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INVESTIGATING THE ROLE OF ARTIFICIAL INTELLIGENCE IN PANCREATIC CANCER ANALYSIS

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ABSTRACT
In a variety of fields, including computer vision, natural language processing, automatic speech recognition, and medical data analysis, deep learning algorithms produce the best results. Because deep learning algorithms concentrate on layer-wise feature learning and make intelligent judgments on their own, they are distinct from traditional machine learning models. Based on structural and physicochemical protein features, this study used a deep learning approach to predict the class of shared Gene Alzheimer Parkinson data. To choose the best feature subset from the CGAP data, the suggested method employs correlation feature selection based on the rank search method. A deep neural network is then used to train the selected feature. The suggested strategy outperformed all other implemented segmentation techniques when the results were compared with some of the current segmentation methods. Significant health study on cancer forecast is available, and it concerns a variety of body parts and has varying appearances. Cancer is predicted to be incurable and incapable of being adequately prevented. Neural networks and machine learning are currently producing promising results for pancreatic picture segmentation. The chance of accurately identifying cancer is substantially increased by the specific machine learning and image processing algorithms that have been offered for previously used screening systems. The field of artificial intelligence known as machine learning (ML) links the challenge of drawing conclusions from a collection of samples with common notions.With its vast array of applications, machine learning has emerged as a major challenge in the biomedical field in recent years. In essence, machine learning (ML) searches an n-dimensional space for the specified collection of data. On the other hand, image processing has been shown to be quite helpful in identifying the early stages of cancer. In essence, it attempts to extract some relevant facts from the image by performing specific procedures on it. Since cancers require a great deal of time and accuracy, machine learning and image processing algorithms provide highly promising results in a very short amount of time. This serves as a source of inspiration for carrying out this research.
keywords, AI,Pancreas, ML, DL.

1. INTRODUCTION

Pancreatic cancer is one of the world's top causes of death. Pancreatic adenocarcinoma (PDAC) is more common in newly diagnosed diabetes individuals over 50. Jaundice is an early indicator of pancreatic cancer, and pancreatic adenocarcinoma was present in over 85% of cases. Over time, anatomical, social, and environmental changes lead to pancreatic cancer and other illnesses that result in pancreatic malfunctions [1]. Acute pancreatitis, chronic pancreatitis, exocrine pancreatic insufficiency, hereditary pancreatitis, cystic fibrosis, and diabetes are among the different conditions. Smoking, diabetes, exposure to chemicals, family history, poor diet, and alcohol use are the main causes of pancreatic cancer [2]. Adenocarcinoma in the pancreas ranked fourth in terms of cancer-related deaths. Medical images such as CT, MRI, PET, and other scans, as well as multimodal health clinical data about pancreatic cancer, are mostly sourced from Electronic Health Records (EHRs) [4]. Lab findings, clinical notes (unstructured EHRs), and medical photographs are examples of structured health records that make up medical (clinical) data. The medical histories of patients are stored in electronic health records, or EHRs [11]. In the contemporary healthcare sector, medical imaging plays a critical role in helping researchers and physicians better comprehend the interior anatomy of people [6].By examining the pictures, radiologists can make an early diagnosis of the illness [14]. Multi-Detector Computed Tomography (MDCT), Magnetic Resonance Cholangiopancreatography (MRCP), Positron Emission Tomography (PET), and Endoscopic Retrograde Cholangiopancreatography (ERCP) are the several imaging modalities used to diagnose pancreatic cancer. One chemical that, when found in the blood, is a biomarker for pancreatic cancer is CA19-9. Because the CA 19-9 level rises as cancer spreads and falls as tumors shrink, a CA 19-9 blood test is used to detect the presence and amount of pancreatic cancer [8]. One of the early signs of pancreatic cancer is jaundice [3]. After assessing CA 19-9 in blood, bilirubin levels are measured in the scleral portion of the eye of individuals with pancreatic cancer. Patients with PDAC typically have elevated bilirubin levels.

