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Original Article

An Innovative Hybrid Deep Neural Network-Based system For Early Detection of Pancreatic Cancer

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Abstract

Pancreatic cancer (PC) can be considered one of the deadliest cancers, with the overall five-year survival at the level of almost 5%. Knowing how to predict and detect early is important in improving patient outcomes. The standard means of diagnosis including CT, MRI with cholangiopancreatography (MRCP) and biopsy, are commonly susceptible to sensitivity and specificity at early stages of the disease. To overcome this, we propose a computer aided diagnostic (CAD) system-based architecture that incorporates various stages involving image processing, segmentation, extraction of features and classification. The first step is preprocessing that goes through the color conversion and isotropic diffusion filtering to improve the image quality and then the segmentation using the Fuzzy K-NN Equality algorithm. The feature extraction is carried out and Deep Convolutional Neural Networks (DCNN) and Deep Belief Networks (DBN) are hybridized in the process of carrying out the classification. Extracted pancreatic features are used to classify tumor cells and datasets were split with the aim of separating into training and testing sets to verify performance. Comparison results show that the proposed CAD system has the benefit of high reliability of classification and a maximum reduction in complexity among all benign and malignant cases. The hybrid framework has a high promise of extending the use of automated diagnostic devices and can be maximized to scan over pancreatic cancer abnormalities.

Keywords: *Computer-assisted diagnosis; image classification; deep convolutional neural network; deep belief network; pancreatic cancer*

Introduction

The pancreas is located at the back of the stomach and helps in the regulation of blood sugar through the release of the hormones and production of digestive enzymes. Abnormal tissue masses or inflammations in the pancreas may result in pancreatic cystic lesions (PCL) that can promote pancreatic cancer. Pancreatic cancer is a malignancy that develops in the tissues of this organ and leads to the death of millions of people all around the world. Its incidence is growing and currently, data compiled in 2018 point to about 1.66 million new cases in the United States alone, of which nearly 586,000 have been fatal. Through such statistics, cancer poses a major health problem to the citizens in all regions hence endangering their health status. The most prevalently diagnosed malignancies that affect the bladder, lungs, colon, rectum and prostate of human beings are cancerous. The most prevalent cancer in women is breast, lung and bronchial, colorectal, uterine, and thyroid cancer, whereas charges of breast cancers and prostate cancer make up a significant amount of cancer in general. Nevertheless, pancreatic cancer, together with brain and lymphatic malignances, is one of the deadliest kinds, especially considering its high death toll in adults and children. The use of computer-aided diagnostic (CAD) systems is becoming more important in enhancing the monitoring, predicting, and classification of pancreatic tumor [4-8]. Notoriously known to have non-outstanding prognosis and low survival rates, pancreatic cancer has so far no definite cure. Depending on the size of the tumor, chances are that it can be removed with the help of the therapeutic formula. When a patient has pancreatic cancer, the cells of the healthy pancreas begin to change abnormally and undergo uncontrolled division with the development of malignant formations. Not only do these cancerous tumors inhibit normal pancreatic functioning but they also have the capacity to relocate (metastasize) to other body parts, further deteriorating patient survival [9-12].

The problem of precise segmentation of pancreatic structures on CT images is also a rather complicated task because of constant diversities of the dataset and the drawbacks of the artificial segmentation procedures. The main problems that complicate this task are low grayscale contrast of anatomical structures and a low degree of differentiation of the pancreas, intestine, and surrounding parenchyma, especially those areas closest to the duodenum.

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Moreover, large variability of peripancreatic fat distribution, inconsistencies in the pancreatic volume, and variable texture of the pancreatic parenchyma increase the complexity of the segmentation task [13,14]. In order to overcome these issues, this paper presents a hybrid computer-aided diagnostic (CAD) system to perform early diagnosis and classification of pancreatic cancer based on CT images. Preprocessing steps on the system will be run before additional processes are completed and include color transformation and isotropic diffusion filtering, in a bid to eliminate image noise and improve quality. The images are subsequently preprocessed after which a fuzzy K-NN equality algorithm is used to identify cancerous areas. Deep learning is used in combination with feature extraction to classify tumor cells, ensuring that cells can be categorized efficiently using features generated by a pancreatic tissue sample [15,17,18,19].

Figure 1. Tissue from a pancreatic cancer CT scan.

