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Article Title: Pancreatic Cancer Identification using Convolutional Neural Networks

Pancreatic Cancer Identification using Convolutional Neural Networks

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ABSTRACT

Rarely is pancreatic cancer discovered in its early stages, when it is most treatable. This is because, in many cases, symptoms do not appear until the disease has progressed to other organs. Treatment options for pancreatic cancer are selected according to the cancer's stage. Options might be radiation treatment, chemotherapy, surgery, or a mix of these. Cancers have fuzzy borders and tiny size, making them challenging to manually annotate and automatically segment. That is why cancer prediction is so important. The convolutional neural network classifier proposed in this study is intended to identify pancreatic cancer. The segmentation method used in the test, Fuzzy C Means, divides the picture into segments. The Gabor based Region Covariance Matrix (GRCM) is used to extract features, and the GW optimization method is used to optimize the process. Using a powerful classifier a Grey wolf Optimization based Convolutional Neural Networks (GWO-based CNN), the outcome is correctly predicted. The findings acquired through the use of CNN Classifier were precise. MATLAB simulation software is used in the implementation of this project. The Accuracy Comparison of the GWO-CNN is 92.5% and Specificity Comparison of GWO-CNN is 93% respectively.

Keywords: GWO, CNN, Pancreatic Cancer, GRCM Classification and Fuzzy C-means Segmentation.

1 Introduction

Pancreatic cancer ranks as the fourth most prevalent cause of cancer-related deaths in the United States. Although the five-year survival rate for patients in the advanced stage is barely 3%, it is around 9% overall. According to recent data from the American Cancer Association, pancreatic cancer was found in 57,600 new cases and 47,050 death cases in 2020 alone. Pancreatic cancer has the greatest rate of fatal new cases (81.68%). Surgical resection is the primary treatment approach used in clinical practice to remove pancreatic cancer in its early stages [1]. There is a chance of a local recurrence at the resection site if surgery is unable to entirely eradicate the malignancy. Achieving total excision of pancreatic cancer requires quick

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intraoperative identification of malignancy from normal tissue. Currently, positron emission tomography, magnetic resonance imaging, and computed tomography are among the most utilized methods for pancreatic cancer detection. Unfortunately, the majority of these methods are not sensitive enough or specific enough for intraoperative tissue identification, and they also take a lot of time, money, and cumbersome equipment [2, 3].

The postsurgical histological analysis of tumor tissues is the most used technique for tissue diagnosis. The final diagnosis report is take many hours to days to get, though, and the quality of the sample, the pathologist's experience, and medical protocols all have a significant role in the analysis's accuracy [4]. One of the primary barriers to pancreatic cancer identification is its delayed clinical presentation. When pancreatic cancer is detected, it is usually rather advanced [5, 6]. One study found that just 7% of pancreatic cancers are first believed to be localized illnesses. This is rather low when compared to other cancers including breast (61%), colon (40%), lung (16%), ovarian (19%), and prostate (91%). Unlike breast lesions, which have palpable external lumps or skin changes that may be noticed during a yearly physical examination, the pancreas is a retroperitoneal organ located deep within the body [7]. It is neither easily evaluated completely and directly by intraluminal endoscopic videography, as is the case with the colon, nor is it accessible by a digital exam like the prostate. When symptoms do appear, they are typically non-specific and include nausea, anorexia, jaundice, weight loss, and abdominal discomfort [8, 9].

Early detection of pancreatic cancer is challenging. This is because during a standard examination, medical professionals cannot feel the pancreas. Your healthcare practitioner could prescribe imaging tests to acquire images of your internal organs if they think you might have pancreatic cancer. It is also possible to conduct an endoscopic ultrasonography [10, 11]. A narrow tube with a camera at the tip is called an endoscopic ultrasonography (EUS), and it is inserted via the mouth and into the stomach. Imaging of the pancreas through the stomach wall is made possible by the ultrasonic probe at the end of the endoscope. During the process, if needed, a pancreatic tissue sample may be taken via ultrasound-guided biopsy [12, 13].

