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Novel computer aided diagnostic system using hybrid neural network for early detection of pancreatic cancer

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ABSTRACT

One of the most dangerous tumours in the world, pancreatic cancer (PC), has an unimpressive five-year survival rate of about 5%. An early PC identification is crucial for raising patient survival rates. Diagnosis of PC requires computed tomography (CT), magnetic resonance imaging (MRI) with magnetic resonance cholangiopancreatography (MRCP), or biopsy. The proposed CAD design approach includes image preprocessing, segmentation, feature extraction, and classification phases. Preprocessing is done by using Colour conversion and an isotropic diffusion filter approaches. After that, proposed Fuzzy K-NN Equality algorithm used in segmentation procedures. Deep Learning with feature extraction is used as a classification tool. Tumour cells are classified using the features collected from the pancreatic sample. Train values and testing datasets are part of the image classification criterion. For the purpose of detecting pancreatic cancer, a hybrid Deep Convolutional Neural Network with Deep Belief Network (DCNN_DBN) algorithm is used. According to the experimental findings, the current CAD system offers massive prospects as well as safety in the automated diagnosis of both benign as well as malignant cancers and produces the accuracy of 99.6%. Using this classifier, computing complexity is massively diminished. The suggested technique could be enhanced to detect more pancreatic cancer cell abnormalities.

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KEYWORDS
Pancreatic cancer; image classification; computer assisted diagnosis; deep convolutional neural network; deep belief network

1. Introduction

The pancreas, which is situated behind the stomach, controls blood sugar levels by releasing hormones into the digestive system. Unusual pancreatic lesions that are inflamed or proliferate are known as pancreatic cystic lesions (PCL). The pancreas, an organ located behind the lower stomach, develops pancreatic cancer in its tissue. The pancreas generates hormones that assist regulate blood sugar levels and releases enzymes to aid in digestion. In this respect, pancreatic cancer is the world's leading killer. In recent years, pancreatic cancer has become more prevalent. In 2018, there were roughly 1,665,540 new cases of the illness in the United States, and 585,720 of those cases resulted in death. Because of this, cancer is a serious issue that jeopardizes the health of all human cultures [1–3]. Unfortunately, this dysfunction affects the organization as a whole, and this choice serves as a crucial test for certain assertions and the suitability of the care that follows. The most prevalent cancers in people are bladder, lung, rectum, colon, and prostate. Women are more likely than men to have cancers in the bosom, lungs and bronchi, colon and rectum, uterine corpus, and thyroid, to name a few. According to these figures, prostate and breast cancer both account for a significant part of all cancer cases in people. Pancreatic cancer, as well as cancers of the mind and lymph nodes, has the highest mortality rates in children.

To monitor, forecast, and categorize the presence of pancreatic tumours, automated classification of pancreatic tumours using computer-aided diagnostic models (CAD) is necessary [4–8]. One of the worst diseases with one of the lowest survival rates at the moment is pancreatic cancer, which is now incurable. The type of treatment needed will depend on the tumour's size, location, and whether it has spread to other parts of the body. In the case of pancreatic cancer, healthy cells in the organ begin to malfunction and proliferate uncontrollably. These malignant cells can accumulate and develop into a mass known as a tumour. Malignant refers to the ability of a cancerous tumour to develop and metastasize to other areas of the body. A pancreatic tumour can eventually migrate to other areas of the body through a process known as metastasis, which can also cause it to damage the pancreas' ability to function [9–12].

The performance of artificial segmentation is not up to par because of the intricate CT pancreatic imaging data set. There are issues with the anatomy's weak grayscale contrast as well as the lack of contrast between the pancreatic intestine and the parenchyma, particularly the duodenum. The complexity of the issue is additionally heightened by the substantial variance in

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peripancreatic fat tissue and the size of the pancreatic volume, in addition to the textural heterogeneity of the pancreatic parenchyma [13,14].

This paper describes hybrid architecture for employing CT imaging for the early identification and categorization of pancreatic cancer. To get rid of the noise there, the suggested solutions include colour transformation and isotropic diffusion filtering. Following the preprocessing stage, the outcomes are sent to a segmentation approach to take out the cancerous areas from the input image. utilized in the segmentation approach is a proposed fuzzy K-NN equation algorithm. Deep Learning with feature extraction is used as a classification tool. Tumour cells are classified using the features collected from the pancreatic sample [15–19]. Train values and testing datasets are part of the image classification criterion. At Each image in the dataset pertains to numerous feature values and attribute categorization. Hybrid method of deep convolutional neural network with deep belief network (DCNN_DBN) algorithm is used for the detection of pancreatic cancer.

The structure of the paper becomes, section 2 deals the review of literature. The proposed system's overall block diagram, as well as descriptions of the proposed hybrid DCNN_DBN architecture is presented in section 3. The outcome of studies performed to test the effectiveness of the proposed deep learning net in both a quantitative and qualitative manner are summarized and explored in Section 4. Various performance parameters for evaluating the proposed classifier's performance are given, along with quantitative data. Finally, in Section 5, recommendations are made and future directions are discussed.

2. Literature review

Bilateral filtering (BF) is a technique for image preprocessing that was introduced by Ajanthaa L et al in 2021 to eliminate noise from the CT pancreatic image. Additionally, the non-interactive Grab Cut (NIGC) approach is used during the image segmentation process. The residual network 152 (ResNet152) model is then used as a feature extractor to create a suitable set of feature vectors. His RDA-BPNN model employs the Rd Deer Algorithm (RDA) Tuned Back Propagation Neural Network (BPNN) as a classification model to determine whether pancreatic tumours are present [20]. Yang et al. [21] introduced a Multi-Channel Multiclassifier Random Forest-ResNet (MMRF-ResNet) deep neural network model to give an objective CT imaging basis for discriminating between mucinous cystic neoplasia (MCN) and serous cystic neoplasia (SCN) of the pancreas. Each CT image is classified according to the lesion type (SCN/MCN) using a variety of image segmentation techniques, including single-channel ROI outline images and multi-channel images, Wavelet, LBP, HOG, GLCM, Gabor, ResNet, and AlexNet, as well as classifiers like KNN, Softmax, Bayes, Random Forest classifier, and the Majority Voting Rule Method [21]. Then, using pathological data as the gold standard, classification results were contrasted based on sensitivity, specificity, accuracy, F1 score, and area under the receiver operating characteristic curve (AUC).

