

Light Gradient-Boosting Machine Edge Detection With Cropping Layer for Semantic Segmentation of Pancreas

Wilson Bakasa

*School of Mathematics, Statistics and Computer Science
University of KwaZulu-Natal, Durban, South Africa*

Serestina Viriri

*School of Mathematics, Statistics and Computer Science
University of KwaZulu-Natal, Durban, South Africa*

Corresponding Author: Serestina Viriri

Copyright © 2023 Wilson Bakasa and Serestina Viriri. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Abstract

Anatomical variations in shape and volume metrics make pancreas medical image processing one of the most difficult subjects. Image processing in pancreas Computed Tomography (CT) is required to detect the class of pancreas anomaly accurately, reducing the possibility of a fatal outcome. It is estimated that a misunderstanding of radiology images accounts for 40% to 54% of all negligence claims. Machine learning advancements have created opportunities to train algorithms to learn patterns in pancreas images and use that knowledge to predict the pancreatic ductal adenocarcinoma (PDAC) overall survival rate. This paper performs feature extraction on CT pancreas images using edge detection techniques. Non-Local Means (NLM) are applied to the images to remove noise and smoothen them to highlight the defect. The experiments achieved an Intersection over Union (AOU) of 0.79 and an accuracy of 0.96. The images are then passed through the cropping layer to remove unwanted sections. The new train set is obtained from aggregating features from the edge detection feature extraction techniques and was then pruned to only eight features using the Principal Component Analysis technique. The train set was loaded into Light Gradient-boosting Machine (LGBM) to train the model to segment all the images.

Keywords: Edge detection, Pancreatic ductal adenocarcinoma, Cropping, Semantic Pancreas Segmentation, LGBM

1. INTRODUCTION

Medical imaging is a critical component in many applications [1, 2], in treating PDAC, such as computer-aided diagnosis (CAD) using CT images to detect PDAC. These applications are found throughout the clinical course of events, most notably in the planning, executing, and evaluating procedures before surgical operations and diagnostic settings. Image segmentation, in general, is splitting an image into individual regions to reduce the complexity of analysis by assigning labels to pixels used to isolate homogeneous pixels of pancreas images.

LGBM [3, 4], is a gradient-boosting framework that generates high-quality prediction models using tree-based learning algorithms. Gradient Boosting Decision Tree (GBDT) [5, 6], is a decision tree-based gradient-boosting implementation. Each GBDT iteration adds a weak learner, such as a narrow decision tree, to the decision function model to approximate the objective's current negative gradient. These weak learners are constructed from arbitrary subsamples of the training set, considering both examples and features. This subsampling reduces overfitting because learners only see a portion of the available information. Gradient boosting [7], is an ensemble technique for producing a single prediction model by combining weak learners stage by stage. Because of its generalisation ability, efficiency and precision are widely used in many machine learning tasks. [8].

Unlike most decision tree learning algorithms, LGBM grows the tree leaf-by-leaf, selecting the leaf with the highest delta loss to grow. Because the leaf-wise algorithm reduces loss by growing deeper trees, this procedure produces better results with fewer trees. To reduce over-fitting, the tree depth must be limited. Furthermore, other approaches that use [9], for decision tree learning, LGBM uses histogram-based algorithms [10]. Histograms divide continuous feature values into discrete bins, which saves memory and speeds up training, allowing LGBM to be used with large datasets.

The main contribution of this work is as follows:

1. A systematic technique for segmenting pancreas PDAC cancer CT images was investigated using LGBM and traditional edge detection feature extractors.
2. The dataset's item segmentation challenges, such as different image resolutions and class imbalance issues, were addressed.
3. A transfer learning architecture was proposed, automatically determining the num leaves parameters (which control the number of decision leaves in a single tree), resulting in improved accuracy.
4. A feature fusion architecture was proposed to improve segmentation accuracy by combining image features extracted by different traditional edge detection feature extractors.

This paper is structured as follows: Section 2 discusses related papers, and Section 3 describes the methodology, dataset, and various architectures investigated in this study. Section 4 summarises the experimental results and analysis, and Section 5 concludes and discusses future work.