Pancreatic cancer frequently advances asymptomatically. When it occurs, upper abdominal pain that travels to the back is typically caused by a lesion in the body or the pancreatic tail. Conversely, pancreatic head tumors typically exhibit the typical painless jaundice along with early cachexia and potentially steatorrhea. The likelihood of excision is increased for tumors originating from the ampulla of Vater because they typically manifest first with jaundice and at an earlier stage. There are no distinct patterns of laboratory value that provide a conclusive diagnosis for individuals with suspected pancreatic cancer using the sort of blood work that is currently accessible as the standard of treatment [14, 15]. Raising the survival rate and early detection of pancreatic cancer. The wiener filter is used during the pre-processing phase to reduce noise in the picture. Fuzzy C-Means is the segmentation algorithm used during the

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segmentation step in order to segment the pictures. GRCM is be used to substantially extract the features. CNNs bases on GWO are used to do classification efficiently.

2 Proposed System

The tissues of the pancreas, an organ in the belly located behind the bottom portion of the stomach, are where pancreatic cancer first appears. Your pancreas generates hormones that assist control blood sugar levels and releases digestive enzymes. The pancreas is capable of developing both malignant and noncancerous tumors. Pancreatic ductal adenocarcinoma, the most prevalent kind of pancreatic cancer, starts in the cells lining the ducts that remove digestive enzymes from the pancreas. About 90% of cases are of the most prevalent kind, pancreatic adenocarcinoma, and the term "pancreatic cancer" is occasionally used exclusively to describe it. The pancreatic region responsible for producing digestive enzymes is where these adenocarcinomas originate. An improved convolutional neural network classifier is used in this proposed study to identify pancreatic cancer.

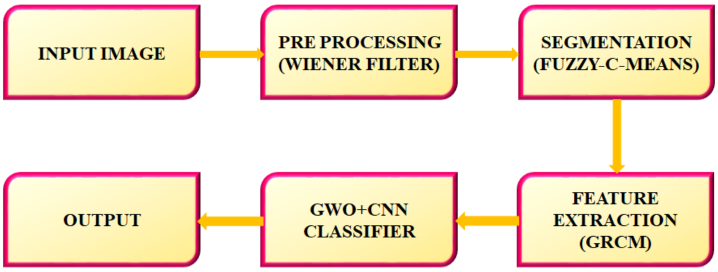

Figure 1: *Proposed System Block Diagram*

In order to produce images of excellent quality, a Wiener filter is used before to image collection. The segmentation step, which divides the pre-processed picture into several segments, uses the fuzzy-c-means clustering algorithm. To facilitate the classification process, many characteristics are extracted from the segmented areas using the feature extraction approach. The approach for extracting features is called GRCM. In image processing applications, this sophisticated method is often employed. Finally, classification is completed with the use of GWO based CNN. It is capable of providing maximum dependability together with superior results. It excels in comparison to other classifiers.

3 Proposed System Modelling

3.1 Wiener Filter

The noise reduction and distortion insertion are balanced by the employment of the Weiner filter. These filters were employed during the ASR system's pre-processing stage. To reduce the recognition performance for AWGN, the effect of noise was used instead of the impact of

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distortion. Eliminating noise from distorted signals is the aim of the Wiener filter. Although the filters are set up to provide an appropriate frequency response, it is not a simple task to construct a Wiener filter. The two primary components of the Wiener filter are the knowledge of the original signal's spectral features and the search for a linear time invariant filter; the outcomes of both would most likely be comparable to the original signal. The primary purpose of the Wiener filter is to reduce the effectiveness of the weak chirp signal's frequency and to identify the dominant chirp signal's frequency relative to the noise signal. In the event that the chirp signal contains noise, the noisy chirp signal is represented as follows:

$$R\,(u) = \frac{H(u)^*}{|H\,(u)|^2 + K} \tag{1}$$

Where $H(u)$ is the signal's Fourier transform and $R(u)$ is is the output. A high pass filter is the inverse filter of a blurry picture. The Wiener filter's lowest-frequency component is correlated with its parameter K. The Wiener filter functions as a band pass filter, with the parameter K responsible for the low pass filter and the inverse filter for the high pass filter. The Wiener filter divides signals according to their frequency spectra and gets its name from Norbert Wiener's optimum estimation theory. There is predominantly signal at some frequencies and largely noise at others.