Chang et al. [1] suggests two algorithms for tissue histology classification based on morphometric scope representations. These procedures employ pixel- or patch-level features to model the background of morphometric detail. The morphometric characteristics are built on a spatial pyramid matching system at different positions and sizes. Because of their utility, morphology features obtain outstanding outcomes even with a limited number of training samples through multiple segmentation techniques and tumour datasets. This approach is highly adaptable to various tumour forms, resilient in the face of numerous technological and biological variations, and invariant across various cell arrays [1].

Chang et al. [2] suggest a deep learning-based technique for single nucleus categorization. To view and categorize nuclei, a spatially limited convolutional neural network is deployed. Immune fluorescence (IF) images were employed as label information instead of pathologists' remarks to give a sufficient number of labeled data. At the single-cell level, a big dataset in addition to a CNN are utilized toward differentiate malignant as well as benign cells [2]. Jiang et al. [4] propose a new method of determining pancreatic cancer categorization. The quantum theorem and the fruit fly optimum algorithm (FOA) are then explored. Then, in order to improve FOA, quantum coding and quantum operations are employed, as well as the development of innovative odour awareness resolve mechanism. The support vector machine (SVM) parameters can be optimized via extended FOA, and the SVM can then be used to build a classifier [4].

Moschopoulos et al. [10] recommend obtaining the bare minimum of biomarkers for pancreatic cancer diagnosis. To identify tissue samples, the Genetic algorithm (GA) was applied to PDAC data. As a consequence, our algorithm generates a listing of biomarkers that participate the majority essential responsibility in this terrible ailment [10]. Pahari et al. [5] develop spectral clustering algorithms. One of the most dangerous tumours is pancreatic ductal adenocarcinoma [5]. This research looks at the high-dimensional PDAC genetic material appearance dataset from the Gene Expression Omnibus (GEO) database. An innovative Shannon's Entropy-base remoteness measurement used in the direction of distinguishes clusters in the pancreatic dataset. KEGG Pathway analysis is used to identify specific biomarkers. The proposed technique is useful designed for defining biomarkers based on biological

understanding and functional similarities of genes as defined by Gene Ontology (GO) terminology.

Normal abdominal ultra sonography is used to detect pancreatic masses, and contrast enhanced ultrasound (CEUS) in addition to contrast enhanced computer tomography (CECT) are used to diagnose and evaluate patients who visit a tertiary referral centre. Using a transab dominal and an endoscopic technique, contrast enhanced ultrasound (CEUS) demonstrated good efficiency for diagnosis and characterization of strong pancreatic lesions. Zanaty and Ghoniemy [22](2016) planned an innovative technique designed for automated threshold used for segmenting MRI images if images by means of low contrast have an opportunity of bringing up the rear information in boundaries to address the difficulty of losing information in boundaries. For datasets of grey matter or white matter MRI, the homogeneity criteria and likelihood are determined for each pixel to get more accurate segmentation [12].

Using the SRG algorithm, JieWul et al. proposed a texture feature-driven computerized approach inten ded for segmenting the pancreatic parenchyma on or after pancreatic CT images depending happening the region of interest (ROI). A new texture feature-based seeded region evolving algorithm is proposed for automatic organ segmentation in abdominal MR images. Segmentation is done by using a proposed texture feature-based automatic SRG algorithm. This algorithm's value is obvious to create a parameter-free development environment with minimal interactivity. This is particularly useful for batch processing or for inexperienced computer users. Prior to the intervention of surgeons who specialize in patients with chronic kidney disease, Kristina Bliznakova et al. [23] suggested an innovative process in addition to implementation contrivance for measuring liver volume in addition to assessing the liver's left over activity. For liver CT scan images, volume segmentation, visualization, and simulated cutting are performed. A multi seeded area rising technique is used for CT image segmentation.

In order to segment MRI breast tumours, Ali Qusay Al-Faris et al. [24] developed a modified regular seeded area growth method built upon the Particle Swarm Optimization (PSO) image clustering paradigm. Stage position active contours as well as morphological thinning are two pre-processing techniques. In this situation, the automatic SRG initial seed as well as threshold value array are based on PSO cluster intensities. SRG algorithm was chosen for tumour segmentation because it is fast, simple, and accurate. Because it performs better than other clustering methods including K-means, fuzzy C-means, K-harmonic means, and genetic algorithms, a PSO-based image clustering strategy was chosen [3].

To automatically segment brain lesions on or after diffusion-weighted MRI, Saad et al. [25] used a region-growing technique. Using region splitting and blending, pixel intensity as well as pixel mean value difference is used toward distinguishes the lesion field, and the thresholding technique is used to simplify the process. For the segmentation method, Jianping Fan et al. [26] created a habitual seeded province increasing algorithm in addition to an automatic seed selection tool. Used for automated moving object extraction, a seed tracking algorithm is also proposed. It is used to detect exposed context and new items, such as moving objects that are situated within the temporal shift mask.

In order to anticipate significant CT scan features, Sekaran et al. [27] developed a convolutional neural network (CNN) model that was inserted in a Gaussian mixture model using the EM algorithm and a projection of the spread of pancreatic cancer [26]. One such field that has extended its work into medical imaging is deep learning. When integrated with a variety of tools like CT/PET Scan systems, deep learning may automate the process of detecting patient issues.

Zhang et al. [28] introduced a hybrid high-performance deep learning model that facilitates automated workflows and ultimately frees up pathologists' priceless time. Convolutional Neural Networks (CNNs) considerably expand Transformer's global modelling by supplying spatial information, introducing the Transformer block for the first time in the area utilizing a distinctive multi-level hybrid design. The method combines the resilience of the induced biases of CNNs and the potent global modelling capabilities of Transformer by utilizing multi-level spatial features as the direction of global attention [27].

Wu et al. [29] have developed a deep learning model based on graph convolutional networks to distinguish between aggressive and malignant pancreatic cancers. In order to extract specific information from each little area of a whole-slide image, our approach employs a convolutional neural network. In order to capture the whole-slide level structure and produce the final forecast, the recovered characteristics from these regions and their positional information are then aggregated by humans utilizing graph architecture. On an independent test set, our model greatly outperformed earlier baseline approaches, identifying neoplastic cells and ductal adenocarcinoma with an F1 score of 0.85 [28].

The major contributions of the research are,

- To develop Artificial Intelligence based automated CAD tools for early detection and classification of pancreatic cancer.
- Preprocessing is done by using Colour conversion and an isotropic diffusion filter techniques. After that Fuzzy K-NN Equality algorithm is proposed for image segmentation.
- To design Hybrid method of deep convolutional neural network with deep belief network (DCNN_

DBN) algorithm for the detection and classification of pancreatic cancer.
- Accuracy, sensitivity, specificity, precision, and error rate are performance metrics used to assess the proposed system's performance.

