x(i,j) = \frac{1}{(2r+1)^2} \sum_{p=-r}^{r} \sum_{q=-r}^{r} y(p,q)$$  \hspace{1cm} (5)

$$\delta_x^2(i,j) = \frac{1}{(2r+1)^2} \sum_{p=-r}^{r} \sum_{q=-r}^{r} [y(p,q) - \hat{\mu}_x(i,j)]^2 - \sigma_n^2$$  \hspace{1cm} (6)

Thus these equations (5), (6), maximize the near edge variance and also the mean is blurred. This ends up with poor de-noised image and occurs with noise. To overcome this noise, Equ(6) is modified as,

$$\delta_x^2(i,j) = \sum_{p=-r}^{r} \sum_{q=-r}^{r} w(i,j,p,q) (y(p,q) - \hat{\mu}_x(i,j))^2$$  \hspace{1cm} (7)

The value of the $w(i,j,p,q)$ is determined by the estimation of center variance, and it is represented as,

$$w(i,j,p,q) = K(i,j) = \left\{ \frac{1}{1 + a \left[ \max \left[ e^2(x(i,j)-y(p,q))^2 \right] \right]} \right\}^{-1}$$  \hspace{1cm} (8)

When $w(i,j,p,q)=0$, then $K(i,j)$ is represented as normalization constant as,

$$K(i,j) = \left\{ \frac{1}{\sum_{p,q} 1 + a \left[ \max \left[ e^2(x(i,j)-y(p,q))^2 \right] \right]} \right\}^{-1}$$  \hspace{1cm} (9)

To remove the outliers, $ae^2 > 1$ is selected and the mean and variance are represented as,

$$\hat{\mu}_x(i,j) = \sum_{p=-r}^{r} \sum_{q=-r}^{r} w(i,j,p,q) y(p,q)$$  \hspace{1cm} (10)

$$\delta_x^2(i,j) = \sum_{p=-r}^{r} \sum_{q=-r}^{r} w(i,j,p,q) (y(p,q) - \hat{\mu}_x(i,j))^2$$  \hspace{1cm} (11)

These equations are adapted for edge and other rapid features and mean and variance are estimated and the blur is minimized.

(b) SEGMENTATION

In the process of segmentation, the input image is distributed to several regions and each one of the region demonstrates various information from the segmented images like texture and intensity. Segmentation is influenced by two characteristics like resemblance and incoherence which occurs in the segmented image. In this process of segmentation, modified region grow model is used to segment the image and it is a simple boundary algorithm with pixel based image segmentation. The normal region growing method is used only to examine the nearby pixels intensity. The level of threshold required for the intensity value is fixed and the nearby pixel which satisfies the obtained threshold value is nominated for region growing. The major disadvantages occurs in the normal region growing are listed as follows, 1) variation in the intensity may cause over-segmentation, 2) pigment of original image is not defined.

Algorithm:

Procedure: Intensity based textural region growing (IBTRG)
Input: Preprocessed image
Output: Regions
Step .1 Start
Step .2 Texture image is obtained by applying the operator Local binary pattern (LBP)
Step .3 Image I is sub-divided into $G_l$ grid.
Step 4 Intensity and texture thresholds ($T_I$ and $T_T$) are fixed.
Step 5 All grids $G_i$ are done;
   a) At grid $G_i$, histogram of each pixel $P_j$ is found.
   b) $Freq_{Hist}$ is used to denote the selected frequent histogram obtained from the grid $G_i$.
   c) SP (Seed point) with intensity $I_p$ obtained from the pixel is assigned by choosing any pixels $P_j$ that relate to $Freq_{Hist}$.
   d) The nearby pixels that contain intensity $I_N$ and texture value $T_N$ and squared for intensity and texture constraints ($|I_p - I_N| \leq T_I$ and $|T_p - T_N| \leq T_T$).
   e) The region is grown at the nearby pixels when both the constraints are satisfied, if it is not satisfied, the region is not grown.
Step 6 Stop.

Fig 2 Region grow algorithm.

The intensity and shape, which are based on the segmented algorithm has gained imprecise results like indefinite and inhomogeneous configuration of a tumor. The characterization of texture is classified into un-sharp, indistinct, inhomogeneous tumor, which is an encouraging function. The segmentation based on a texture, which is required for the CT image has been proposed by novel indication. The modified region growing contains two thresholds, one for intensity and one for orientation. This novel method, which is based on the value of texture intensity has the detachment and refinement in various pattern of intensity for the determination of tumor. This results in maximizing the sensitivity and specificity for the detection of tumor. This modified method is superior when associated with the normal region growing technique. It is constituted by three stages like gridding, selecting seed points and applying region grow to the specified point. At the initial stage of gridding, the single image is segmented into various less significant images by imaginary grid drawing over it. The region growing for the formation of grid is used in the seed point selection, which is the second step in modified region growing. Histogram is used to choose the seed point from each grid. While the seed point is selected, the region is grown at that point and the nearby pixels are compared with every seed point and the region is grown.

