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Deep Learning Algorithms to Detect Human Pancreatic Cancer from MRI Scan Images

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Abstract: The idea of this project is to implement a Computer-Aided Detection system (CAD) for the early detection of pancreatic tumors based on the UNet++ architecture. Contrast Limited Adaptive Histogram Equalization (CLAHE) and Boosted Anisotropic Diffusion Filter (BADF) methods are used to enhance the MRI image. The pancreatic region associated with a lesion is precisely separated from the MRI image by segmentation. The best subset of texture characteristics is assessed by creating a classification system based on texture features that integrate HHO-based CNN and HHO-based Bag of visual terms. This will enhance classification accuracy. Transfer learning and Fine-tuning model using VGG 16 classifiers are utilised to create an automated system for classifying different grades of tumors in MRI Images. For various tumor classes, quantitative analysis is performed. The accuracy of the classification of the proposed classifier is validated and it is compared with the state-of-the-art approach.

Index Terms— *Detection, Classification, Pancreatic Cancer, Magnetic resonance imaging, Computer Aided Detection, Deep learning.*

1. Introduction

The primary goal of this Research Is To Use A Computer-Aided Detection (CAD) Model To identify And classify Pancreatic Cancer (PC) In Magnetic resonance images (MRI). The early detection and treatment of PC are extremely difficult. An organ called the pancreas is located behind the lower portion of the stomach. The American Cancer Society reports that the death rate for PC patients is increasing and currently stands at the fourth highest level in the country. The distribution of PCs is still widespread in undeveloped nations. To help doctors give the best treatment plan for each stage of pancreatic cancer and enable patients to obtain early medical interventions before advanced degrees of pancreatic cancer form, comprehensive preoperative PC prognosis and staging are very crucial, especially in the identification of pancreatic cancer staging. Using MRI scans, Computer Aided Diagnosis (CAD) methods were created to identify PC in their early stages. To collect the quantitative data needed to diagnose pancreatic nodules, the CAD system was created.

2. Literature Survey

The proposed UNet++[1], an encoder-decoder architecture based on the UNet, has produced good results on several medical image segmentation tasks. So this model is used to shorten our training time and produce better results. It also has a side-by-side scientific comparison between Unet and Unet++ architectures, which brought us to the conclusion of adopting Unet++ for our implementation. The use of AI in medicine is on the rise, particularly in the discipline of gastroenterology. In imaging-based testing and clinical diagnostic prediction, AI can help gastroenterologists. A branch of artificial intelligence called machine learning uses mathematical methods to build prediction models by identifying patterns in datasets without explicit programming [2]. In order to detect pancreatic cancer early, screening is frequently used in high-risk individuals nowadays. To find the high-risk group & accomplish early detection and prompt treatment of PC, we may need to fully comprehend the risk factors and pathophysiology of the disease. This paper gave us an insight into the different aspects of pancreatic cancer and how important the work that we are doing for the medical community is [3]. Researchers have focused a lot of attention on the Harris Hawks Optimization (HHO) method because of its performance, the calibre of the findings, and its tolerable convergence when handling various applications in real-world problems.

> Due to the rising attention, there have been several applications of HHO to diverse optimization issues in various fields.

The review's findings showed that even though the HHO algorithm is still in its infancy, its advantages over other well-known metaheuristic algorithms in terms of speed and accuracy for solving a variety of benchmark problems and solving many real-world optimization problems have been

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made clear. These observations lead us to adopt HHO-based CNN for the segmentation of the MRI scan images. Deep learning methods recently demonstrated remarkable progress in the accuracy of brain tumor identification and classification using MRI [5]. Here we present a transfer learning-based CNN DL model for the classification of brain cancers from MRI images. The implemented system explores many convolutional neural network architectures, namely ResNet, Xception, and MobilNetV2. This led us to adopt transfer learning in order to achieve the desired results with limited resources in detecting the tumor cells from the abdominal MRI scan images. Due to its capacity to detect endogenous, nontoxic 13C-labeled probes that can track enzymatic conversions through important biochemical pathways, hyperpolarization -based magnetic resonance is an imaging modality method that offers data on previously inaccessible aspects of biological processes [6]. Since PDAC and advanced pancreatic preneoplastic lesions can now be detected at the smallest size for which there are presently no techniques of detection, HP-MR offers an intriguing possibility to recognize and comprehend early metabolic abnormalities. Genetic mutations have the potential to activate particular signalling pathways linked to metabolic changes that may be highly sensitively identified by HP techniques. In various biological processes, the P53 protein, which is encoded by the tumor suppressor gene TP53, can prevent cell proliferation. The proliferation, invasion, and survival of tumor cells are encouraged by mutated TP53 genes [7].