3. Proposed methodology

The usage of the red Pancreatic Cell Tumour Categorization PCCD dataset photos, which include both benign and malignant phase sample photographs, is the main topic of this section. Through the help out of the chapter 2 survey, a new algorithm is implemented at each phase of image processing. The block diagram of proposed methodology was shown in Figure 1.

Pre-processing an image is an important step in any categorization since it prepares the image for later processing. To make the process easier, the pancreatic model CT scan figure RGB colour images are first rehabilitated to HSV images. Colour conversion and an isotropic diffusion filter were used as preprocessing approaches. After the pre-processing stage, the recital from this phase is sent on the way to segmentation technique on the way to eliminate the malignant region from CT images. Proposed Fuzzy K-NN Equality algorithm used in segmentation procedures. Deep Learning with feature extraction is used as a classification tool. Tumour cells are classified using the features collected from the pancreatic sample. Train values and testing datasets are part of the image classification criterion. At Each image in the dataset pertains to numerous feature values and attribute categorization. Hybrid method of deep convolutional neural network with deep belief network (DCNN_DBN) algorithm is used for detecting pancreatic cancer.

3.1. Data base

The proposed system use the Pancreatic Cell Images dataset (PCCD), by means of the 534 patients pancreatic 200 benign and 200 malignant images.

The dataset is stratified at random, with 80% of the testing set and 20% of the evaluation set being included. Deep learning models may be hampered by a limited number of examples in the training collection. As a result, we used an image segmentation technique to add more images to the training set by rotating and flipping the WBC images. We employed pre-trained models from the Image Net Dataset in this research, and our training set fine-tuned their weight. The best models were chosen using five-fold cross-validation and were chosen based on validity accuracy. The number of epochs is the tuning parameter for both models. All training data were utilized to generate a model with the optimal configuration when the optimal epoch was found. The test set is used to evaluate the model.

3.2. Pre-processing

Pre-processing an image is an important step in any categorization since it prepares the image for later processing. The most popular method of colour conversion is blending, which produces RBC subtractive colour layers, which aid in the application's use by describing the colour mixture. To achieve better results, an isolateral filter is used, which adjusts image intensities to improve both background and foreground contrast. This method is commonly used to improve image global contrast, especially when the image's available data is given in near contrast values. For the segmentation procedure, the final improved image has superior visual clarity and nodules are plainly evident.

3.3. Segmentation

This segment discusses a novel Fuzzy K-NN Equality algorithm. The probabilistic module FK-NNE's individual neighbour membership is also the beginning point of the procedure that leads to the abandonment of association in order to perform vector elimination from K-NN. Assign the pattern vector as a function set membership. It contains individual neighbour memberships of promising classes, and vector distances from the K-NN method. After K points, the average distance is taken into account to test the data. The output class values are calculated and saved using the reduced mean value distance. This clustering method does an excellent job at identifying pixel groupings. Fuzzy K-Nearest Neighbour Equality is the first step in the offered solution. The average distance between allocated pixels and cluster centres is decreased by allocating pixel shapes to clusters that fit the image. Based on past knowledge of the image collection, the suggested semantic segmentation is applied to identify the minimal area threshold values. The region's boundaries in the foreground pixels are widened using it. The segmentation of an image depends on its attributes and structural composition.

Structure of FK-NNE:

FK-NNE Convolutional Systems are a type of convolutional system. Three types of strata are often used to construct a structure. Convolutional, Pooling, or totally related layers are all possible. Impeach type of layer has separate tenets for forward and error reverse signal propagation. There are no precise guidelines for how individual layers should be constructed. However, in the case of late advancement, FK-NNE is usually divided into 2 portions. The feature extraction segment uses a combination of convolutional in addition

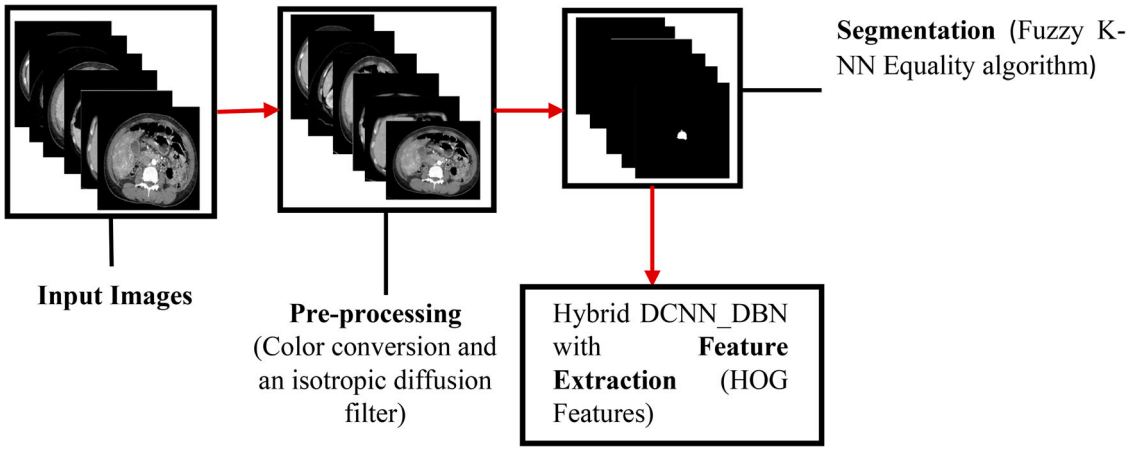

Figure 1. Block diagram of proposed methodology.

to pooling layers. The next component is called categorization, and it involves using layers that are entirely related.

Cartesian coordinates is defined as,

$$(x-a)^2+(y-b)^2=r^2 \tag{1}$$

Deep learning is the most inconvenient way for detecting hidden layers, as well as it classifies specific malignant cells since a broader microscopic dataset, with the equation gives the image's fitness value as,

$$f=(A-K+2E)/S+1 \tag{2}$$

Where, W – Input size of the input
K – Size of kernel
S – Number of pixels
E – Padded image
The significance of P can be found as,

$$\mathrm{E}=(\mathrm{K}-1)/2 \tag{3}$$

3.4. Feature extraction

Histogram-based features, in which the feature is dependent on threshold-based values, are mostly evaluated for feature extraction. The pancreatic cancer image is classified using these features by the classifier. The feature in Histogram-based features can be obtained by generating the histogram. The ResNet-50 inceptive synergic network classifier is a feature-extraction-capable classification system. 200 images of benign and malignant stages of database images were acquired for testing purposes. These database photos are used to extract histogram-based attributes.