3.2 Fuzzy C Means Segmentation

In digital image processing and analysis, image segmentation is a widely used technique that divides a picture into various portions or areas, usually depending on the properties of the image's pixels. Image segmentation is breaking down a picture into a group of pixel-rich areas that may be represented by a labeled image or a mask. Finding abrupt discontinuities in pixel values, which usually represent edges that define an area, is a frequent approach. Comparing different areas of a picture is another popular method. This strategy is used in the region expanding, clustering, and thresholding approaches, among others. Over time, several alternative methods for segmenting images have been created, utilizing domain-specific expertise to efficiently address segmentation issues in certain application domains. So let's begin with fuzzy C-Means segmentation, one of the clustering-based methods used in image segmentation.

When using the FCM approach for picture segmentation, the label is created after an unsupervised fuzzy clustering process. It works well with pictures' ambiguous and unclear qualities. Nevertheless, the FCM ignores the local peculiarities of the data and merely takes use of the homogeneity within the feature space. The fuzzy membership idea is used by the iterative FCM method to identify clusters in data rather than designating a pixel to a particular cluster. Every pixel on every cluster have a unique membership value. By minimizing an

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objective function represented in the following equation, the Fuzzy C-Means algorithm seeks to identify clusters within the data:

$$J = \sum_{I=1}^{N} \sum_{J=1}^{C} \mu_{ij}^{m} \left| x_i - c_j \right|^2 \tag{2}$$

Therefore the objective function is denoted by J. The value of J is lower after the algorithm runs through one iteration. It indicates that the algorithm is approaching or convergent upon a satisfactory division of pixels into clusters.

- The picture has a pixel count of N.
- The number of clusters that the algorithm uses, C must be determined before it is run.
- The membership table, denoted by μ, is a table of NxC entries that includes the membership values of every cluster and every data point.
- The fuzziness factor, m, has a value greater than 1.
- N's ith pixel is denoted by x_i .
- The Euclidean distance between xi and c_j is denoted as $\left|x_i - c_j\right|$.

3.3 Gabor based Region Covariance Matrix (GRCM) Feature Extraction

A technique for extracting an image's visual content for indexing and retrieval is called feature extraction. Either domain-specific characteristics or universal features, such the extraction of color, texture, and form, it is found in primitive or low-level picture features. Simplifying the number of resources needed to correctly represent a big collection of data is the goal of feature extraction. Analysing complicated data is one of the main tasks. One reason for the issue is the sheer quantity of variables at play. Generally speaking, analysis including a lot of variables needs a lot of memory and processing capacity, or else the classification method over fits the training set and performs badly when applied to fresh samples. The phrase "feature extraction" refers broadly to techniques for creating variable combinations that circumvent these issues while providing an accurate enough description of the data.

The GRCM (Gabor based Region Covariance Matrix) approach is used to process the segmented areas and extract features. GRCM plays a very important role in the feature extraction process as it helps identify lesions as accurately as possible. Pixel position and Gabor coefficient contribute to the formation of the covariance matrix. A few component subordinates vanish from the picture when GRCM is applied. Further efforts are made to enhance Gabor stage data in order to effectively recover the highlights. Color, texture, and form are used to describe the region. One crucial feature for classifying and identifying items is their texture. Texture is described using energy, entropy, homogeneity, contrast, and dissimilarity. Using texture pictures and GRCM, intensity changes are quantified. Through the GRCM, the segmented picture is retrieved.

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3.4 GWO-CNN Classifier

A particular kind of artificial neural network used in image identification and processing that is made especially to handle pixel data is called a convolutional neural network (CNN). The items in a picture may be identified using this approach. RGB combination data is present in images. Three dimensional arrays are used to store color pictures. The height and breadth of the picture (the number of pixels) are represented by the first two dimensions. The last dimension relates to the hues of red, green, and blue that are found in every pixel. To achieve superior categorization, an enhanced CNN methodology is necessary.
The GWO algorithm mimics the hunting strategy and leadership structure of natural grey wolves. Alpha, beta, delta, and omega are the four distinct kinds of grey wolves that are used to simulate the leadership hierarchy. Four steps may be used to categorize the hunting features of grey wolves:

- Searching for prey
- Encircling prey
- Pursuing (hunting)
- Attacking prey.