The classification model is dependent on training and test sets, each image in the set is represented by a series of features and attribute classification. A DCNN-DBN model is applied to the robust tumor detection task as the data is very challenging in nature and this variation is effectively dealt by the model.

Section 2 of this paper gives a thorough review of the related literature. Section 3 provides the top-level system design consisting of the block diagram, a description of the proposed hybrid DCNN-DBN architecture in detail. The results are presented in section 4, both quantitatively and qualitatively analysing the proposed framework. The quality measurement indices and analysis values in gauging the efficiency of the classifier are also furnished. Lastly, Section 5 provides a conclusion and recommendations on the future research.

Literature Review

In the recent years couple of more advanced techniques have been suggested to detect pancreatic cancer through CT imaging. Ajanthaa et al. (2021) published a preprocessing of bilateral filtering (BF) to eliminate noise in CT pancreatic scans. The segmentation of the authors was done using NIGC technique, feature extraction was performed using the ResNet152 model which Vectors give robust features. Diagnosis was conducted in terms of RDA-BPNN model, the Back Propagation Neural Network (BPNN) was optimised by the Red Deer Algorithm (RDA) to attain diagnostic excellence [20]. Yang et al. [22] developed a multi-channel and multi-classifier model (MMRF-ResNet) that classifies the MCN and SCN neoplasia in the pancreas. Single channel ROI outline images, multi-channel, advanced feature descriptors like waves, LBP, HOG, and GLCM, and deep-learning methods such as ResNet and AlexNet were all integrated into their system. In terms of classification they compared different approaches such as KNN, Softmax, Bayesian classifiers, Random Forests and a Majority Voting Rule method. A quantitative measure with values such as sensitivity, specificity, accuracy, and F 1 -score, and area under the curve was used to measure the performance against pathology-based ground truth, which proved a robust imaging-based decision framework [21]. Chang et al. [1] considered histological classification of tissue and used morphometric tissue characteristics as intermediate representations. They used pixel- and patch-based features in combination with spatial pyramid matching at the various scales to learn detailed morphometric patterns. Each of these features demonstrated the high classification accuracy with comparatively small training sets, which made them powerful even across a variety of tumor morphologies and unperturbed in the face of biological and technical variation [1]. Chang et al. [2] conducted another study, where they offered a deep learning strategy in the classification of single-cell nucleus. Focused image-label supervision (FIS) was employed, where CNN was used to learn the label of each pixel using IF images as labels to compensate the weaknesses of limited pathologist-annotated datasets. The approach allowed to classify malignant and benign cells reliably at the single-cell level based on large-scale data [2]. Jiang et al. [4] proposed a new pancreatic cancer classification model that incorporated quantum theory and the fruit fly optimization algorithm (FOA) into one. The authors integrated quantum coding and quantum operation in the enhancement of FOA, as well as a novel mechanism of odor-awareness. This is used to optimize a FOA, and apply to fine-tune the parameters of a support vector machine (SVM), a final classifier, showing its better performance in discriminating between pancreatic cancer cases [4]. Moschopoulos et al. [10] pointed out that finding a small, but important number of biomarkers associated with the detection of pancreatic cancer was important. They have used a Genetic Algorithm (GA) on pancreatic ductal adenocarcinoma (PDAC) data and this generated a reduced list of biomarkers that are pivotal in disease progression. Equally, Pahari et al. [5] performed a spectral clustering research to study PDAC gene expression data of high dimension available at GEO. Their approach has been able to cluster the pancreatic data set because they used a measure of distance based on a Shannon entropy. KEGG pathway analysis was used to help identify biomarkers in the study, and functional similarity of genes were backed up by the use of Gene Ontology (GO), which further validated