2. LITERATURE REVIEW

A pre-processing strategy based on soft computing techniques has been described by Lakshmi A. et al. (2014). It appears to be effective and well-suited for functional MRI data segmentation. Specifically, the image denoising approach based on the curvelet transform turns out to be an effective way to remove noise. Additional quantitative confirmation of the method's accuracy and stability is still required, utilizing several clinical scans and realistic phantoms. Enhancing the quality of low dose CT scan images was suggested by Mao et al. (2014). Gaussian noises superimposed on CT images are known as low dose artifacts, and they are frequently brought on by photon hunger and inadequately calibrated detectors.An accelerated 3D total variation minimization approach utilizing Complete Unified Device Architecture is described in order to minimize these low dosage artifacts [10]. Quantitative metrics have been used to test the suggested algorithm's performance [16]. The findings of both simulations and actual experiments demonstrate that the suggested method improves image quality and has a fast computation speed. An image-improved technique was used by Mokhled S. AL-TARAWNEH (2012) for early disease identification and treatment phases. In order to identify the aberrant tissues in target images, the time factor was considered [12]. Gabor filter-based low pre-processing methods were used. Pixel percentage and mask labeling with high accuracy and reliable operation are the two primary aspects that this technique relies on for accurate picture comparison.In order to retain image information and brighten the edges of CT scan pictures of pancreatic tumors, Jeenal Shah et al. (2015) suggested using a low pass filter. The scan also shows the liver, stomach, spleen, vertebra, right kidney, and left kidney in addition to the pancreas. The organs in the picture are then categorized using a minimum distance classifier. Using a confusion matrix, the accuracy was determined to be 61.59%. The Adaptive Switching Median Filter (ASMF) was proposed by J. Aalavandan et al. (2012). This technique is an adaptation of the Switching Median Filter (SMF) method. This approach uses two phases to remove noise. Finding the noisy area in the first stage. Here, thresholding values are used to construct a binary picture, with 0s denoting noisy pixels and 0s denoting noise-free pixels [5]. Noise is eliminated in the second stage by employing an adaptive switching median filter. This suggested approach maintains important and edge details while providing the optimal performance based on performance indicators. Salt and pepper sounds can be eliminated using the suggested technique. Wei Zhao et al. (2019) created an accurate pancreatic target localization method based on deep learning. Results from pancreatic image-guided radiation treatment were clinically reasonable. The developed method was universal and applicable to a wide range of cancer kinds. With less complexity, a deep neural network identified the target of a pancreatic tumor. Joel Saltz et al. (2018) developed a computational stain based on deep learning to identify tumor-penetrating cells. TILs were developed based on the hematoxylin and eosin pictures. Computational staining using the trained convolutional neural network for image labeling was used to create TIL maps. Tumor type was distinguished by taking into account both spatial construction and TIL concentrations [13]. Additionally, it reproduced specific tumor cell aberration states by spatial penetration. Convolutional neural network authentication for automatic CPR formation using the main pancreatic duct was described by Yuji Koretsune et al. in 2022. A few radiologists secretly carried out qualitative robotic and formed image detection. A four-point rating system was used to assess the image quality. Both generated and automated CPR pictures were evaluated using weighted κ analysis.

3. METHODOLOGY

The CAD framework receives the images as input. During the entire processing step, the obtained image is digitalized and examined for the clear visibility of anatomical components. In order for the features that are extracted to accurately characterize the properties of tumor tissues, pre-processing aims to retain the pixels in the tumor region. The feature extraction methods used to generate descriptive characteristics determine the analysis's amount. At this point, the effectiveness of the features in the quantification of tissue characteristics is recognized using the clinical expertise and knowledge of the clinician. Images of various age groups are utilized as a reference database and to enhance machine learning techniques. At the moment, doctors discuss the type of pathology implicated.After the CAD system is implemented, test photos of an unidentified category are used to evaluate the discrimination capacity. In addition, the doctors are given information about the category at the time of diagnosis. Such a CAD system is presumed to be able to meet the many possibilities as well. Figure 1 shows the proposed framework's overall architecture diagram. When the sound is eliminated, the pancreatic cancer CT/MRI image has noise due to patient movement, miscalibrated detectors, etc. In image processing, the noise reduction feature is essential for image analysis. There are various linear and non-linear denoising methods available to remove noise and maintain data. Non-linear filters preserve the visual data while also sharpening the edges. Depending on this kind of noise present in the image an apt filter is employed to de-noise the image. [9].