A 3D spiral transformation-based multi-modal fine-grained prediction technique was presented[8].The final probability value is produced by spiralling multi-modal MRI 3D images into a 2D plane, which is used as the model's input. This approach is composed of three components: feature extraction network, spiral transformation and data augmentation, as well as a novel model-driven constraint term in the feature fusion technique. In order to distinguish between pancreatic cancer and mass-forming pancreatitis, this paper will examine the practical value of CT symptoms in conjunction with MRI-DWI, MRCP, and magnetic resonance cholangiopancreatography [8].

A retrospective analysis of the imaging data of sixty one patients with pancreatic mass lesions detected in a hospital from May 2013 to May 2020 was done. The lesions were identified based on postoperative pathology. Additionally, the combined image diagnostic value of 1.5T MRI-DWI and 128-slice CT is examined. Clinical pancreatic cancer diagnostic sensitivity can be increased by using the MRI-DWI method, MRCP, and CT signals together.

The dataset consists of the “Pancreatic Cancer Methylation Database(PCMDB, http://crdd.osdd.net/raghava/pcmdb/), a comprehensive database devoted to the methylation of genes in pancreatic cancer”, to help advance the search for biomarkers. Data were carefully gathered and compiled from the available literature. For the methylation state of 4342 distinct genes, PCMdb has 65907 entries. Both data for “cancer tissues (12343 entries for 3078 tissue samples) and cancer cell lines (53566 entries for 88 cell lines)” were compiled in PCMdb [9].

For the associated genes, 47.22 per cent of these entries indicated a high degree of methylation, whereas 10.86 percent of these entries reported a low level of methylation. “PCMdb” includes information on 5 main subtypes of PC, the majority of entries (88.38 per cent) and mucinous neoplasms were assembled (5.76 %). Data browsing, searching, and analysis now have a user-friendly interface. The search for pancreatic cancer biomarkers should benefit from PCMdb, according to our predictions. Numerous web tools have been included in PCMdb to help the cancer biology community analyze the “methylation data” produced by NGS in the form of sequences and short reads. Due to various mechanisms, both “pancreatic ductal adenocarcinoma and chronic pancreatitis” can cause cachexia, sarcopenia, and osteoporosis. Patients’ gender, age, or body weight are not reliable indicators of whether these metabolic alterations will have a major negative influence on their Quality Of Life (QOL) or how well their treatments will work [10].

The goal of this study was to compare radiographic body composition changes in people with CP and PDAC to body mass, quality of life, and signs of exocrine and endocrine pancreatic deficiency. For the analysis, a hundred patients with CP or PDAC diagnoses had their prospectively collected data used. CT, MRI, and dual-energy X-ray absorptiometry were done on each subject. “EORTC QLQ-C30, developed by the European Organization for Research and Treatment of Cancer”, was used to measure QOL. Additionally evaluated were diabetes and alterations in faecal elastase-1. Patients with pancreatic cancer and chronic pancreatitis frequently have sarcopenia and osteoporosis/osteopenia. Routine detection of these major metabolic alterations may be possible using CT and MRI-based assessments of body composition and pancreatic fibrosis.

For gastroenterologists, detecting pancreatic cancer in its early stages continues to be difficult. One of the most crucial factors in the successful treatment of this malignancy is the early diagnosis of cancer. A good differential diagnosis of focal pancreatic lesions is essential for diagnosing chronic pancreatitis from PC or autoimmune pancreatitis from PC