results of the study and rendered them more conclusive and significant. Clinically, the greatest challenge in imaging of the pancreatectomy is the use of abdominal ultrasonography as a primary mode of identifying the mass, whereas contrast-enhanced ultrasound (CEUS) and contrast-enhanced computed tomography (CECT) have found applications high in referral institutions. In the management of solid lesions in the pancreatic gland, CEUS has presented a commendable accuracy in the identification and characterization of such lesions using transabdominal as well as an endoscopic approach. To overcome these limitations of imaging, Zanaty and Ghoniemy [22] described a new automated thresholding method to segment MRI images interestingly, specifically low-contrast images where the information at the boundaries may be corrupted. A SRG algorithm to segment pancreatic parenchyma based on texture features was proposed by JieWu et al. Its optimized texture-driven SRG approach can automatically and parameter-free segment abdominal MRI, providing cost-effectiveness in batch processing and accessibility to non-experts. Beyond the pancreatic imaging, Bliznakova et al. [23] have created a new framework in liver CT scans that facilitated segmentation, volume calculation, visualisation and virtual cutting that helped in surgical planning to patients with chronic kidney disease, using multiple embarked region growing method. Some researchers have applied optimization-based forms of segmentation. To illustrate, Al-Faris et al. [24] presented a modified SRG approach that contains PSO to segment brain tumour in MRI. Morphological thinning and active contours were used as preprocessing steps and then combined with PSO-based clustering with the aim of better seed selection and thresholding. The performance was found to be better than that of other traditional cluster solutions like the K-means, fuzzy C-means and the genetic algorithm. Similarly, Saad et al. [25] employed a region-growing approach to the automatic segmentation of brain lesion in diffusion-weighted MRI. Their approach utilized differences in pixel intensities and mean-value, whereas Yianping Fan and colleagues [26] used a seeded region growth algorithm with tracking seeds that was able to detect motion and dynamic regions. The use of deep learning has made significant dynamic progress in medical imaging analysis. The investigation introduced by Sekaran et al. [27] shows promise of machine learning in the automation of CT scan diagnostics by suggesting an integrated CNN and a Gaussian mixture model employing the EM algorithm to make CT scan feature predictions of pancreatic cancer. Most recently, Zhang et al. [28] proposed a hybrid deep learning architecture that utilized both the capacity of Convolutional Neural Networks (CNNs) to extract the spatial features and the global learning ability of Transformer networks. The description of this multilevel hybrid design offers an advantage of increasing automated processes of medical imaging that offer precise and efficient diagnosis support with a decreasing burden on pathologists, and their workload. Wu et al. [29] presented a deep learning model based on graph convolution networks with the aim of distinguishing between aggressive and malignant pancreatic cancer. Their method takes advantage of convolutional neural networks to derive detailed data out of localised areas of whole-slide images. This extracted set of features along with their spatial associations are merged via a graphed system structure in order to produce the final classification. Assessed on a held-out test set, the model performed better than the baseline approaches, scoring 0.85 on F1 to identify neoplastic and pancreatic ductal adenocarcinoma cells [28]. The principal findings of our study have been the following: Research in AI-driven computer-aided-diagnostic (CAD) algorithms to automate the detection of pancreatic cancer early and its classification. Application of a preprocessing technique like color space transformation and isotropic diffusion filtering and then the addition of a fuzzy K-NN equation-based algorithm that actualizes a robust image segmentation. Designing a neural network architecture by combining deep convolutional neural networks with the deep belief networks (DCNN-DBN) to improve robust detection and classification. Evaluation of system performance according to standard metrics, e.g. accuracy, sensitivity, specificity, precision and error rate.