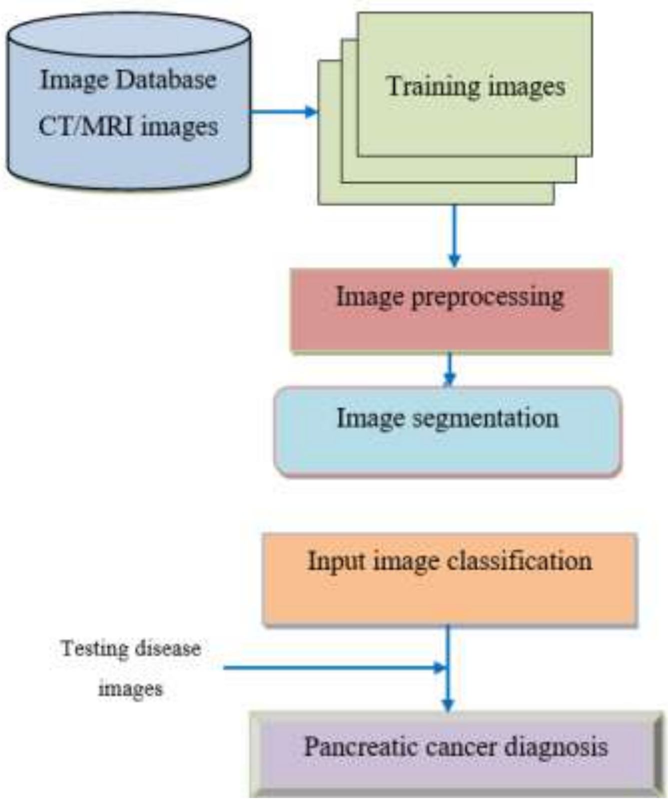

Figure 1: Proposed flow

Preprocessing is crucial, particularly when reducing the resources required to eliminate redundant data without sacrificing crucial and crucial information. It makes it much easier to reduce redundant information, which reduces the amount of data that needs to be taken into account. Since clinical photos are included in our study, a vast amount of data will be collected from the photographs as well. Finding the optimal preprocessing strategy, which is essentially lacking in the current systems, becomes even more important. The key problem for image recognition is still the medical image. By dividing the image into several classifications, a precise classification algorithm lets physicians diagnose illnesses more accurately.

4. STATISTICAL MEASURES

Doctors still primarily use their professional expertise to classify medical images, which is time-consuming, exhausting, and prone to mistakes. The optimal classification strategy for the selected preprocessing method is still up for debate. Even while modern medical technology has advanced significantly, the accuracy with which diseases like cancer are recognized is still inadequate [15].

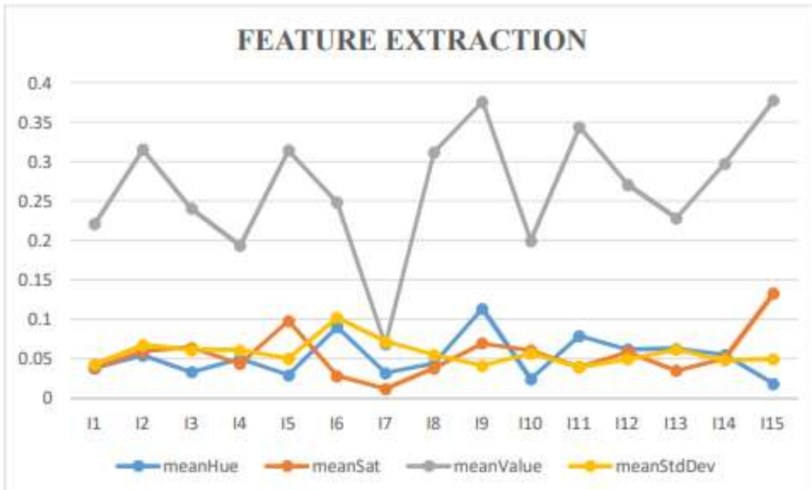

Figure 2: Feature Extraction

Despite this, there are still substantial rates of false positives and false negatives, which puts patients at risk for either an overdiagnosis or an underdiagnosis. As far as diagnosing the disease accurately, the current systems have yet to produce satisfactory results..[10].

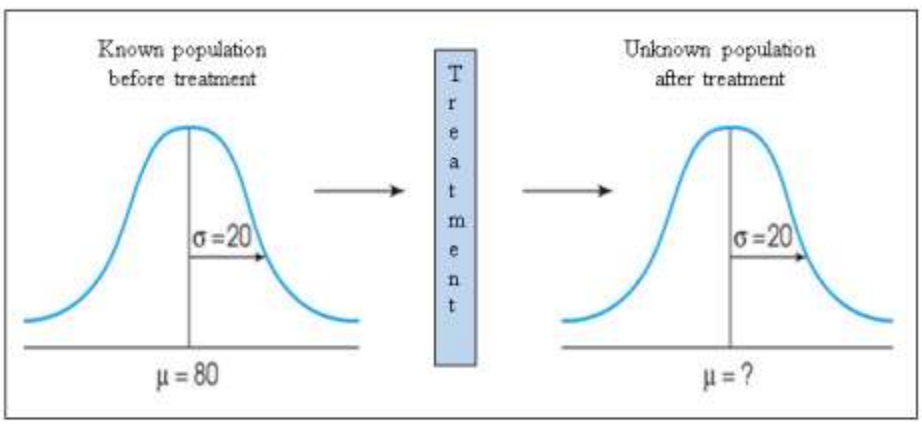

Figure 3: population prior to treatment as well as unknownpopulation behind treatment having pancreatic

The process of choosing a subset of particular features (variables, predictors) to be used in model creation is known as feature selection. By lowering overfitting, this technique is useful for a variety of reasons, including preventing the dimensionality curse and enhancing generalization. For the creation of dynamic models, many machine-learning practitioners believe that feature selection must be adequately optimized. The underlying presumption when employing a feature selection technique is that the data contains certain features that are neither redundant nor obsolete and may be removed without causing data loss..