GWO is straightforward, adaptable, scalable, and simple to use. The grey wolf method iterates faster than other optimization algorithms because it compares and ranks various options in relation to the ideal solution.
Among various meta-heuristic strategies, the Grey Wolf Optimizer (GWO) algorithm is well-liked for its quick convergence and precise solution determination. The relevant and optimal hyper-parameters of the CNN network are calculated using a well-liked swarm intelligence method called GWO. By using the GWO approach, "classification" mistakes are decreased. When compared to conventional models, the proposed GWO-based CNN model performs better in classification. Therefore, picture classification and crop stage detection applications are where the GWO-based CNN model finds its usefulness, particularly in remote applications with constrained processing resources.

4 Result and Discussion

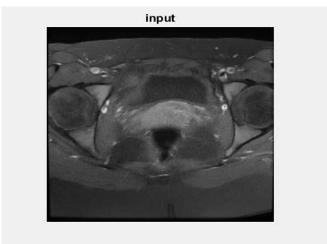

Figure 2: *Input image of pancreas*

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The above figure 2. shows the pancreas image, which is to be tested.

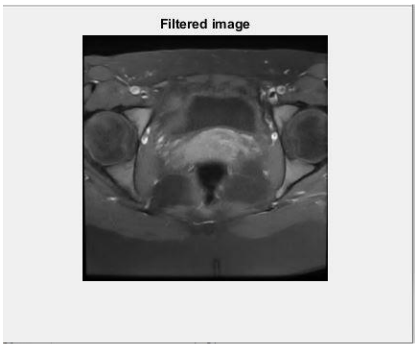

Figure 3: *Filtered image*

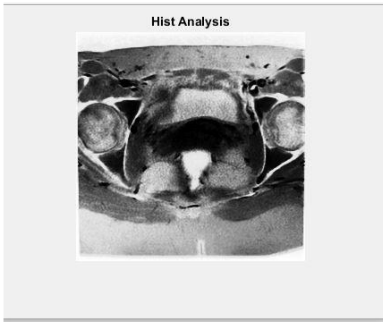

Figure 4: *Histogram Analysis*

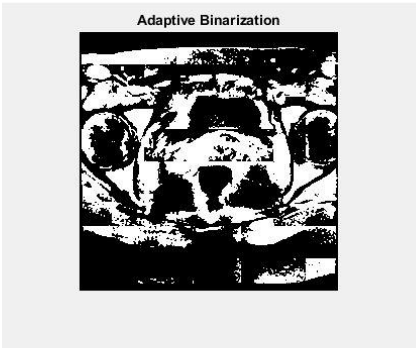

Figure 5: *Adaptive Binarization*

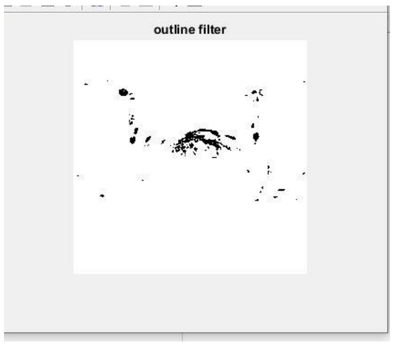

Figure 6: *Adaptive Binarization*

Pre-processing is the process of eliminating noise from the raw picture. Wiener filter is used to eliminate noise from the input picture. Figure 3. above displays the filtered, or noise-removed, picture.

Figure 4. shows an example of a histogram analysis. Similar photos to a query image are processed by Histogram Analysis. Past researchers and pathologists who have closely examined pathological specimens have generated several significant discoveries about illnesses including cancers and infectious disorders. Professional pathologists is also profit from it, particularly when uncommon cases are anticipated.

Figure 5. shows an adaptive image binarization where the page is seen as a collection of smaller pieces like text, background, and pictures. It tackles the problems caused by light, noise, and various degradations connected to source types.

In Figure 6, the outline filter is demonstrated in use. The purpose of applying filters is to adjust or improve the characteristics of the photographs and/or extract useful data from them, such blobs, corners, and edges.