Proposed Methodology

In this section, the suggested solution to detect the pancreatic cancer using the Pancreatic Cell Tumor Categorization Dataset (PCCD) composed of benign and malignant pancreatic cell images is presented. Considering the drawbacks in the literature review (Section 2), a new algorithm has been implemented in each stage of the image processing pipeline. The general process involves inputting information about the particular patient into the computer, typing the symptoms and medical terms and locating the desired information. The process is initiated with preprocessing of images that prepare images that are obtained through CT scan to further analysis. First, RGB pancreatic images are transformed into HSV color space, and then they are enhanced with an isotropic diffusion filter to eliminate noise and to enhance contrast. Segmentation is performed after preprocessing in order to extract the malignancy areas of the CT images. To do that, we propose new Fuzzy K-NN Equality (FK-NNE) algorithm. After carrying out segmentation, deep learning is applied to undertake feature extraction and feature classification. A hybrid Deep Convolutional Neural Network combined with Deep Belief Network (DCNN-DBN) is utilized to classify the data, and thus properly detect the tumor cells. The data are divided into training and test subsets, and a classifier is produced basing on extracted feature and learned attributes.

- **Dataset:** The proposed system utilizes the Pancreatic Cell Images Dataset (PCCD), which contains the samples of 534 patients, where 200 of them have benign and 200 malignant samples. The dataset has been stratified randomly where80 percent will be used in training and 20 percent in assessment. Due to the small sample size, which would work against the deep learning model performance, data augmentation methods, including image rotations and flipping were employed as a means of enlarging the training set.
- Also, pre-trained models trained on ImageNet w ere utilized, the parameters of which were additionally adapted to this project. Model optimization was performed by applying five-fold cross-validation with the best configuring being chosen according to the validation accuracy. We considered a number of epochs as a tuning parameter and when this parameter had been determined the final model was trained on the entire training set. The evaluation was performed based on the independent test set.
- **Pre-processing**: Image preprocessing is also very instrumental in the overall classification. First of all, the RGB images are converted to HSV color space that better represents color data and expands the contrast between structures. Then an isotropic diffusion filtering is used to diminish noise and normalize pixel intensities in order to enhance both the foreground and the background. The specific method allows improving the contrast of images on the globe, especially when the pixel ranges are located in a close intensity range. Consequently, the processed images are of a better quality, rendering the nodules and abnormal structures better identifiable, as it is crucial in the next stages, segmentation.
- **Segmentation:** Segmentation is carried out based on the suggested Fuzzy K-NN Equality (FK-NNE) algorithm, which is effective in identifying the malignant regions in CT-sintered images. The approach involves the use of probabilistic membership that means every adjacent point can influence the membership to a class. FK-NNE can be seen as extending the traditional K-NN, where the distances between the vectors are to be evaluated and the membership values determined on the basis of the average distance to the neighboring elements. This lessens noise and makes class assignments more reliable. The algorithm is useful in clustering pixels because it minimizes the average distance between assigned pixels and their cluster centres. In addition, semantic segmentation is applied to set small area threshold parameters so that tiny tumor areas can be detected. To exclude all malignant cells, the foreground boundaries are elastically expanded. This segmentation method combines the features of lack of spatial features and structural composition to the maximum and hence the certainty of tumor region identification is assured.

FK-NNE convolutional networks reflect a streamlined type of convolutional schemes, generally divided into three primary categories of rubrics convolutional, pooling and fully connected ones. All these layers observe different principles of forwardpropagation and backpropagation of errors. Although there are no strict regulations, as to how these layers should be arranged; recent developments largely connect FK-NNE networks into twobroad parts. The first is the feature extraction section that uses a mixture of convolutional and pooling sections to render protruding and structural details. The second is the classification stage whereby, the extracted features are classified by means of using fully connected layers.

Cartesian coordinate system is mathematically defined as:

$$(x - a)^2 + (y - b)^2 = r^2 \qquad (1)$$

Through this formulation, the model is able to retain spatial dimensions throughout the convolution processes so that it extrapolates the required characteristics and achieves maximum accurate classification.

$$f = (A - K + 2E) / S + 1 \qquad (2)$$

where:
AAA = input image size,
KKK = kernel size,
SSS = stride (number of pixels),
EEE = padding applied to the image.

$$E = (K - 1) / 2 \qquad (3)$$

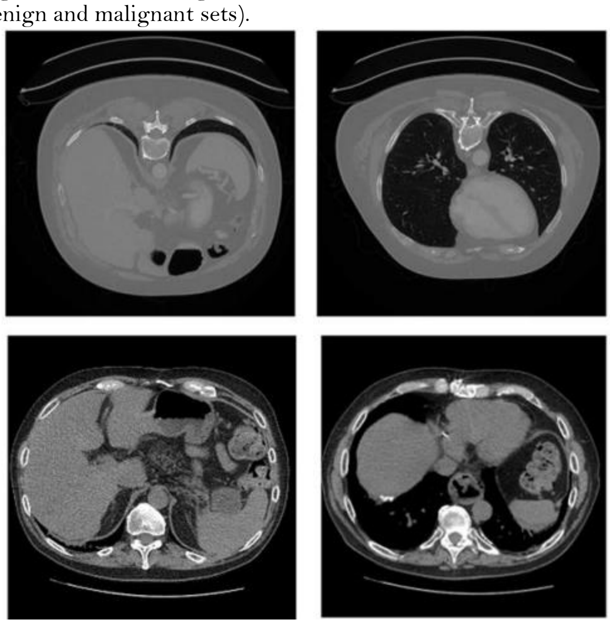
- **Feature Extraction*;*** Histogram-based features are widely applied to acquiring the information of medical images where the values are calculated contingent upon thresholds. In this contribution, such features are used to differentiate between benign and malignant pancreatic tissues. A histogram of each picture is computed and the statistical properties acquired are further used in subsequent investigations. To contribute better performance, the inception-synergic network is established with ResNet-50 as the feature extraction model. The method was validated by utilizing a total of 200 images containing both benign and malignant stages and were chosen along with the dataset. Such images are used as a source of deriving histogram-oriented features that are then used during classification.
- **Classification Using Hybrid DCNN-DBN*:*** A hybrid deep learning framework as a combination of the Deep Convolutional Neural Network (DCNN) and Deep Belief Network (DBN) is applied on the classification process. The hybrid architecture aims at enhancing the correct classification of pancreatic cancer images. The role of DCNN modules is hierarchical feature learning, whereas the higher-level dependence on extracted features is learned by the synergic network and DBN. The parameters of DCNN and synergic layers could be refined during the end-to-end training to optimize the performance of the classification. This combination accounts not only to stable detection, but also enhanced contrast between the malignant and benign pancreatic cell images.