2. RELATED WORK

Extracting features from images is necessary because they can contain useful information. The detection of these features is required for image segmentation for diagnostic purposes. Edge detectors work well on clean images but are extremely sensitive to noise. Because of their excellent soft tissue contrast and high spatial resolution, CT image systems have recently become a massively valuable technique [11, 12]. On the other hand, image noise is the primary cause of degeneration, making it more difficult to distinguish fine detail in images during diagnosis examination. Then, because edge detectors are susceptible to noise, extracting features from Magnetic resonance imaging (MRI)

images is difficult. As a result of this problem, researchers devised several methods for extracting features from CT images. [13, 14].

Roy et al. [15], proposed using brain MRI to investigate automated brain tumour identification and classification. Brain tumour segmentation was an important technique for extracting information from complex MRI brain images. In [4], Khuntia et al. developed and tested a method for segmenting brain tumours from two-dimensional MRI data. Tumours found in three dimensions are also shown. High-pass filtering, histogram equalisation, thresholding, morphological methods, and linked component labelling were used to detect cancer. The tumour volume was calculated after the 2D images were reconstructed into 3D volumetric data.

Havaei et al. [16], developed a semi-automatic method based on the KNN classifier. The researchers used the well-known BRATS 2013 dataset for both whole and core tests, achieving Dice similarities of 0.85 for the entire tumour region and 0.75 for the core tumour area. Mohsen et al. proposed classifying a dataset containing three distinct brain tumours using a deep learning-based classifier with discrete wavelet transform (DWT) and PCA. Four other deep learning-related studies with similar goals use the same dataset as we did in this study, which is critical for comparing and evaluating the performance outcomes of the proposed model.

3. MATERIALS AND METHODS

This section discusses the implementation of edge detection techniques as feature extractors and the segmentation of pancreas CT images using LGBM to analyse how the model can augment today's medical imaging segmentation. First, to reduce noise, the NLM technique is used. Feature extraction is done using edge detection techniques, followed by the aggregation of features extracted and then feature pruning is done before the segmentation process.

3.1 Non-Local Means

Non-local means (NLM) is a denoising algorithm implemented in image processing that provides post-filtering clarity and preserves image details compared to local mean algorithms. The NLM [17, 18], fine-tuned individual pixel values with a weighted average of all pixels in the image. In this paper, we performed denoising using NLM to each image changed from DCM to tiff files to work easily with them. The tiff has an alpha channel that reserves discrete pixel transparency and colour information. While preserving the quality of files, the method provides a fast and simple decompression and compression of images. A tiff file is a great choice when high quality is the goal [19, 20]. The technique is based on changing the pixel colour to the average of the colours of nearby pixels [21, 22].

$$NLU(p) = \frac{1}{X(p)} \int f(d(Y(p), Y(q)))u(q)dq \quad (1)$$

where image patches Euclidean distance is given by $d(Y(p), Y(q))$, centred respectively at p and q , $C(p)$ is the normalising factor, and f is a decreasing function.

3.2 Cropping Layer

The definition of the term crop is “to trim” or “to cut back”. To remove the outer margins of a digital image during pre-processing. Cropping can be used to adjust the aspect ratio (ratio of the image’s length to width) and/or reduce the size of an image (in pixels). Cropping an image typically involves removing an unwanted segment or unimportant detail, changing the image’s aspect ratio, or enhancing the composition [23]. A cropping operation is required to centre the pancreas CT images and remove extraneous portions of the image. Different locations within the image may also be used for separate pancreas imaging. By cropping the image and adding pads, we can ensure that nearly all images are in the same area of the overall image.

3.3 Feature Extraction based on Edge Detection

The comprehensive feature extraction process is important in predicting PDAC patient survival days using machine learning algorithms, according to [24]. The model’s accuracy improves by removing redundant data from the input data and computing its features. This phase generates a new set of features by combining and transforming the original feature set. We extracted features using traditional edge detection methods such as Sobel, Prewitt, Gaussian, Median, Scharr, Farid, and Canny.