[11]. One of the key diagnostic indicators for type 1 AIP is increased serum immunoglobulin G4 (IgG4) levels that are IgG4 levels can increase in PC patients as well, but they often do not go above twice the normal amount. IgG4 levels were checked in 15 patients with histologically proven PC during the years 2012 and 2017. Histological resection specimens or bioptic specimens from a pancreatic lesion from patients with PC and a high IgG4 level (over 135 mg/dL) were analyzed to precisely detect the presence of IgG4, plasmocytes, and alterations indicative of type 1 AIP in the pancreatic tissue. It was discovered that distinguishing AIP from PC, in particular, can be challenging in the early phases of a cancer diagnosis. IgG4 levels may also be modestly increased in PC cases. When a localized type of AIP is suspected, the preferred technique is a targeted pancreatic biopsy. [12] Modern MDCT is the principal modality for assessing the majority of pancreatic disorders, including "pancreatic ductal adenocarcinoma, neuroendocrine tumors, acute pancreatitis, and trauma" [1–10]. It performs whole-abdominal exams at isotropic resolution in a matter of seconds.

Conventional MDCT still has some drawbacks, including the inability to accurately assess small lesions (especially those that are less than 0.5 cm in size), radiation exposure, particularly in young patients who need follow-up exams, the need for unenhanced phase imaging to measure tissue enhancement, the inability to distinguish between residual or recurrent tumour and post-treatment change in PDAC, and the lower accuracy of CT than MRI, MRCP, and endoscopic ultrasound when evaluating cystic neoplasm. [13].

For 25 patients with resectable and potentially resectable PDAC after nCR, MRI and pathological data were retrospectively assessed. The Wilcoxon matched pairs test was used to compare the mean ADC levels in tumors before and after nCR. The connection between pathological treatment response and ADC readings was assessed using the Pearson's correlation coefficient test and receiver-operating-curve analysis. The ADC may be utilised to assess treatment response for PDAC because changes in pre- and post-treatment ADC values closely correlated with pathological treatment response in PDAC patients receiving chemoradiation therapy. [14] In this retrospective diagnostic study, contrast-enhanced CT images from 375 PC patients and 3205healthy controls from a Taiwanese institution were manually labelled and randomly selected for training, validation, and testing groups (275 pancreatic cancer patients and 250 healthy controls).and testing groups in this retrospective double the usual value.

diagnostic study (75 patients with PC and 64 controls; local test set 1). A CNN was trained to separate preprocessed, malignant, or benign portions of images. People were classified as having pancreatic cancer or not based on the percentage of patches that the CNN classified as malignant, using a cutoff created using the training and validation set. The CNN was tested further using a US dataset and a second local test set consisting of 88 controls and 101 patients with PC (local test set 2). Radiologists' reports on images of pancreatic cancer from the local test sets were retrieved for comparison. In contrast to images of people from several racial and ethnic backgrounds, CNN was successful in differentiating PC on CT with acceptable generalizability. CNN might back up the radiologists' interpretation.

Two processes—training and verification—went into the creation of the AI system used to diagnose PC using consecutive contrast-enhanced CT scans. All 4385 CT scans from 238 individuals with PC in the database were employed in our study's training process as the training data set [15]. Additionally, they started the feature extraction network with VGG16. VGG16 contained thirteen convolutional layers and three fully connected layers. It was pre-trained in image net. Sequential clinical CT scans from 238 PC patients served as the experimental data for the verification experiment. These scans were then fed into the learned faster region-based convolution network model. A total of 1699 pictures from 100 PC patients were included for clinical verification. Faster R-CNN AI is a very accurate and efficient method for diagnosing pancreatic cancer.

3. Methodology

Here, information from the Clinical Proteomic Tumor Analysis Consortium Pancreatic Ductal Adenocarcinoma (CPTAC-PDA) cohort of the National Cancer Institute is used. The block diagram below uses several actions taken in this DL model to highlight various processes.