A Deep Belief Network (DBN) is a particular sort of deep neural network which can be utilized as a probabilistic graphical model, with a sequence of layers of hidden variables. These latent variables are bridged across the layers but not within one layer and one layer only CBF DBN can be viewed as stacked learning modules in which each module may be interpreted as a Restricted Boltzmann Machine (RBM) with explicitly defined layers. The first generalizable layer is the hidden layer that maps information on the input to the following layers that encode higher-order correlations in the data. A weighted, is symmetric matrix networks the layers together The hierarchical way in which representations are learned allows their propagation across levels.

Results and discussion

The following section demonstrates the results of a comparative analysis carried out by the use of pancreatic tumor samples retrieved using a publicly available dataset. The subject of experimental dataset (consisting of 1800 CT images belonging to the PCCD database) is both benign and malignant pancreatic tumors. During the preprocessing part the color space was converted and isotropic diffusion filtering was implemented to improve image quality and reduce noise. The region of tumor identification was performed exactly with a Fuzzy K-Nearest Neighbor Equality (Fuzzy KNN-E)–based segmentation response. Histogram of Oriented Gradients (HOG) features were afterwards extracted and these features were then classified using a hybrid architecture integrating deep learning models. This solution is suitable to assist in segmentation and classification by using the computer-aided diagnostic (CAD) system applicable to assessing pancreatic tumors. In order to evaluate the performance of the system, confusion matrices and ROC curves of each classification strategy were given. The simulations and the statistical analyses were carried out in MATLAB 2019b.

Samplae Image: Experiment images were taken using the PCCD dataset. A total of 1800 CT images were used in selecting 180 representative images (both the benign and malignant sets).