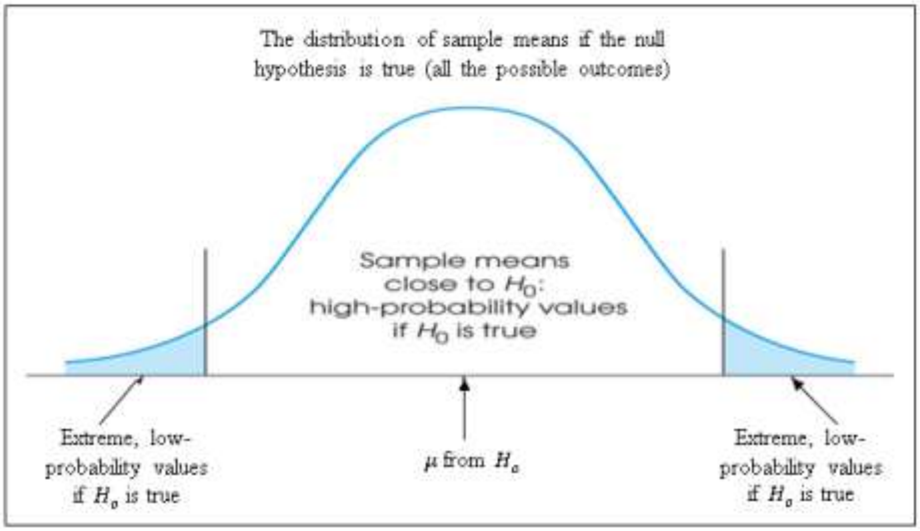

Figure 4: probability hypothesis of the population

The outcomes of these approaches show the possible benefits of employing feature selection strategies to increase classification accuracy while utilizing fewer feature subsets. While the unnecessary features from the pancreatic PET/CT image samples are eliminated, the best features are chosen using the whale feature selection approach. This demonstrates the importance of the feature selection methodology. The unknown feature vectors from PSO and whale are thus divided into two predetermined classes by the SVM classifier.

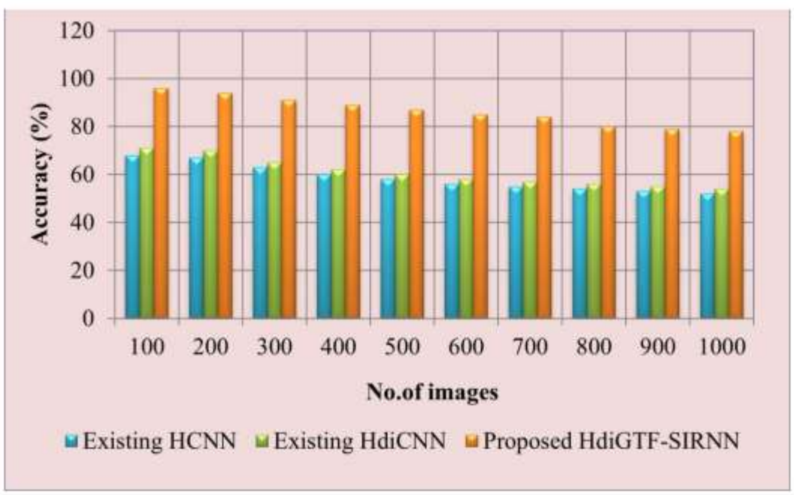

Figure 5: Accuracy plot

By using an Optimized Feature-Based framework for pancreatic cancer diagnosis, the proposed approach improved classification accuracy. The features have been retrieved from either the spatial or frequency domains based on the methodologies currently in use. Better findings are obtained, though, because the features in this suggested study are derived from both the spatial and frequency domains..