Edge detection techniques [25–27], are generally used to find and identify sharp discontinuities in images. For medical image recognition of the pancreatic, edge detection is crucial.

4. FEATURE FUNCTION

The feature functions [28], is written as $Vin(v_0, \dots, v_n)$. TABLE: 1 shows some examples of feature functions. A new feature function could be created by combining several feature functions. The extracted feature’s depth is determined by three factors, which are as follows:

1. The initial raw features extracted from images by feature extractors;
2. The feature function;
3. The number of times feature function operators were used.

We will use the sum function in this formulation to aggregate all features extracted from the edge detection feature extractors. Compositions of different feature functions are an easy way to express more complex feature functions. Feature functions are important not only for transferring but also for interpreting features [29].

Table 1: Feature Functions [29], [28]

Functions	Mathematical Definitions	Representation
Sum	$V\langle G, k \rangle = \sum_{g \in G} k_g \quad (2)$	Sum
Weight.Lp	$V\langle G, k \rangle = \sum_{g \in G} k_g - k_{g'} ^2 \quad (3)$	Diff
Hadamard	$V\langle G, k \rangle = \prod_{g \in G} k_g \quad (4)$	Mul
Mean	$V\langle G, k \rangle = \frac{1}{ G } \sum_{g \in G} k_g \quad (5)$	Mean

5. FEATURE PRUNING

The edge detection feature extractors’ output features are then evaluated. The feature evaluation routine selects the important features from the feature functions. The feature evaluation function is used to select the subset of important features. We chose the following characteristics: We began by determining the evaluation score for each feature. The feature score is calculated by comparing it to the threshold value and the basic feature score. If the feature score exceeds the sum of the two, the basic feature is discarded [30].

5.1 Principal Component Analysis

The computation of features is an important step in the segmentation process. However, not all extracted features contribute equally to the prediction task. As a result, feature reduction is required to select the most weighted features, thereby improving the machine learning algorithm’s accuracy. Using the PCA method, traditional edge detection models generate many features that can be reduced to a lower dimension.

PCA [31–33], is a widely used dimensionality reduction method for reducing the dimension of large datasets while retaining the majority of the information. PCA is used to eliminate those irrelevant features, resulting in lower computational overhead for the proposed method while retaining the same accuracy.

5.2 Feature Map

A feature map is a function that maps a data vector to a feature space. The main logic in machine learning is to provide data that can be segmented to the learning algorithm. It refers to mapping features from input space to kernel Hilbert space, which is common in very large dimensions [34, 35].

A filter uses traditional methods to measure how closely an input region resembles a feature, which can be achieved after the pre-processing stage. Any pronounced aspect, such as a vertical edge, a horizontal edge, an arch, or a diagonal, can be considered a feature. The function of a filter is to serve as a single template or pattern that, when convolved across the input, identifies correspondences between the stored template and various locations in the input image [20, 36].

Some of the feature maps obtained from our images are shown in FIGURE: 1.