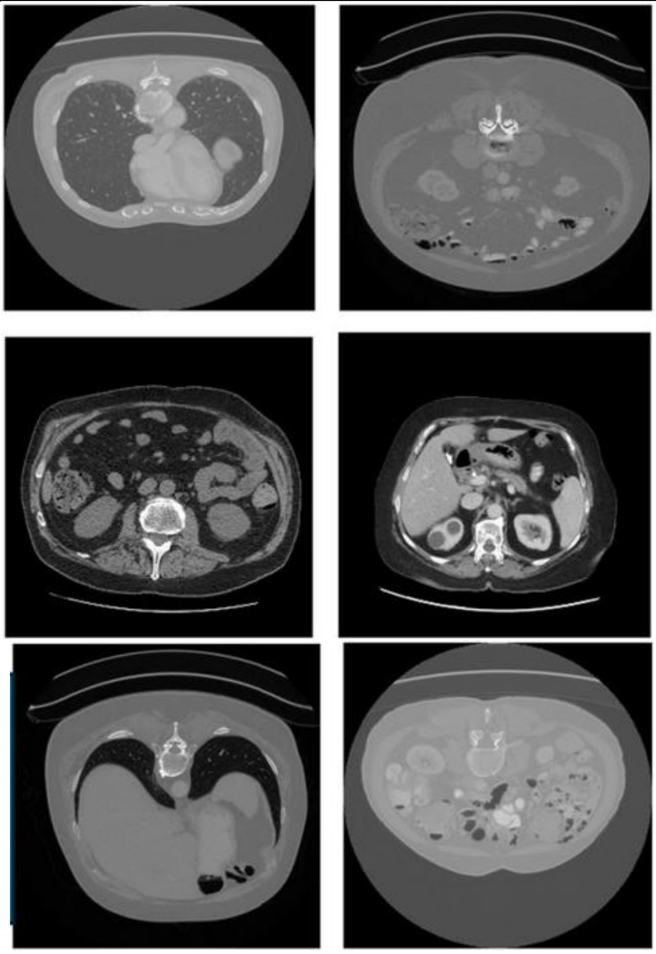


Figure 2.Complete collection of pancreatic CT scans.

Such samples were applied to determine whether a hybrid diagnostic model could segment discourse and classify it.

Two sets of 180 pancreatic tumor samples were chosen where each 180 sample was used as a training and test set. Figure 2 shows some pictures taken out of PCCD dataset.

1. **Pre-processing**: Pre-processing is an important part of the medical image classification process, since it improves upon the data entering further operation. In this research, subtractive coloring on the tumor pancreatic pictures was carried out by mixing the colored layers of the picture so as to enhance image clarity. Next, isotropic diffusion filters with a weighted volume was used to eliminate noise and retain structural information that is of importance. The results of this pre-processing step are as seen in Figure 2.
2. **The images are segmented:** Following pre-processing, segmentation was carried out to remove malignant areas of the CT scans. In medical imaging, segmentation is critical in the differentiation of tissues, organs, pathological areas and physiologically important structures. The task can, however, often be complicated by issues like low contrast, background noise, overlapping textures, etc. In order to overcome these issues, it is considered to maximize Markov Random Field (MRF) function, which can work efficiently to label the pixels accurately so as to identify characteristic traits present in the pictures. Results of the segmentation outcomes obtained on the benign and malignant pancreatic tumor samples of PCCD dataset are illustrated in Figure 3. Each foreground region is covered in the proposed method, such as a normal pancreatic region, so that no segment is missed out. Techniques of expansion in the foreground were used to refine the limits of tumor regions. At first the smaller units of the images were derived and then Fuzzy K-Nearest Neighbor Equality (FK-NNE) technique was applied. The approach is valuable to distinguish normal and abnormal cells in the pancreatic structure.

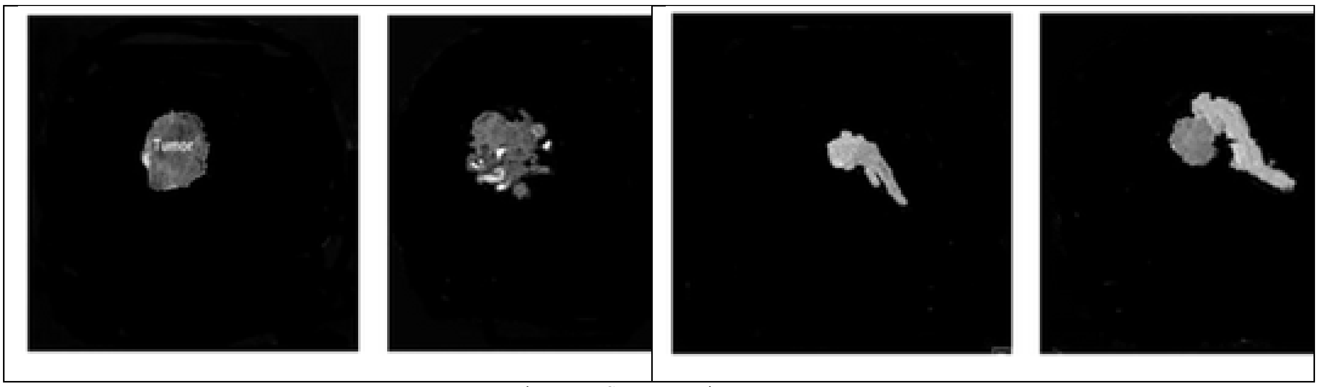


Figure 3. Segmentation output

Because of the ability to concentrate on the areas with greater intensity on the image background, FK-NNE provides fast and accurate segmentation. This can even in constricted or areas of difficult pancreatic tissue successfully distinguish between healthy and malignant cells.