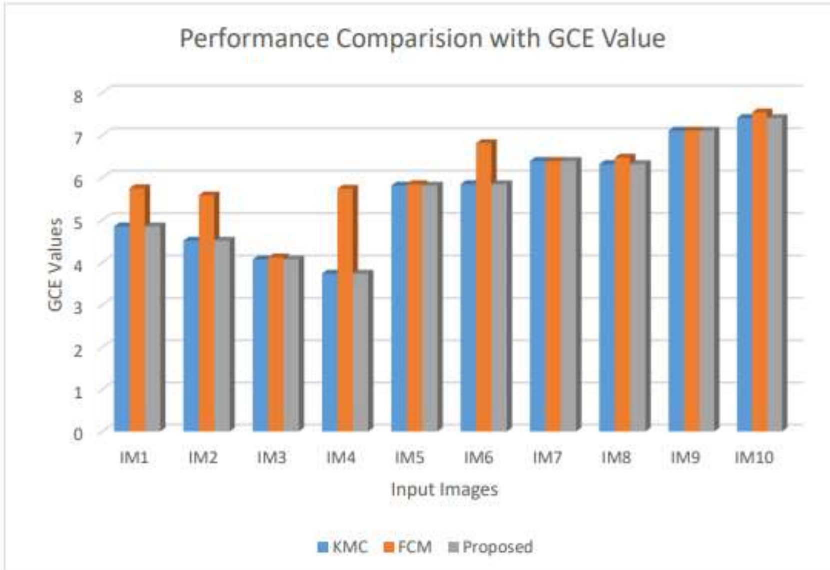

Figure 6: GEC value

When compared to the results of other classifiers, the output indicates that the suggested classifier achieves higher classification accuracy in both classification scenarios. The accompanying table shows that the suggested DL classifier yields superior outcomes..

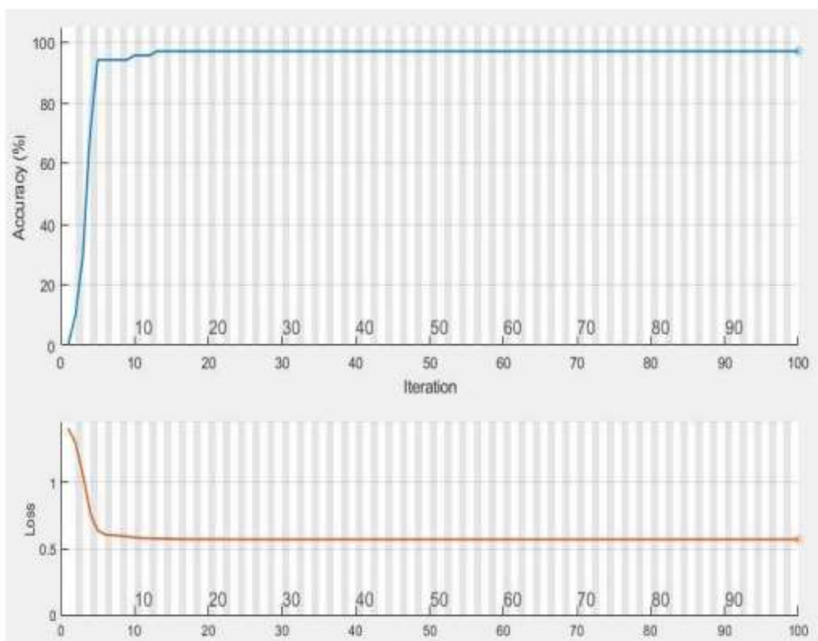

Figure 7: training and validation plot

According to the results, the suggested approach outperforms the other current approaches in every situation by offering the highest levels of accuracy, sensitivity, specificity, and F-score rates, while also having a very low error rate. The majority of research in this field merely discusses how prediction accuracy has increased using deep learning and convolutional network techniques with various classifiers; it doesn't identify which of the two approaches has performed better.

5. CONCLUSION

In addition to frequently being asymptomatic, pancreatic cancer is often detected early. By the time of the crucial diagnosis, almost half of the patients had metastatic disease, which is inferred from the persistent character of the cancer. Increased mortality from pancreatic cancer highlights the dire need to improve molecular pathways for diagnosis and pathogenesis for effective therapy. With a 5-year survival rate of 10% in the USA at the time of analysis, the prognosis is often quite poor. The only effective treatment option is to completely remove the tumor surgically. Based on pancreatic CT images, each patient's risk severity level comprises the detection of pancreatic tumors as well as the segmentation and measurement of the pancreatic cells.Since CT images are grayscale, complicated, changeable, and comprise noisy values, segmenting the region of interest from them is a difficult task. The primary goal of this study is to create a number of strategies based on multimodal clinical data to address the problems of pancreatic tumor segmentation, automatic morphological change detection and assessment, and risk level classification of pancreatic disease.

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