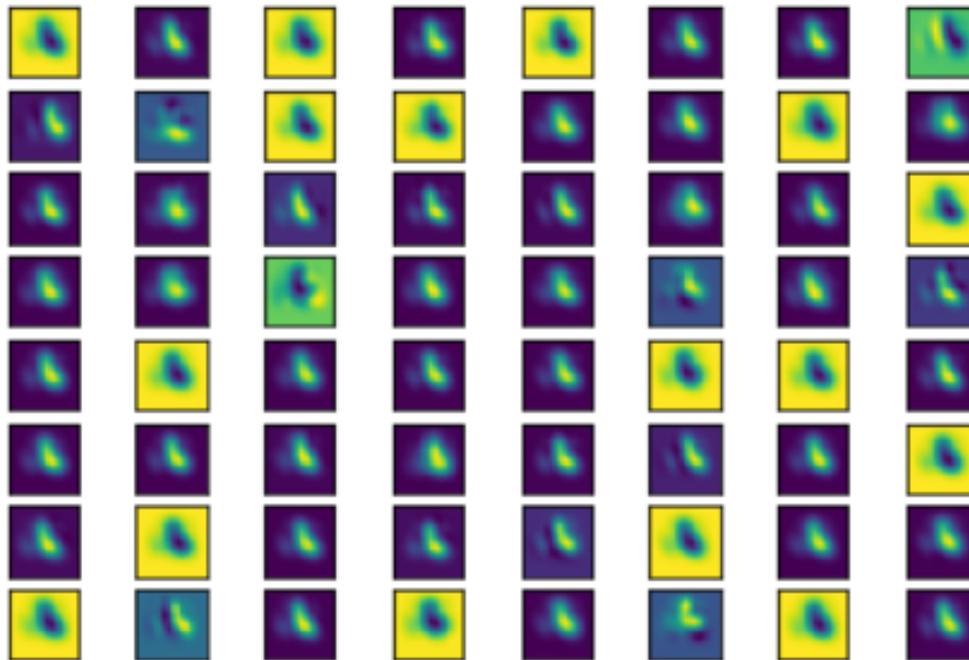


Figure 1: Some selected Feature Maps for the images

6. Implementing LGBM for Segmentation

Compared to deep learning algorithms, traditional approaches are frequently easier to interpret. Certain applications, such as the segmentation of medical images, may require this. When compared to deep learning methods, conventional methods frequently require less processing power. Applications that demand real-time performance may find this to be crucial.

In some circumstances, deep learning approaches or conventional methods alone may not be superior to ensemble methods. For instance, a study [37], demonstrated that, for the segmentation of skin lesions, a combination of deep learning and conventional techniques produced superior results to either methodology used alone. Standard and deep learning methods will be used depending on the particular application. To improve segmentation outcomes, ensemble approaches, however, might be a potent tool.

LGBM [3, 38], is a high-performance gradient-boosting algorithm based on decision trees, similar to Random Forest. It splits the tree using the best-fit algorithm, unlike other boosting algorithms. The algorithm is widely used due to its fast and efficient training, requiring less memory than other algorithms.

First, load the image, convert it to grayscale, and preprocess it to form a blob. Then apply, traditional edge detection methods Sobel, Prewitt, Gaussian, Median, Scharr, Farid, and Canny as feature extractors method to the blob image. The edge features will then be extracted from the image, and a training dataset will be created with the edge features and the ground truth labels. The LGBM Classifier model will then be trained on the training dataset. Finally, the model will be evaluated on a test dataset.

FIGURE: 2 shows the images are pre-processed using the cropping technique in the cropping layer to remove unwanted pixels that might be considered during feature extraction. The cropped images