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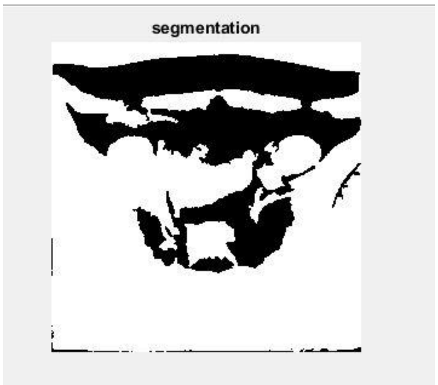

Figure 7: *Segmented image*

The division of a digital picture into many pieces is called segmentation. In order to distinguish between tumor and non-neoplastic regions during segmentation, the pixel range must first be standardized by intensity standardization. After that, the segmentation result is achieved and the non-brain areas are masked. Next, as seen in figure 7, the filtered picture is segmented using the fuzzy-C-Means segmentation approach.

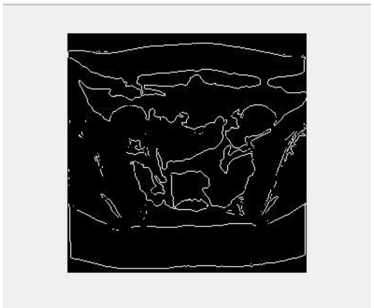

Figure 8: *Edge detection*

Edge detection is used in Figure 8. to identify object boundaries in pictures. In fields including image processing, computer vision, and machine vision, edge detection is utilized for data extraction and picture segmentation. It operates by looking for brightness discontinuities.

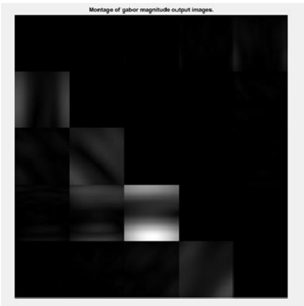

Figure 9: *Montage of Gabor Magnitude Output Images*

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Figure 9. shows the output images Montage of Gabor Magnitude. The Gabor filter is a linear filter that is used for texture analysis. To put it another way, it looks for particular frequency content in the picture in particular directions in a confined area surrounding the point or region of study.

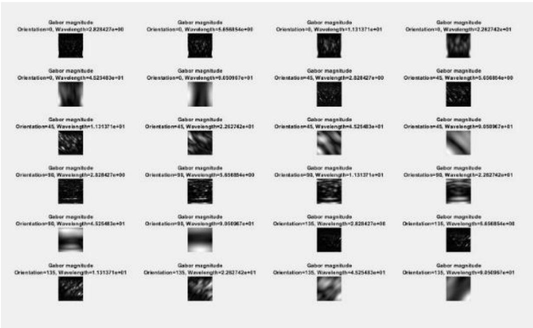

Figure 10: *Gabor Magnitude*

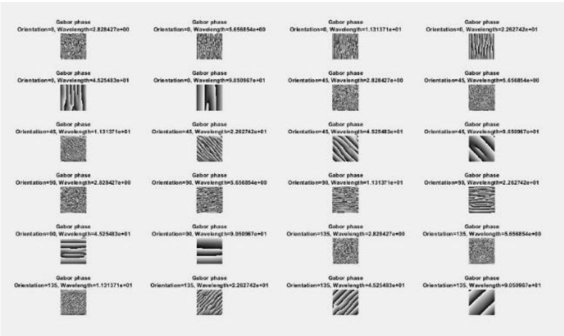

Figure 11: *Gabor Phase*

Two Gabor characteristics that are resistant to changes in light are Gabor phase and Gabor magnitude. In particular, the Gabor magnitude feature is known to be resilient to changes in illumination, and the large-step quantizing procedure used in the proposed quantized Gabor phase codes likewise provide resilience. The Gabor phase and magnitude performances are displayed in Figures 10 and 11 respectively.

Figure 12 shows the optimization of GWO. Image processing difficulties are among the many time-consuming challenges for which the gray wolf optimization approach is employed. This graph illustrates the relationship between the number of functions and the optimum cost. The operating cost of the overall complicated problem is typically decreased by using the gray wolf optimization approach.