Pairs of image representations must be fed into the synergic signal scheme. The property of a pair is denoted by choosing image pairs at random from the training results.

$$S(x_A,x_B)=\begin{Bmatrix}1\ if\ y_A=y_B\\0\ if\ y_A\neq y_B\end{Bmatrix} \tag{4}$$

contrast	$C_t=\sum_{a}^{N}\sum_{b}^{N}(a-b)^2p(a,b)$
Correlation	$\sum_{\mathrm{i=0}}^{\mathrm{N_{p-1}}}\sum_{\mathrm{j=0}}^{\mathrm{N_{p-1}}}\frac{(\mathrm{i}-\mu_i)(\mathrm{j}-\mu_j)\mathrm{p(i,j)}}{\sigma_i\sigma_j}$
Dissimilarity	$D=\sum_{a,b=1}^{N}C_{a,b}\lvert a-b\rvert$
Cluster prominence	$C_p=\sum_{a=0}^{N-}\sum_{b=0}^{N-1}\{i+j-\mu_x-\mu_y\}^4*p(a,b)$
Cluster Shade	$C_s=\sum_{a=0}^{N-}\sum_{b=0}^{N-1}(a+b-\mu_x-\mu_y)^3p(a,b)$
Maximum Probability	$maxprob=max_{a,b}p_d[a,b]$
Entropy	$E=\sum_{a=0}^{N}\sum_{b=0}^{N}p(a,b)log(p(i,j)$

where XA and XB are the outputs of FC1024-A and FC1024-B, respectively, and yA and yB are the real labels of XA and XB.

Here, "S = 1" is a pair of positive and "S = 0" is a pair of negative.

The number of positive pairs in a batch should be between 45 and 55 percent to prevent the unbalanced data problem. Different features extracted as,

3.5. Classification using hybrid DCNN_DBN

This research method is used in hybrid model to classify the image. For this hybrid DCNN and deep belief network (DBN) are used.

n-DCNN modules and C_n^2synergic networks make up the proposed model. The DCNN parameters and synergic network can be changed if required during the end-to-end preparation.

$$\begin{cases}\theta^{(i)}(q+1)=\theta^{(i)}(q)-\eta(q).\Delta^{(i)}\\ \theta^{d(i,j)}(q+1)=\theta^{d(i,j)}(q)-\eta(q).\Delta^{s(i,j)}\end{cases} \tag{5}$$

Where $\eta(q)$ denotes the vector rate, d(i, j) denotes the DCNN- i and DCNN- j synergic network, and

$$\Delta^{(i)}=\frac{\partial g^{(i)}(\theta^{(i)})}{\partial\theta^{(i)}}+\lambda\sum_{j=1,j\neq1}^{n}\frac{\partial g^{d(i,j)}(\theta^{d(i,j)})}{\partial\theta^{d(i,j)}} \tag{6}$$

$$\Delta^{d(i,j)} = \frac{\partial g^{d(i,j)}(\theta^{d(i,j)})}{\partial \theta^{d(i,j)}} \tag{7}$$

And λ denotes the trade-off between error of subversion classification and error in synergic. Algorithm 1 summarizes SDL^2 model's phase of training, which can be generalized to the SDL^n model's training.

Algorithm 1: The proposed model's training phase

Insert:

Batches of images $M_1 = \{M_1^{(1)}, M_1^{(2)}, M_1^{(3)} \ldots\ldots\ldots, M_1^{(V)}\}$, $M_2 = \{M_2^{(1)}, M_2^{(2)}, M_2^{(3)} \ldots\ldots\ldots, M_2^{(V)}\}$ and $M_3 = \{M_3^{(1)}, M_3^{(2)}, M_3^{(3)} \ldots\ldots\ldots, M_3^{(V)}\}$, $\theta^{(1)}, \theta^{(2)}, \theta^{(3)}$ *and* $\theta^{(S)}$ initialization parameters of dual DCNNs and synergic network, learning rate (t), and hyper parameter

Step 1: Forward Propagation:

$$L_1 = q(M_1, \theta^{(1)})$$

$$L_2 = q(M_2, \theta^{(2)})$$

$$L_3 = q(M_3, \theta^{(3)})$$

Step 2: ConcatenateL_1, L_2 and L_3 to $L_{102} = \{L_{102}^{(1)}, L_{102}^{(2)}, L_{102}^{(3)} \ldots\ldots\ldots, L_{102}^{(M)}\}$ where $L_{102}^{(1)}$ represents the combination of $L_1^{(1)}$, $L_2^{(1)}$ and $L_3^{(1)}$, and add them to the network of synergies. All four supervisions have the following labels:

$$\begin{aligned}
\text{W_1} &= \{\text{W_1}\hat{}((1)), \text{W_1}\hat{}((2)), \text{W_1}\hat{}((3)). \\
&\quad \ldots\ldots\ldots, \text{W_1}\hat{}((\text{M}))\}, \\
\text{W_2} &= \{\text{W_2}\hat{}((1)), \text{W_2}\hat{}((2)), \text{W_2}\hat{}((3)). \\
&\quad \ldots\ldots\ldots, \text{W_2}\hat{}((\text{M}))\}, \\
\text{W_3} &= \{\text{W_3}\hat{}((1)), \text{W_3}\hat{}((2)), \text{W_3}\hat{}((3)). \\
&\quad \ldots\ldots\ldots, \text{W_3}\hat{}((\text{M}))\}, \text{ and} \\
\text{W_s} &= \{\text{W}_\text{s}\hat{}((1)), \text{W_s}\hat{}((2)), \text{W_s}\hat{}((3)). \\
&\quad \ldots\ldots\ldots, \text{W_s}\hat{}((\text{M}))\},
\end{aligned}$$

Where,

$$\begin{aligned}
&\text{W_s}\hat{}((1)) - 1 \text{ if } \text{W_1}\hat{}((1)) - \text{W_2}\hat{}((1)), \\
&\quad \text{otherwise } W_s\hat{}(1) = 0.
\end{aligned}$$

Step 3: Update parameter $\theta^{(1)}, \theta^{(2)}, \theta^{(3)}$ *and* $\theta^{(S)}$ by using back-propagation algorithm.