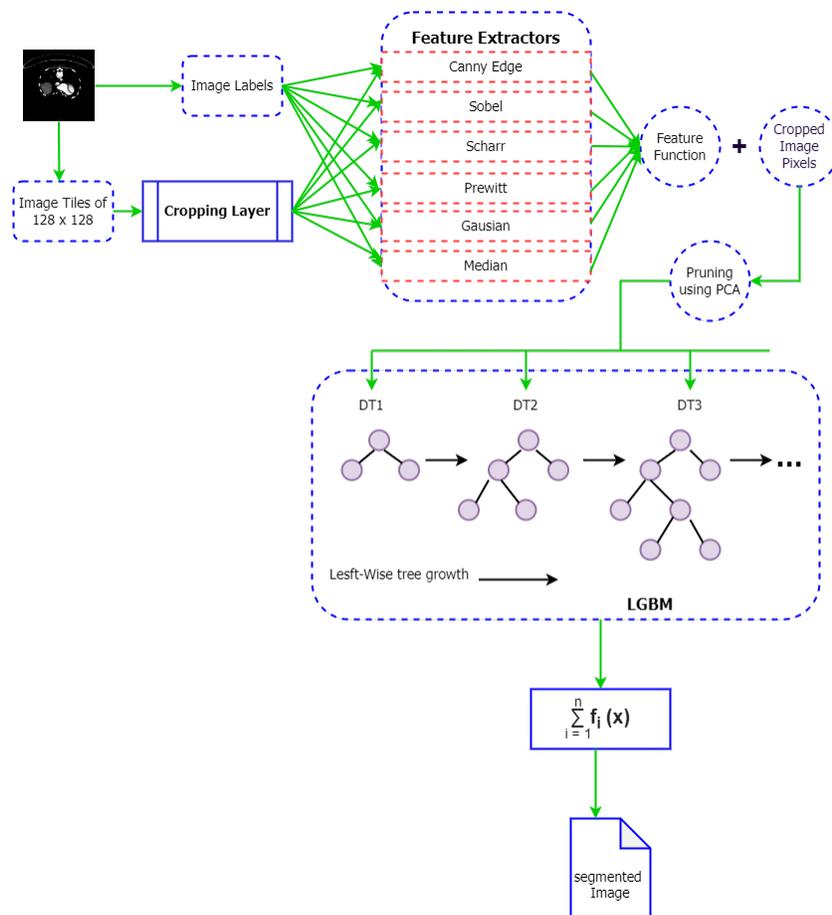


Figure 2: Images pass through the cropping layer for pre-processing, followed by Transfer Learning of features from traditional edge detection methods to the LGBM for segmenting the CT pancreas images. Features from the feature extractors are fused and added to the cropped image pixels. Pruning is then done to reduce the number of features before they are fed into LGBM as a new training set for image segmentation.

are then passed as input to feature extractors to extract various features combined with the feature function. Results from the feature function and the features from the cropped image are then summed and passed through a pruning stage using the PCA, and the output is sent as input for segmentation using LGBM. Algorithm: 1 shows the processing done by the model.

LGBM can handle massive amounts of data while consuming very little memory. It emphasises outcome accuracy. Scientists use LGBM [39], to create research applications because it supports GPU learning. LGBM is an ensemble learning algorithm that performs segmentation by combining the outputs of multiple base learner models. The Light GBM, a gradient-boosting framework, employs tree-based learning methods. It is intended to be widely disseminated and efficient, with the following benefits:

- Fast when training and improved accuracy.
- Less memory requirement.
- Very efficient.
- Provide GPU learning Support.
- Capable of handling Large-scale data.

According to [40], LGBM grows trees vertically, whereas other tree-based learning algorithms grow trees horizontally. LGBM grows in a tree, whereas other algorithms grow in the form of levels. It will grow the leaf with the greatest delta loss. When expanding the same leaf, a leaf-wise algorithm can reduce loss more than a level-wise method.

7. RESULTS

Ten decom files were randomly selected from the Cancer Imaging Archive (TCIA) Public Access dataset, consisting of 3D CT scans of 512×512 -pixel resolution from 53 males and 27 female subjects 18-76 age group [41], 370 patients with PDAC and 320 controls' contrast-enhanced CT images from the Taiwanese Centre dataset were used to train CNN. Using these datasets, researchers can examine how to use CT imaging to predict PDAC overall survival [42].

7.0.1 Cropped images

First, the images are passed through the cropping layer to remove unwanted sections. FIGURE: 3 shows some results for the non-cropped images (A1 - A4) and cropped images (B1 - B4). The first column shows the original image; column two shows images after setting the blob as the input to the network and performing a forward pass to compute the edges; column three shows connected component-based labelled images; and column four shows created a false colour image with the black background and coloured objects.