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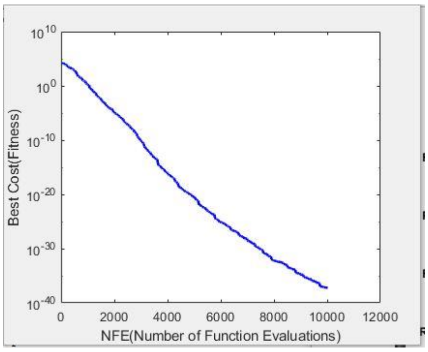

Figure 12: *GWO Optimization*

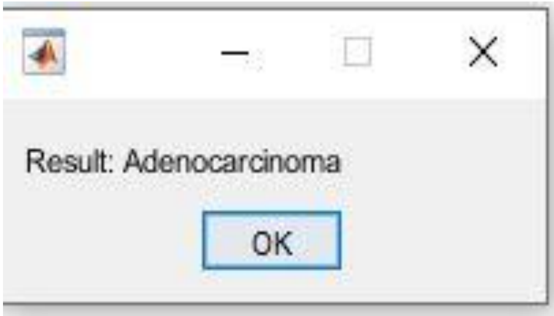

Figure 13: *Output Image*

The sort of pancreatic cancer that is discovered is seen in figure 13. above. A clear categorization of cancer kinds, including pancreatic cancer, is provided by the proposed technique. This approach is helpful not just for categorization but also for early cancer diagnosis, which is critical for prompt treatment.

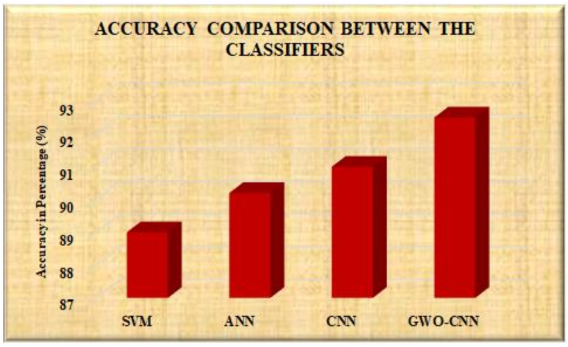

Figure 14: *Accuracy Comparison*

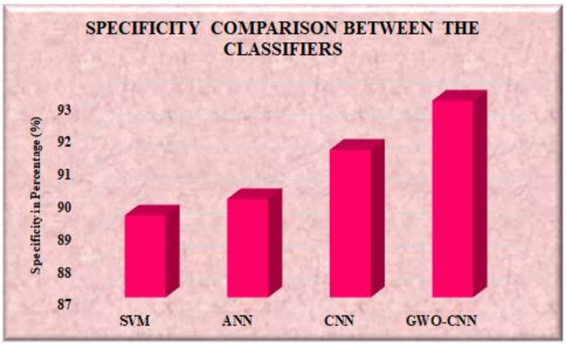

Figure 15: *Specificity Comparison*

The Accuracy Comparison of the Classification values are listed in Figure 14, in which they are listed as 89%, 90.2%, 91% and 92.5% for SVM, ANN, CNN and GWO-CNN Classier Respectively.

The Specificity Comparison of the Classification values are listed in Figure 15, in which they are listed as 89.5%, 90%, 91.5% and 93% for SVM, ANN, CNN and GWO-CNN Classier Respectively.

5 Conclusion

This research develops a convolutional neural network classifier for the diagnosis of pancreatic cancer. Pre-processing is the approach used to obtain high-quality photographs. Wiener filter is used in the pre-processing method. The pre-processed picture is separated into many segments using the fuzzy-c-means clustering approach, which then divides the processed

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image. To facilitate classification, many features are extracted from the segmented areas using a feature extraction approach. The feature extraction for the advanced approach makes use of the GRCM technology. Convolutional neural networks are finally used for categorization. The CNN Classifier is tailored to provide an accurate diagnosis of pancreatic cancer. In contrast to other classifiers, the CNN classifier has superior performance. In this project, MATLAB simulation software is used. The Accuracy Comparison of the GWO-CNN is 92.5% and Specificity Comparison of GWO-CNN is 93% respectively.

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