Compute loss:

$$\begin{aligned}
&\text{k}\hat{}((1))\ \theta\hat{}((1)), \text{k}\hat{}((2))\ \theta\hat{}((2)), \text{k}\hat{}((3))\ \theta\hat{}((3)) \\
&\quad \text{and } \text{k}\hat{}((\text{s}))\ \theta\hat{}((\text{S})),
\end{aligned}$$

Compute gradient:

$$\Delta^s = \frac{\partial k^s(\theta^{(s)})}{\partial \theta^s}$$

$$\Delta^{(1)} = \frac{\partial k^{(1)}(\theta^{(1)})}{\partial \theta^{(1)}} + \lambda \Delta^s,$$

$$\Delta^{(2)} = \frac{\partial k^{(2)}(\theta^{(2)})}{\partial \theta^{(2)}} + \lambda \Delta^s$$

and

$$\Delta^{(3)} = \frac{\partial k^{(3)}(\theta^{(3)})}{\partial \theta^{(3)}} + \lambda \Delta^s$$

Parameters are updated:

$$\theta\hat{}((1))(q+1) \leftarrow \theta\hat{}((1))(q) - \eta(q).\Delta\hat{}((1))$$

$$\theta\hat{}((2))(q+1) \leftarrow \theta\hat{}((2))(q) - \eta(q).\Delta\hat{}((2))$$

$$\theta\hat{}((3))(q+1) \leftarrow \theta\hat{}((3))(q) - \eta(q).\Delta\hat{}((3))$$

and

$$\theta^s(q+1) \leftarrow \theta^s(q) - \eta(q).\Delta^s$$

As the qualified SDL^n model is applied in the X where, X is the test image, each DCNN variable DCNN- i produces a prediction error of vector $D^{(i)} = D_1^{(i)}, D_2^{(i)}, D_3^{(i)} \ldots\ldots\ldots, D_K^{(i)}$, where the signals in last totally connected sheet are represented by this. The class mark on this test picture can be projected as

$$W(x) = arg_j max \left\{ \sum_{i=1}^{n} D_1^{(i)} \ldots\ldots \sum_{i=1}^{n} D_j^{(i)} \ldots\ldots \sum_{i=1}^{n} D_k^{(i)} \right\} \tag{8}$$

Algorithm 2: The testing process of the proposed model.

Input:

Program Y, property ϕ, abstract input Z^3, abstract domain D

Output:

Result H, refined abstract input Z'^3, program invariant $Inv_b^{Z^3}$

Step 1: if size checking (Z^3) then

Step 2: H = be testing (Y, $Z^{\#}$)

Step 3: $\boldsymbol{Z'^{\#} \leftarrow \perp}$

Step 4: $\boldsymbol{Inv_b^{Z^{\#}} \leftarrow \perp}$

Step 5: Else

Step 6: (res, $Z'^{\#}$, $Inv_b^{Z^{\#}}$) = Abstract testing (p, ψ, $Z^{\#}$, D)

Step 7: End if

Step 8: Return res $Z'^{\#}$, $Inv_b^{Z^{\#}}$

A deep belief network (DBN) is a type of deep neural network that produces graphical models, made up of layers of latent variables. The latent variables are connected to each other, but not to the entities within each layer. DBN can be viewed as a set of simple learning modules. Each module is a specific type of her RBM with obvious unifying layers. Information is represented by this layer. The second layer of hidden units represents features of the data that record higher-order correlations. There are no links between the two levels, which are connected by a matrix of symmetrically weighted links (W). The RBM-trained DBN weights (w) specify both the hidden vector's (h) (v|h,w) and the

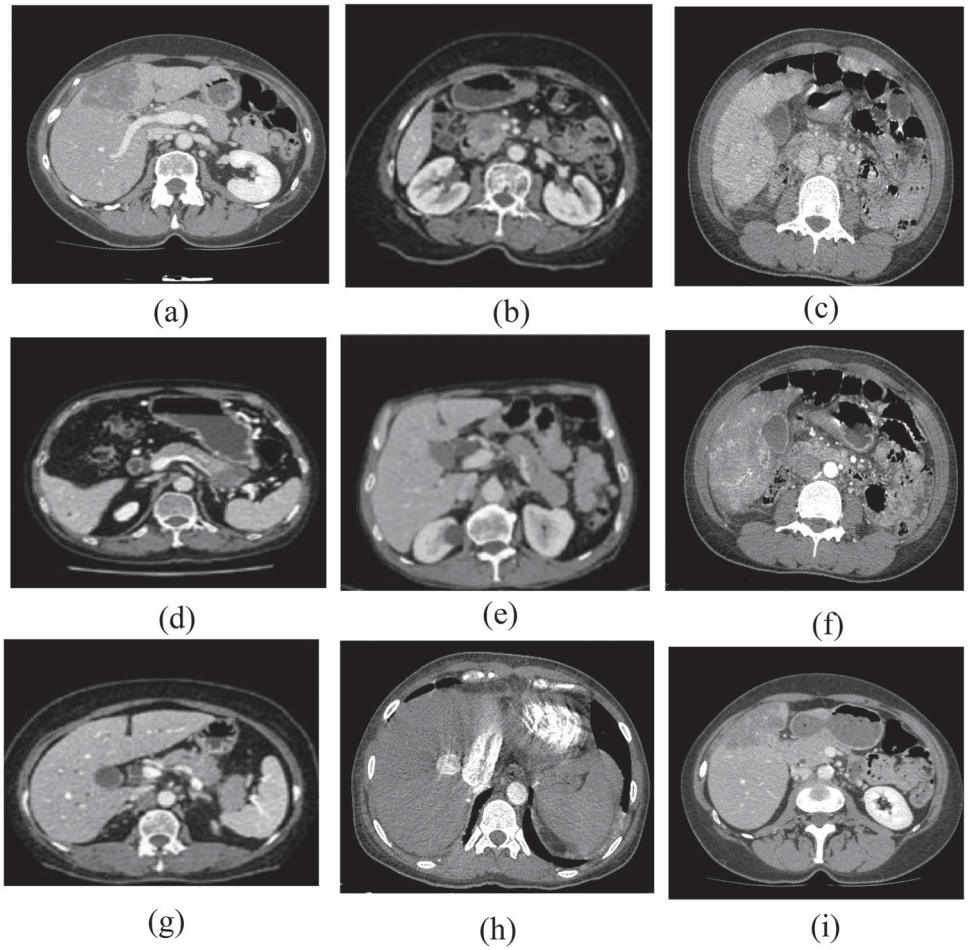

Figure 2. Pancreatic dataset samples.

prior distribution's (h|w) parameters. Given by, is the likelihood of creating a visible vector.

$$\rho(v) = \sum_{h}(\rho\ (\mathrm{h}\ |\mathrm{w})\ \rho(\mathrm{v}|\mathrm{h},\mathrm{w})) \tag{9}$$

RBMs can be layered and trained using a greedy method to create a DBN, a computational structure. He created the DBN quick learning technique. The weight updates between visible v and concealed h are listed below.

$$\Delta w_y = \varepsilon(\langle v_i, h_j\rangle^0 - \langle v_i, h_j\rangle^1) \tag{10}$$

The numbers 0 and 1 in the calculation above, respectively, stand in for network data and rebuild state.