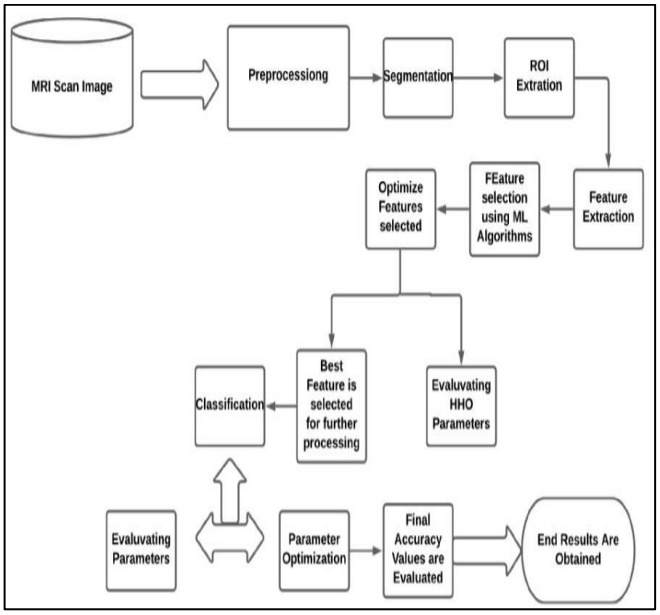

Fig 1: Block diagram of the architecture

A. Preprocessing

Images are enhanced at the preprocessing step using CLAHE & BADF. To improve low-contrast medical images, CLAHE was first used. The CLAHE approach divides an input original image into contextual sections that don't overlap, known as sub-images, tiles, or blocks. Histogram equalization is applied to each contextual region by the CLAHE approach. The original histogram is cropped, and the clipped pixels are redistributed to each grey level. Because each pixel intensity is restricted to a predetermined maximum, the redistributed histogram differs from the conventional histogram. The lowest and maximum grey values, however, are the same for the improved and original images. To improve the utility of a graphic display for presentation and analysis, it emphasizes or sharpens image elements such as edges, boundaries, or contrast. The features of the image are enhanced by utilising a revolutionary enhancing method.

The suggested BADF adds a Partial Differential Equation (PDE) after creating the diluted image. This provides the current anisotropic diffusion technique with an additional benefit. Diffusion, which is absent at the borders and boundaries, is another method for achieving smoothing. It is a very effective unsupervised machine-learning method for improving images.

In addition to preserving some significant aspects like the edges and textures, it also smooths up the image. Good results were obtained when the iteration number was set to 20, according to extensive experiments. Next, the image's dimensions are established so they may be utilized to compute the four nearest neighbour differences. Here, the goal metrics PSNR, MSE, and SSIM are computed for the Contrast Limited Adaptive Histogram Equalization and Boosted Anisotropic Diffusion Filters.

B. Segmentation

The MRI image is segmented in order to isolate the nodules as part of an image classification procedure. The UNet++ design, which is a more potent architecture for medical image segmentation, is used in this work for segmentation. In this architecture, the encoder and decoder sub-networks are coupled through many nested, dense skip routes, effectively creating a fully supervised encoder-decoder network. The semantic gap between the feature maps of the encoder and decoder sub-networks is intended to be closed by the newly developed skip paths. The optimizer would deal with a simpler learning task if the feature mappings from the decoder and encoder networks were semantically comparable.

C. Feature Extraction and Feature Selection

Here, HHO-based CNN and HHO-based BOVW are used to extract and select the features. Popular swarm-based algorithm HHO has many active, time-varying phases of exploration and exploitation. Utilizing textural features, the segmented tumor is then retrieved. The two fundamental components of a CNN are feature extraction and classification. Multiple convolution layers are followed by max-pooling and an activation function in the feature extraction process. The classifier often has layers that are fully coupled. We employ the HHO algorithm to achieve great precision and effectiveness. Popular swarm-based optimization algorithm HHO features multiple active and time-varying phases of exploration and exploitation. This algorithm, which was first released in 2019, offers a flexible structure, excellent performance, and excellent outcomes. The primary rationale for the HHO approach is based on the cooperative attitude and "surprise pounce" pursuing patterns of Harris hawks.

The NLP algorithm is extended by the bag of visual words, which uses a supervised model of learning. The surf algorithm is used to automatically extract the features. A “bag of terms” utilized for classification of images. The major goal of this classifier is to save time. It will choose the features that go along with this categorization on its own. Aside from CNN, it's a relatively typical occurrence. The BOV method, created by C. Wang et al., basically creates a language that can more effectively extrapolate features from an image. It employs the Computer Vision Toolbox TM tools to define the image categories by constructing a bag of visual words. Based on the occurrences of visual terms, the method generates a histogram of the image. The image category

classifier is trained using this histogram. Harish Hawks Optimizer (HHO) techniques in BOVW is applied to reduce loss by modifying variables like weights and learning rates.