1. **Feature Extraction:** The task of extracting features plays an important role in the processing of medical images since it allows to represent not only the texture features but also the structural ones of a picture in a simplified and manageable state. In case the input dataset is vast, dimensionality reduction will be necessary in order to make the processing straightforward without losing meaningful data. Here, raw image data are converted into a predetermined pattern of discriminative features that may be further subjected to classification. The histogram-based feature extraction is one of the many methods, where it uses intensity threshold values in order to obtain the statistical image characteristics. Histograms do not only give information on the distribution of pixel intensities but also get useful features that can distinguish normal and abnormal occurrences. In this research, histogram-based characteristics were derived on 200 CT images of pancreatic tumors (benign and malignant) obtained in the database. The features thus extracted were used subsequently as inputs to the classification framework.
2. **Proposed Classifier:** The last developments in the field of deep learning allowed automatizing cell detection and classification of cancer-affected areas with high precision. The classic approaches tended to use microscopic-scale segmentation and feature extraction by hand, which restricted their effectiveness. Deep learning models, and especially multistage hidden layer networks, are instead highly effective at automatic cancer cell identification and classification on large and complex datasets, without needing engineered features. A hybrid classification model based on Deep Convolutional Neural Networks (DCNN) and Deep Belief Networks (DBN) has been proposed in the proposed framework. This type of DCNN-DBN hybrid takes the advantage of the feature extraction capability of convolutional layers and the probabilistic learning potential of belief networks, which leads to higher predictive accuracy. The model forecasts on the basis of representative features derived on the dataset variables and categorize the tumor samples into benign or malignant.
3. **Performance Evaluation:** The efficiency of the suggested classification of pancreatic cell tumor was tested using the CT scan images of benign and malignant cases. The evaluation of performance was conducted in relation to the use of standard measures, i. e. classification accuracy, sensitivity, specificity, precision and the rate of error. The outcomes showed that the true positive (TP) and true negative (TN) scores on the hybrid machine learning model were more than those on the traditional techniques.

Accuracy: Describes the overall effectiveness of the classifier in correctly identifying both tumor and non-tumor regions in CT images.

$$Accuracy = \frac{Pc+Nc}{Pc+Pi+Nc+Ni} \times 100\% \qquad (4)$$

Sensitivity (Recall): Represents the proportion of actual tumor regions that the classifier correctly detects.

$$Sensitivity = \frac{Pc}{Pc+Ni} \times 100\% \qquad (5)$$

Specificity: Indicates the percentage of normal/background regions correctly identified as non-tumor.

$$Specificity = \frac{Nc}{Nc+Pi} \times 100\% \qquad (6)$$

Precision: Refers to the percentage of correctly identified tumor regions out of all the regions predicted as tumors.

$$Precision = \frac{Pc}{Pc+Pi} \times 100\% \qquad (7)$$

Error Rate: Measures the proportion of misclassified regions (false detections) relative to the total tumor regions.

$$Error = \frac{Pi+Ni}{Pc+Ni} \times 100\% \qquad (8)$$

On the dataset of 683 samples of CT scans, given the proposed hybrid model, the accuracy was 99.6%. Among them, the properly identified cases were =0.

The classifier, therefore, had a high sensitivity and specificity of 100% and 99.39, respectively. The model tried also took 22 seconds to execute a task, a very short time in comparison to traditional classifiers.

Conclusion

This paper used the PCCD database to test pancreatic cancer detection using images. In the preprocessing stage, anisotropic filtering and color space conversion was used to improve the quality of the images. The FK-NNE approach was used to segment tumor regions and then histogram-based features were extracted. A hybrid classification system, an integration of Deep Convolutional Neural Network (DCNN) with Deep Belief Network (DBN) was then used to classify benign and malignant pancreatic tumors. Sensitivity, specificity, precision and rate of error were considered to test the proposed model. The strength of the DCNNDBN hybrid method was highlighted as the experimental outcomes showed that the classification accuracy is remarkable (99.6), and the sensitivity and specificity were one hundred percent and ninety-nine-point four seven percent, respectively. Further directions in the work could be to improve segmentation accuracy by adding more sophisticated deep learning-based approaches and extend the framework on stage-wise classification of pancreatic tumors to facilitate more accurate clinical decision-making.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper

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