It features a network trainer, numerous nonlinear hidden layers, generative pretrained, a nonlinear dimensionality reduction of the input feature vector, and the ability to be fine-tuned as a neural network. If the data is given enough priority, this increases accuracy.

4. Results and discussion

This section presents the findings of a comparative examination using pancreatic tumour samples from the database image. 1800 PCCD dataset CT images are used in this innovative application of pancreatic tumour classification, which comprises both benign and malignant stage sample images. For the first stage of pre-processing the sampled images, colour conversion and isotropic diffusion filter are utilized. To differentiate the pancreatic tumour cell from the tumour region, we have employed a Fuzzy KNN Equality segmentation technique followed by deep learning with Feature HOG features extracted and classified using the hybrid architecture based on severity. This contributes to the development of segmentation and classification algorithms for using the CAD system to diagnose pancreatic tumour sample images. A confusion matrix and ROC curve are plotted for each of the above classification algorithms. The data were plotted using MATLAB 2019b software, which contains statistical capabilities.

4.1. Sample image

The images for the input are aquired from the PCCD dataset. The proposed method was used to segment and classify 180 benign and malignant samples from 1800 individuals obtained from the PCCD database.

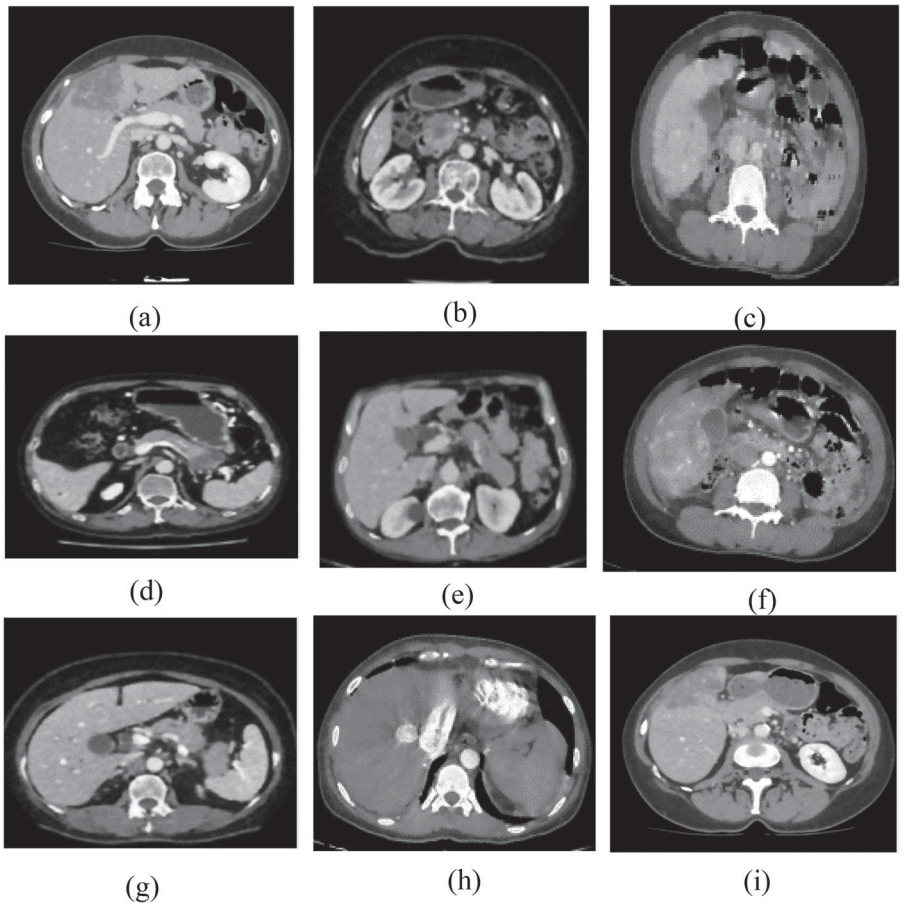

Figure 3. Pre-processed image.

180 pancreatic tumour samples were utilized for testing and 180 tumour samples were used for preparation. Figure 2 shows the sample images obtained from PCCD dataset.

4.2. Pre-processing

Pre-processing an image is an important step in any categorization since it prepares the image for later processing. Colour conversion is accomplished by combining pancreatic tumour subtractive coloured layers for a given application and colour combination. This phase is followed by isotropic diffusion filtering of the image. The preprocessing output is given in Figure 3.

4.3. Segmentation of images

The output from pre-processing phase is delivered to segmentation technique toward eliminate the malignant locale as of the CT images after the pre-processing level. Parts of medical imaging are frequently applicable to a variety of tissue types, organs, diseases, or physiologically related structures. This type of RBC segmentation can be seen during small dissimilarity rising noise components as well as extra imaging issues. The maximize MRF function corresponds to the detection of attribute value by means of allusion toward label in the image in terms of the function applied to the proposed segmentation assignment. The segmentation findings of PCCD benign as well as malignant Pancreatic Cell tumour sample of the proposed system are exposed in Figure 4.

In our proposed segmentation, all the foreground objects are considered which includes even the normal tissue parts. To widen the field borders in the foreground pixels, the segmentation region is used. The image may be segmented based on the image's form and characteristics. Initially, the image's tiny components are extracted. The FK-NNE is focused on various image processing methods that are used to distinguish between normal and tumour cells in the pancreas. Segmenting the picture that has lighter points in the background at the portion of the cells is a quick but effective solution. Even at the narrower region of the pancreatic cell, this segmentation often divides the cancer cells. The proposed semantic segmentation is carried out for proper diagnosis as well as automated segmentation for proper use in medical research. This approach overcomes many of the limitations of current approaches for distinguishing cancer cells from unaffected cells, resulting in reliable visual performance.