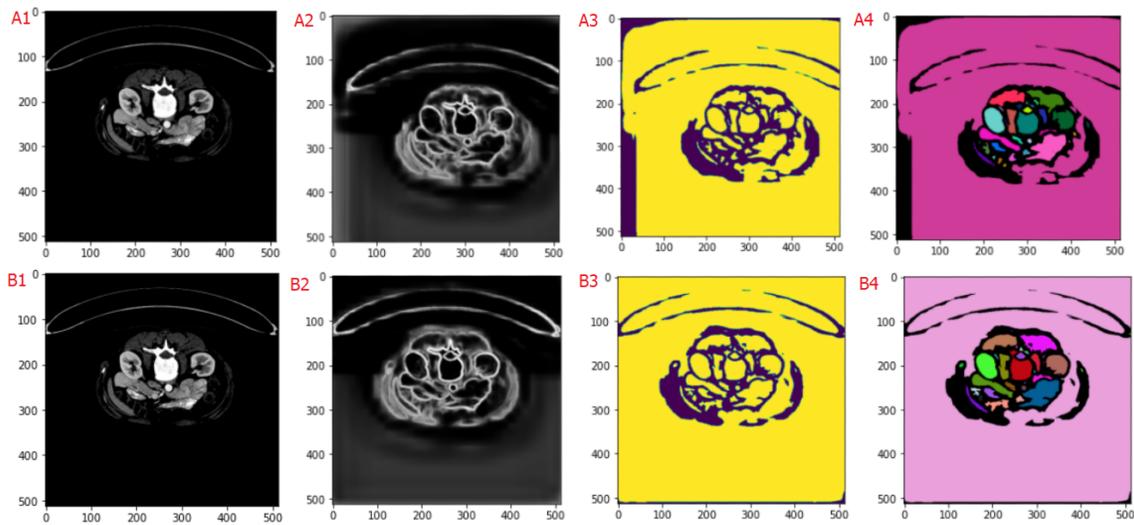


Figure 3: Cropping Layer implementation to the pancreas CT images. A1 (Uncropped) and B1 (Cropped) - Original Image, A2 (Uncropped) and B2 (Cropped) - blob (preprocessed image), A3 (Uncropped) and B3 (Cropped) - Segmented binary image, and A4 (Uncropped) and B4 (Cropped) - False colour image with a black background and coloured objects.

7.0.2 Data frame

A Data Frame is a data structure that organises information into a two-dimensional table of rows and columns. The two tables, TABLE: 2 and TABLE: 2, shows data frame prints before and after implementing cropping. Pandas, the popular Python data analysis library, uses Data Frames as its primary data type [43].

Table 2: Dataframe without cropping

Label	Area	Equivalent diameter	Mean intensity-0	Mean intensity-1	Mean intensity-2	Solidity
2	1702	46.551624	117.602233	117.602233	117.602233	0.792734
3	1849	48.520304	86.833423	86.833423	86.833423	0.724246
4	65	9.097284	101.984615	101.984615	101.984615	0.802469
6	103	11.451798	247.922330	247.922330	247.922330	0.811024
10	175	14.927053	30.697143	30.697143	30.697143	0.935829

TABLES: 2 and 3 show parameters for the data frame before and after implementing cropping to the images. Solidity is calculated as the difference between the number of pixels in the object and the convex hull image. This can measure the object’s compactness. The image passed through the cropping layer has a high solidity of 0.97, which is better than that of an image not cropped, 0.94. The area for up to ten (without cropping) and thirteen (with cropping) different labels is calculated, which shows the cropped images had a high area of 2017 at label 5 and non-cropped images had

the least area of 65 at label 4. The equivalent diameter is calculated to give the circle’s diameter, whose area is the same as the contour area. This shows the highest equivalent diameter for the cropped image of 51.35 at label 5, which has the highest area, and the least equivalent diameter of 9.1 at label 4, which has the least area. The mean intensity at any given pair of coordinates (x,y) is a two-dimensional function f(x,y), where x and y are spatial coordinates. Solidity is also calculated for various labels. The mean intensity is highest at label 9 for the cropped image, which is 249.2, but that will record a low solidity for the same image.

Table 3: Dataframe after cropping.

Label	Area	Equivalent diameter	Mean intensity-0	Mean intensity-1	Mean intensity-2	Solidity
4	1718	46.769921	48.939464	48.939464	48.939464	0.852605
5	2071	51.350551	43.259778	43.259778	43.259778	0.828731
9	2012	50.613812	249.214712	249.214712	249.214712	0.784405
12	196	15.797308	41.306122	41.306122	41.306122	0.915888
13	1933	49.610201	138.455251	138.455251	138.455251	0.966983

7.0.3 Feature importance

The node impurity in Scikit-learn is calculated using Gini importance [44], and feature importance is essentially a reduction in a node’s impurity weighted by the number of samples reaching that node relative to the overall number of samples, which is node probability.