The entire region of the image is represented as $R$ and the segmentation is done by partitioning the region $R$ into sun-regions $n$ like $R_1, R_2, ..., R_N$. The region joining association is done as,

- $\bigcup_{i=1}^{n} R_i = R$, union of the detected regions for the whole image. All pixel be appropriate to the region.
- $R_i$ as the regions connected, $i=1,2,\ldots,n$;
- $R_i \cap R_j = \emptyset \forall i, j, i \neq j$, regions that are disjoined.
- $P(R_i) = True, i=1,2,\ldots,n$, each pixels with similar intensity;
\[ P(R_i \cup R_j) = \text{False} \quad \forall i,j, i \neq j, \text{ pixel intensity varies for different regions;} \]

Where \( R_i \) as logical predicate for the point at the set \( R_i \), and \( \emptyset \) represent the null set.

(c) FEATURE EXTRACTION

The process at which the redundant input data with large measurement is converted into a minimized feature has set the representation. This conversion of input data into the set of features is known as feature extraction. The widely used feature is the SIFT (Scale invariant feature transform) and it is utilized as the major feature in this proposed system. SIFT has no dependence on color, key-point extraction and gray space features and it extracts the distinct feature invariance of the image. After extracting the features, the image key-points are located and it is also known as descriptors and these descriptors are independent of modification. The SIFT algorithm constitutes detection of scale space extreme, accurate localization of key-points, orientation of assignment and description of local image.

The detection of scale space extreme is the initial step that is performed to find the candidates of key-points. The pyramid of blurred Gaussian image is developed with various scale \( k\sigma \) and Gaussian filters \( GF(X, Y, k\sigma) \) with image \( S_k \) these are convolved initially where, \( S_k = S(x, y, k\sigma) = GF(x, y, k\sigma) \ast S_{k-1} \) (12)

When \( k=1 \), then the input image is \( S_{k-1} = S_0 = I(x, y) \), also

\[ GF = \left( \frac{1}{2\pi(k\sigma)^2} \right) e^{-\frac{(x^2+y^2)}{2(k\sigma)^2}} \] (13)

This convolved image is then gathered by octave and the number of convolved image for each octave is provided with the value \( k \). The frame of pyramid in the Gaussian blurred image is demonstrated with scale and octave, \( G[\text{octave, scale}] \). Thus the Gaussian pyramid is defined as,

\[ G[0,0] = I(x, y) : \text{original frame} \] (14)

\[ G[0,1] = GF(x, y, \sigma) \ast G[0,0] \] (15)

\[ G[m,k] = GF(x, y, k\sigma) \ast G[m, k-1], \quad m, k \geq 0 \] (16)

In which, \( G[m,0] \) is attained by sampling downward. Then the Difference of Gaussian (DOG) in blurred image is computed as,

\[ \text{DOG}[m, k] = G[m, k + 1] - G[m, k] \] (17)

By this DOG, the local maxima or minima candidates of key-points are found by comparing the pixel with each nearby scale. At the stage of key-point localization, some stable key-points are localized by eliminating few corrupted key-points during the detection of edge and contrast. The rejection of extreme unstable location by low contrast test is given as,
\[ \hat{x} = -\left( \frac{\partial^2 \text{DoG}^{-1}}{\partial x^2} \right) \left( \frac{\partial \text{DoG}}{\partial x} \right) \]  

(18)

Low contrast threshold that obtained from the DoG is given as,

\[ \text{DoG} (\hat{x}) = \text{DoG} + \frac{1}{2} \left( \frac{\partial \text{DoG}}{\partial x} \right) \hat{x} \]  

(19)

Detection of edge is given as,

\[ \frac{\text{Tr}(H)^2}{\text{Det}(H)} < \frac{(r+z)^2}{r} \]  

(20)

Where, edge sharpness is represented as r, the trace and 2x2 Hessian matrix determination is derived from Tr(H) and Det(H)

\[ H = \begin{bmatrix} \text{DoG}_{xx} & \text{DoG}_{xy} \\ \text{DoG}_{xy} & \text{DoG}_{yy} \end{bmatrix} \]  

(21)

\[ \text{Tr} = \text{DoG}_{xx} + \text{DoG}_{yy} = \alpha + \beta \]  

(22)

\[ \text{Det} = \text{DoG}_{xx}\text{DoG}_{yy} - \text{DoG}_{xy}^2 = \alpha \beta \]  

(23)

From this derivative, it is given that when the feature point is verified as the candidate, the SIFT begins to calculate its orientation. However, the SIFT is used to recognize the object in visual features.