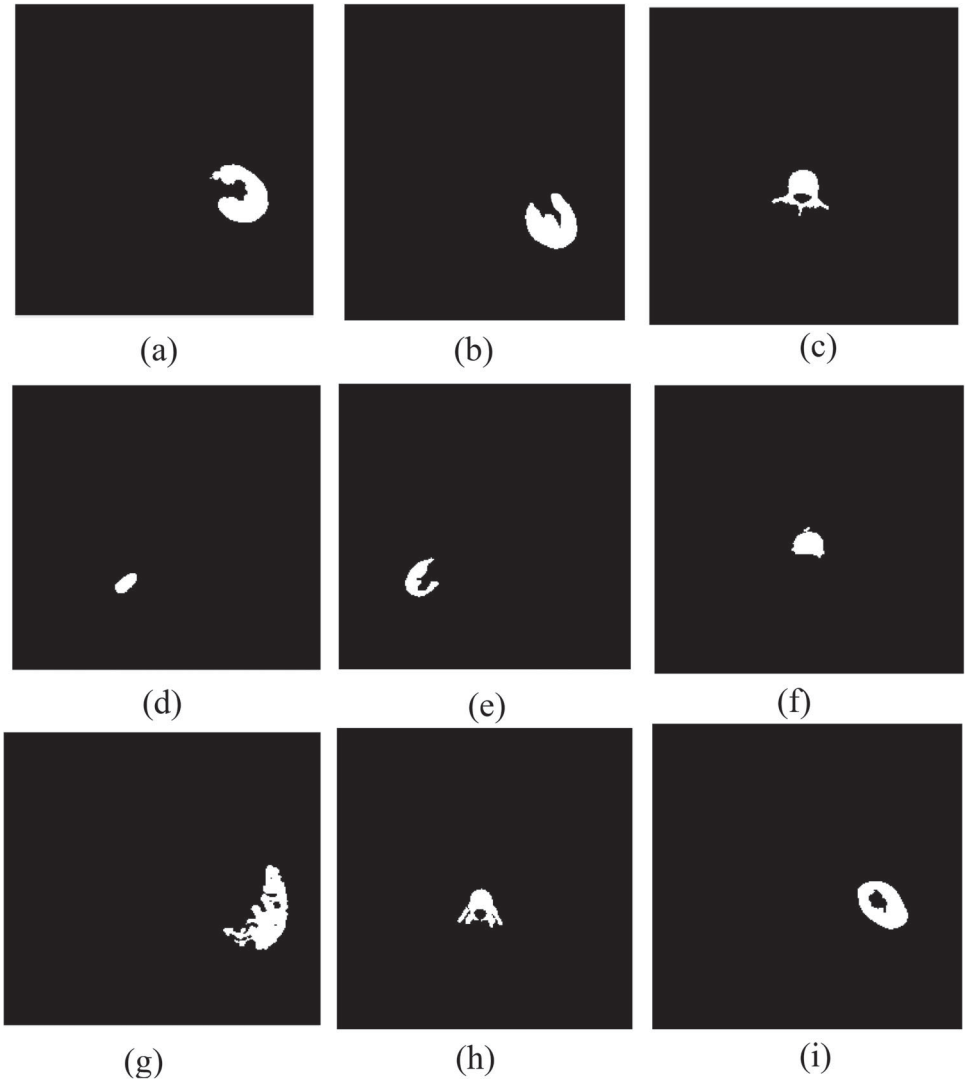

Figure 4. Segmentation output.

4.4. Feature extraction

Feature extraction is a technique for assessing the texture of an image. The outcome is visible when both object shape and texture are identified. If the method's input data set is huge, it should be scaled down for processing simplicity. The process of turning an input image into a predetermined set of features is known as feature extraction.

The major evaluation method for feature extraction involves histogram-based features, whose features depend on threshold-based values. The classifier categorizes lung disease in photos using these features. Histograms can be created, and characteristics can be derived from them. Hybrid DCNN_DBN Classifier is an effective feature extraction and classification technique for deep learning. 200 images from the database, including both benign and malignant stages, were collected for testing. Histogram-based characteristics are retrieved from these database images (Table 1).

Table 1. HOG Feature Extraction.

Image	Contrast	Correlation	Energy	Homogeneity
(a)	0.783028	0.926455	0.054512	0.757352
(b)	0.481376	0.948325	0.100345	0.852946
(c)	0.833245	0.924934	0.061324	0.762435
(d)	0.437586	0.960132	0.104352	0.876582
(e)	0.481287	0.957821	0.140121	0.893675
(f)	0.461984	0.951013	0.101015	0.857371
(g)	0.259839	0.973321	0.078812	0.874435
(h)	0.456727	0.951895	0.100012	0.853271
(i)	0.773924	0.924623	0.048154	0.750156

4.5. Proposed classifier

Using deep learning techniques, automated cell detection in cancer-affected areas has been established and has classified under *various* subclasses. Deep learning of neural networks requires large amount of training sequences. The proposed method outperformed earlier identical method because it does not involve image segmentation at the microscopic stage, which is needed

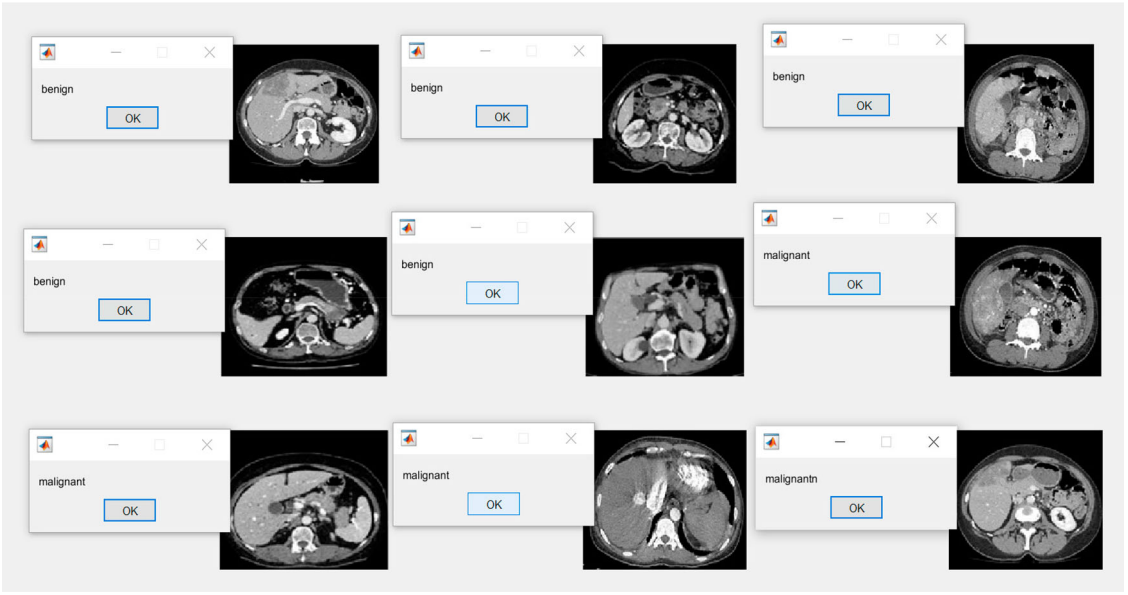

Figure 5. Classified image.