D. Classification

By applying Transfer learning and fine-tuning the model with VGG-16, the classification stage tries to distinguish between normal and pathological tumor images. Transfer learning is the process of using the expertise acquired while resolving one problem and applying it to another, unrelated challenge. One Convolution Neural Net (CNN) architecture known as a very good model for image classification is VGG-16.

To implement the work process, several researchers use MATLAB. To accomplish the PC detection in our research, we use Python programming. The results demonstrate how well the suggested method performs. The use of the suggested strategy for tumor early detection is shown to increase clinical practice's effectiveness and accuracy.

Figures and Tables

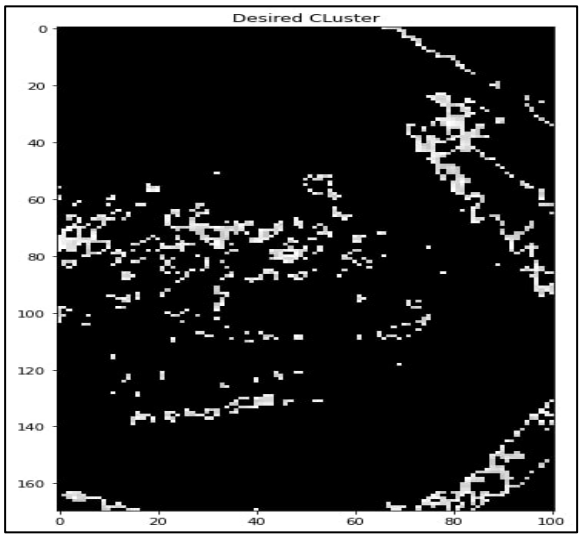

Fig 2: Unet classification

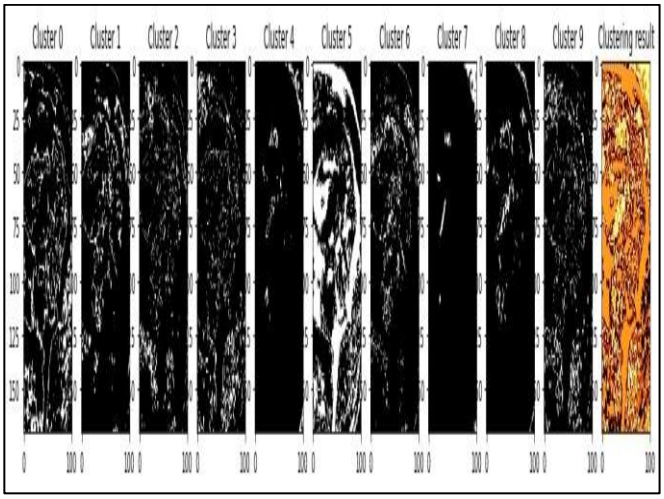

Fig. 3: K-means segmentation

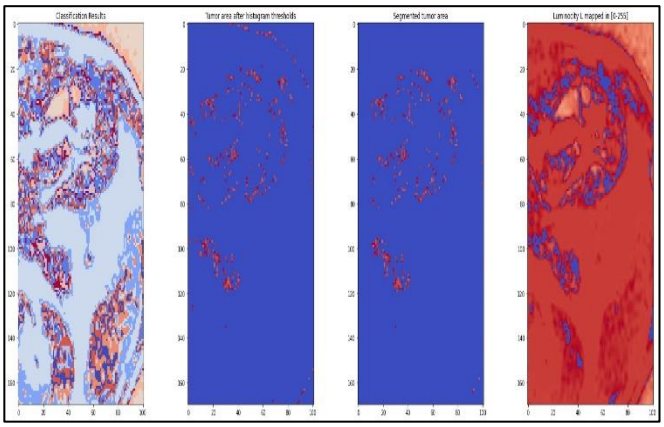

Fig. 4: K mean segmentation instance

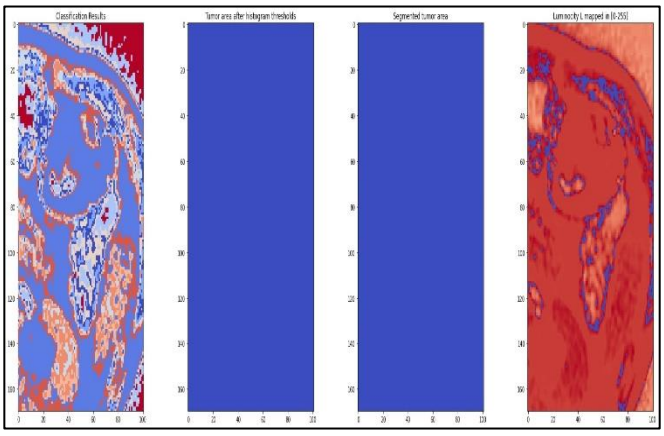

Fig. 5: K-means segmentation

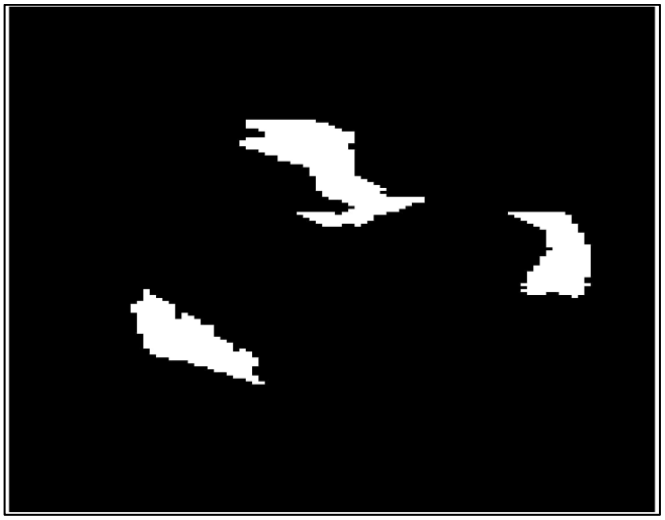

Fig. 6: Classification demo

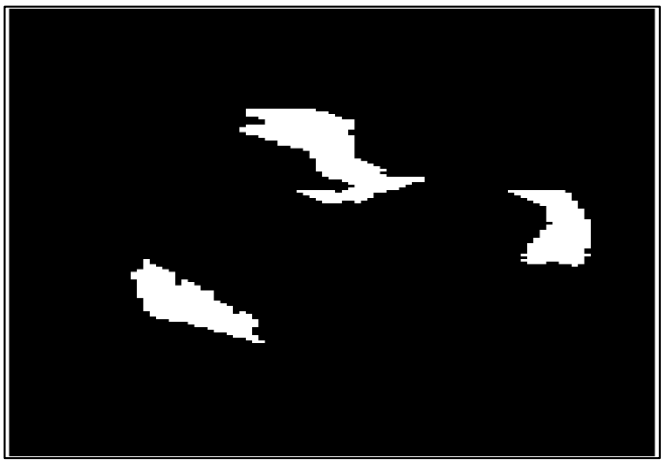

Fig. 7: classification demo 1

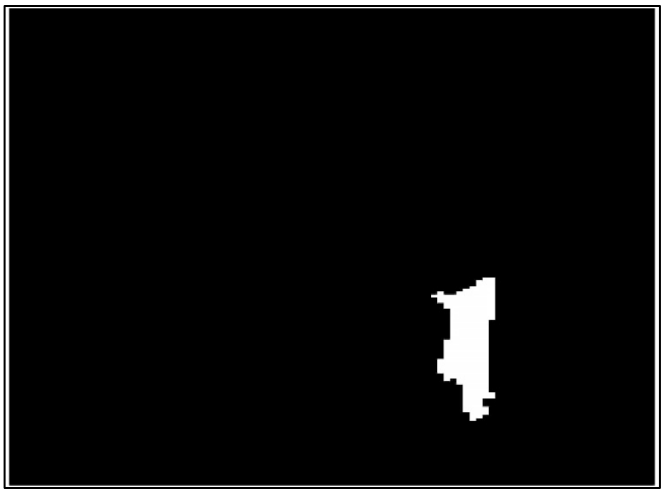

Fig. 8: Classification demo 2

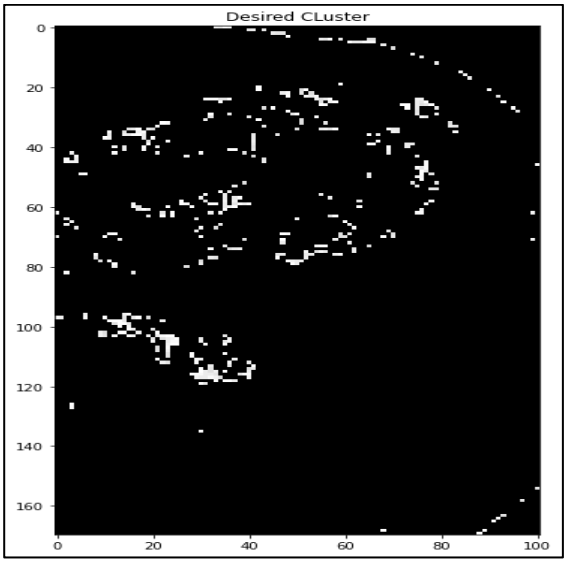

Fig. 9: Classification based on a cluster instance

E. Assessment Metrics