(d) FEATURE SELECTION

The linear transformation is used to extract the set of new attributes from set of data attributes by using feature selection method. The gathering of new data set from the innovative data set is known to be principal component analysis (PCA), the major aim of this PCA method is to obtain the high variance data and it is used with training data task for visualization, reduction in dimension and performance improvement. In this analysis, PCA is used to examine the pancreatic cancer which is obtained from the CT image and also the texture, symmetry and radius of the tumor have been characterized. Initially it is investigated that the PCA is able to divide the tumor from the normal tissues, and it is classified into test data and training data and the process is done only in the training data.

Fig.4 Steps to obtain PCA based tumor detection.
The PCA is obtained by these following steps; initially the covariant matrix of the data set is developed in a mathematical form, after this the covariance matrix’s Eigen vectors are evaluated through which, the Eigen vectors with peak value is selected to store the single data set and finally the principal components are selected by choosing the attributes with high variance. The image with size m×n pixel with m×n-dimensional vector is represented by the PCA and the mean is calculated by evaluating the average of all dimensions and mean vector is used as a subtract in all vectors. The product of the mean vector is subtracted and its transpose is known to be covariance matrix and it is expressed as,

\[ C = X'X^T \]  

(24)

Where, \( X' \) is represented as mean vector and its column is given in the vectors, which are trained. From the covariance matrix, Eigen vectors and values are calculated and this selection of highest mean value is represented as the Eigen-faces. With the use the Eigen face, the transformation matrix is developed in a manner of row, thus the extracted value \( y_i \) is equated with the \( x_i \) input as,

\[ y_i = W(x_i - \bar{x}) \]  

(25)

Where, \( W \) is the matrix representation and \( x \) is the mean. The modified PCA is the modular PCA method in which the single input image is sub-classified into similar sized N images and this classified images are processed with the help of PCA. The outcome of this process is eigen face and it is evaluated by the following steps. Initially the amount of trained images are considered as M and classified image as N and these images are classified into equal N sub-images and the mean for each sub-image is evaluated as,

\[ \bar{x}_n = \frac{1}{M} \sum_{m=1}^{M} x_{mn} \]  

(26)

Where \( \bar{x}_n \) is the mean for the n sub-image and \( x_{mn} \) as the vector for both n and m sub-images. All the sub-images are subtracted by the mean value as,

\[ x'_{mn} = x_{mn} - \bar{x}_n \]  

(27)

Where \( x'_{mn} \) is a mean subtraction of sub-image n from the m image, the covariance of the sub-image is expressed as,

\[ C_n = X'_{mn}X'_n^T \]  

(28)

Where \( C_n \) is the covariance of the n sub-image. From this, the eigen value and vectors are evaluated and the peak value is selected and transformation matrix is constructed (\( W_{n} \)) and the features from all the sub-images are evaluated as,

\[ Y_{mn} = W_{n}(x_{mn} - \bar{x}_n) \]  

(29)

Where \( Y_{mn} \) is represented for the features obtained by the sub-images n and m and also the transformation matrix is represented as \( W_{n} \).

(e) CNN CLASSIFIER

The final stage is the classification and in this proposed system, Convolutional neural network (CNN) is used and it delivers more improved and precise outcomes. The combination of various feature outputs are used to calculate the classifier and the tumor is identified. The CNN comprises of three layers that are reference, middle and the output layer. The initial reference layer is also known to be the input layer in which the inputs are recognized or the image is passed as the input through this layer. The second layer is the middle layer that contains several amounts of program nodes, which are required for this process. And finally the output layer which produces the required data to the process. The convolutionary operation, which is performed between the pixel in the image matrix and kernel matrix has been done by the convolution layer. The kernel matrix slides the image matrix with the matrix of pixels and the values are evaluated. This is executed to identify the size of the output with the required filter map. Generally the CNN is used to recognize the image, in which the input image is sub-divided with the help of filters. Initially the extraction of the pancreatic region is obtained from the CT image, and CNN is used to identify whether the pancreas is affected or not. Generally the CNN requires four layers they are convolution, pooling, fully connected and soft-max.
In convolution layer, the filter is multiplied by the input image where the extraction takes place. At pooling layer the representation of the spatial size and the frame is minimized in the network evaluation. The multi-layer function is done by the fully connected layer in which the output of a single neuron is given as the input for next neuron. The interpretation occurs in the N×1 matrix, which requires probability distribution function in the softmax layer. The combination of both convolution and pooling layer is used in several applications under the architecture of CNN. Two operations like max and mean pooling are used for the execution of pooling; the nearby average feature points are evaluated by mean pooling whereas the maximum feature evaluation is done by the max pooling. The limitation of error and gain of background data is done by the mean pooling and the max pooling limits the deviated mean error and gain texture data.