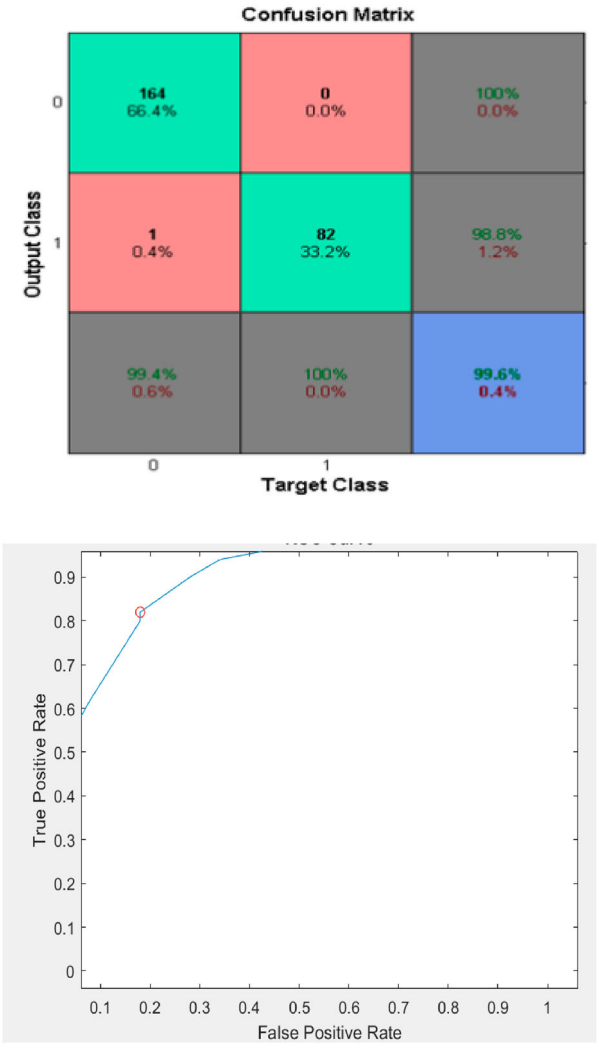

Figure 6. Classifier outputs for proposed hybrid classifier: (a) Matrix of Confusion, (b) ROC Curve.

by additional feature extraction method. Deep learning hidden layers are most efficient at automatically identifying and classifying individual cancer cells from larger microscopic data sets. A hybrid Deep Convolutional Neural Network with Deep Belief Network (DCNN_DBN) approach is used to create a classification model based on predictions of specific reference characteristics of current values of dataset variables. A classification image is shown in Figure 5. The confusion matrix and ROC curve of the hybrid approach of Deep Convolutional Neural Network and Deep Belief Network (DCNN_DBN) classifier are shown in Figure 6.

4.6. Performance evaluation

Performance of Pancreatic Cell tumour CT scan database images (benign and malignant) are analyzed by classification accuracy, sensitivity, specificity, error and precision. The performance parameters are defined in equations (5.1-5.5). The number of TPs and TNs obtained with the Machine learning classification model is higher than with other approaches.

Accuracy – The accuracy of the classification system used to distinguish tumour regions from pancreatic CT images is called accuracy.

$$Accuracy = (TP + TN)/(TP + FP + TN + FN) \times 100\% \quad (11)$$

Sensitivity – Sensitivity is the proportion of the real cancerous area that the classification system has correctly identified.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{FN} + \text{TP}} \times 100\% \quad (12)$$

Specificity – The percentage of the true backdrop of the malignant area that the normative system has detected.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \quad (13)$$

Precision – It shows what percentage of the detected area is the true region.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \text{X}100\% \quad (14)$$

Error – It measures the discrepancy between backgrounds and object region.

$$\text{Error} = \frac{\text{FP} + \text{FN}}{\text{TP} + \text{FN}} \text{X}100\% \quad (15)$$

Accuracy of the proposed hybrid classifier, total number of test samples $((1-0.63836) * 683) = 247$, true positives (TP) = 82, true negatives (TN) = 164, false positives (FP) = 1 and false Negative (FN) = 0.100 * TP / (TP + FN) = 100 percent sensitivity 100 * TN / (TN + FP) = 100 * 164/165 = 99.39 percent specificity Accuracy rating is 99.6 percent.

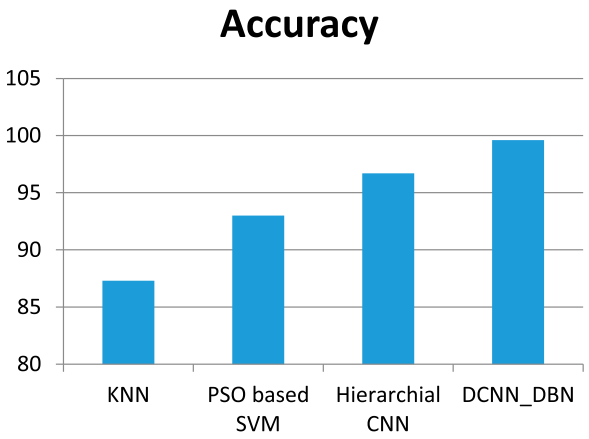

Figure 7. Comparative analysis of accuracy.

Table 2. Computation time.

Model	Computation time
[30]	0.2 s
Proposed method	0.15 s

The accuracy obtained using proposed hybrid classifier is 99.6% which is higher than that those obtained using various attributes. The probability of the positive and negative labels being valid is approximated by the specificity and sensitivity. Time is 22 s which is low when compared to other classifier. Comparative analysis of accuracy is depicted in Figure 7. Table 2 represent the computation time.

5. Conclusion

In this research, images from the PCCD database of pancreatic cancer were used. As a preprocessing procedure, Colour Conversion and Anisolateral filter are applied to the database image. FK-NNE is used to segment tumour areas, and Histogram-based features are extracting. A hybrid Deep Convolutional Neural Network with Deep Believe Network (DCNN_DBN) classifier is used to categorize pancreatic cell tumour images as benign or malignant. The classifier's sensitivity, specificity, precision, error value, and precision are assessed. The overall accuracy of the neural network increased to 99.6% with 100% sensitivity and 99.47% specificity using a hybrid Deep Convolutional Neural Network approach with a Deep Believe Network (DCNN_DBN) classifier. In the future, the classification performance of the proposed technique can be enhanced using DL-based segmentation algorithms. Also further classification done on stages of pancreatic tumour cell.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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