The accuracy, sensitivity, and specificity of the proposed method have all been used as performance measures in the evaluation. According to the number of hidden neurons utilised in this model, Table 1 shows the value of the aforementioned parameters. Figure 10 displays a visualisation of the data in Table 1 on a graph.

As shown in Figure 4 and Table 1, the suggested Unet++ model's accuracy, sensitivity, and specificity values are superior to those of existing models like K-means and FC-means models.

A table that frequently describes how well a classification model performs on a set of test data for which the true values are known is known as a confusion matrix. A matrix with actual values and values predicted by the ML model is used to display the errors in the model's performance.

Let TP (True Positive) represent the result where the model accurately predicts the positive class, TN (True Negative) represent the result where the model accurately predicts the negative class, FP (False Positive) represent the result where the model inaccurately predicts the positive class, and FN represent the result where the model inaccurately predicts the negative class. Then the above-mentioned performance metrics can be described as:

F.Accuracy

It measures the proportion of accurate predictions to all input samples. It is a measure of how well the model performs across all classes and shows how frequently the algorithm properly identifies a data point.

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

G. Sensitivity

The sensitivity is measured by the proportion of actual positives that can be correctly identified. It pertains to the capacity to recognise fruitful outcomes.

$$\text{sensitivity} = \frac{TP}{TP+FN}$$

H. Specificity

The specificity is determined by the ratio of effectively distinct negatives. It has to do with having the ability to spot undesirable outcomes.

$$\text{Specificity} = \frac{TN}{TN+FN}$$

Methods	Accuracy	Sensitivity	Specificity
Proposed method (Unet++)	94	98	99
K-means	86	83	92
FC-means	87	84	91

Table 1: Comparison table showing various performance metrics associated with the proposed model and other pre-existing models

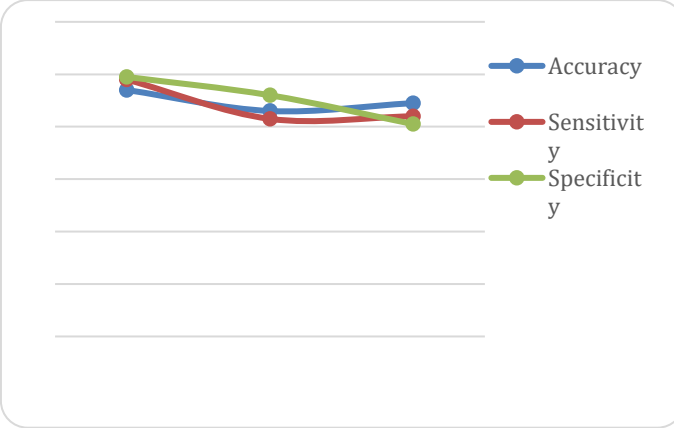

Fig. 10: Plot of various performance metrics associated with the proposed model and other pre-existing models

4. Conclusion

Uncontrolled cell growth in a part of the pancreas can lead to the development of pancreatic cancer. Exocrine cells or neuroendocrine cells can both contribute to its development. The prognosis for pancreatic cancer is dismal because it spreads quickly and is frequently found late. In the early stages, there are no symptoms. Later stages are associated with non-specific symptoms like lack of appetite and weight loss. Different algorithms are applied to the input MRI scan image for classification through a step-by-step process. The proposed UNet++ model produced an accuracy value of 94% which is more than the accuracy value of other latest models. Also, this UNet++ model has a sensitivity of 98% and a specificity of 99%. Thus, this CAD-based DL model can be considered an efficient method for the classification of PC.

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