III. RESULT AND DISCUSSION

In this proposed system, the execution of the proposed model is characterized by the MATLAB execution. In this, the input images are gathered from the CT image with the size of 256*256 and these images are combined with the professional guides to track the tumorous margin effectively. Due to the rigorousness of the PC, several samples are gathered and categorized. Thus the CNN classifier is used to perform the process more accurately. To obtain advanced classification, the CNN undergoes various processing steps to implement classification.
The preprocessing is implemented to improve the quality of the image and the subsequent steps are also initiated. The obtained CT images are in gray color and thus the color conversion is not required. The outcome image after the preprocessing process is free from noise and the resultant image is resized using the adaptive Weiner filter. These filters are good in eliminating the inaccurate frequency bands from the CT image, permits different frequencies to pass through, the loss is minimized and aid the data set to attain maximum acknowledgement, and hence the process is improved.

Fig.6 Input images
Fig. 7 Preprocessed images
The level of intensities with perfect illustrations is provided by the histogram representation for the grayscale image and it is also known as the amplitude feature. The identification of average gray value determines the average image intensity; this identification is performed by histogram.

1500 Iterations 1500 Iterations 1500 Iterations

1500 Iterations 1500 Iterations 1500 Iterations

1500 Iterations 1500 Iterations 1500 Iterations

Fig. 8 Modified region grow
Based on the characterization of the pixel value, the segmentation is performed in which the objects are separated into groups. To gain data, the image segmentation is used, however the test data and the trained data are not conceded. From this, the radiologist separates the significant and insignificant arrangements. The modified region grow model is used to segment the images.
The characteristics of the PC CT image is optimized by PCA algorithm, thus the segmented image with the applied features is used to perform the classification process. The cancer tissues and normal tissues are separated by using the CNN filter, each data sets are compared with the trained data to clarify the tumor and each set of compared data has been stored.

**Fig. 9 Modified region grow segmentation**

**Performance Metrics:**

The performance of the CNN classifier is compared with the present SVM and ANN classifiers. While comparing this proposed classifier with the others, it provides strong tolerance to the input noise and also the maintenance of execution is easy and requires less time to process. The classification is performed by calculating accuracy, sensitivity, specificity, recall and precision.
The sampling of image is given as sensitivity and the sampling of the segmented image is given as recall and both are used to evaluate the patients with the disease. Sensitivity and specificity are used to evaluate the accuracy where, the sensitivity shows the individuals with illness which has been mentioned as TP and the specificity shows the individuals free from illness which has been mentioned as TN. In which the TP is viewed as the positive and TN is viewed as the negative. The accuracy determines the true value and the precision gives the repeated same value.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} 
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN} 
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} 
\]

\[
\text{Precision} = \frac{TP}{TP + FP} 
\]

\[
\text{Recall} = \frac{\text{Total true classified samples}}{\text{Total supplied samples}} 
\]

The accuracy of the proposed classifier is shown in Fig. 11. Comparatively, CNN provides better performance than other classifiers and obtains the accuracy of about 95%.

The proposed classifier provides the sensitivity of about 86.8%, when compared with the other classifiers and its performance is shown in the Fig. 12.
The specificity, which is produced by the proposed classifier is about 93.5%, and comparatively it is better than the other classifiers and its performance is represented in the Fig. 13. By these performance analysis, the accurate size and location of the pancreatic cancer is identified and removed from the non-pancreatic cells.

IV. CONCLUSION

Pancreatic cancer is the fourth leading cause of death, however it is unable to determine in the early stage. In our proposed system, the discriminative features are retrieved through several processing techniques and it is finally processed by using CNN classifier. This classifier is used to minimize the complexity of the trained data and only the pre-trained data are used to extract the features of the image. To prove the superiority of this classifier, the CNN is compared with the SVM and ANN and the obtained accuracy for the entire process is 95%. There is no compensation in the performance of the training and testing data, and the value of the accuracy maintains the same even when the size of the image is varied. However, by identifying the size and location of the trained image, the cancerous tissues are determined. Through this set of process, the PC cells are separated from the non-PC cells.

References