$$n_j = s_i C_i - s_{left(i)} I_{left(i)} - s_{right(i)} I_{right(i)} \tag{6}$$

Where: n_j = node i importance, s_i = number of samples weighted, reaching node i , I_i = the impurity value of node i , $left(i)$ = child node on left of node i and $right(i)$ = child node on right of node i

To determine the feature importance for each decision tree, this equation provides us with the importance of a node j . The tree’s different branches can each use a particular feature.

$$f_j = \frac{I_j}{\sum_{j \in \text{nodes}} I_j} \tag{7}$$

The features are divided by the total number of trees in our random forest, and the result is the overall feature relevance. The features are normalised against the sum of all feature values in the tree. With this in mind, you can understand the significance of features in random forests.

Depending on how well a feature may improve the purity of the leaves, each tree in a random forest, LGBM, or XGBoost can determine how important that feature is. The significance of the characteristic increases as the increase in leaf purity increases. This is carried out individually for each tree, averaged across all trees, and then set to one. Using feature selection can aid in better comprehending the problem that has been handled and occasionally result in model enhancements. A higher score indicates that the particular feature will have a greater impact on the model being used to forecast the particular variable.

The feature importance graph is plotted to see which feature extractors did the best to extract features. To avoid ignoring important features, we had to set a threshold which was the original image. Gaussian was the best, and different feature ranges are shown in FIGURE: 4, 5 and 6. The original image (cropped image) pixel values have also indicated that they are important for feature extraction [45].

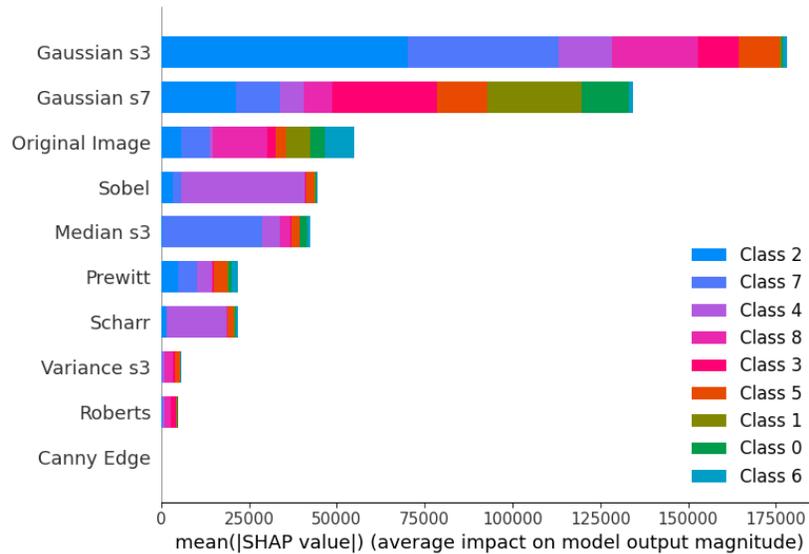


Figure 4: Implementing LGBM for segmentation with different feature extractors: The feature importance graph demonstrates which feature extractor extracted the most important features in predicting the target variable. Gaussian at Sigma 3 was the best, and Canny Edge was the least. The original image is the cropped image.

Feature importance refers to techniques that assign a score to input features based on their usefulness in predicting a target variable. Statistical correlation scores, coefficients calculated as part of linear models, decision trees, and permutation importance scores are all common examples of feature importance scores. Feature importance scores are important in a predictive modelling project because they provide insight into the data and the model and the foundation for dimensional reduction and feature selection, which can improve the efficiency and effectiveness of a predictive model on the problem [46].

Any features extracted by all those methods below the original image will be discarded. LGBM produced better results by adding important features from Gaussian Sigma 3 and 7. For random-Forest and XGBoost, all the methods failed to extract features above the threshold and all features were discarded.

7.1 Improving Segmentation Speed

The PCA was implemented to improve the segmentation algorithm as it would calculate the maximum number of features that can be used. This is to avoid inputting many features, thereby

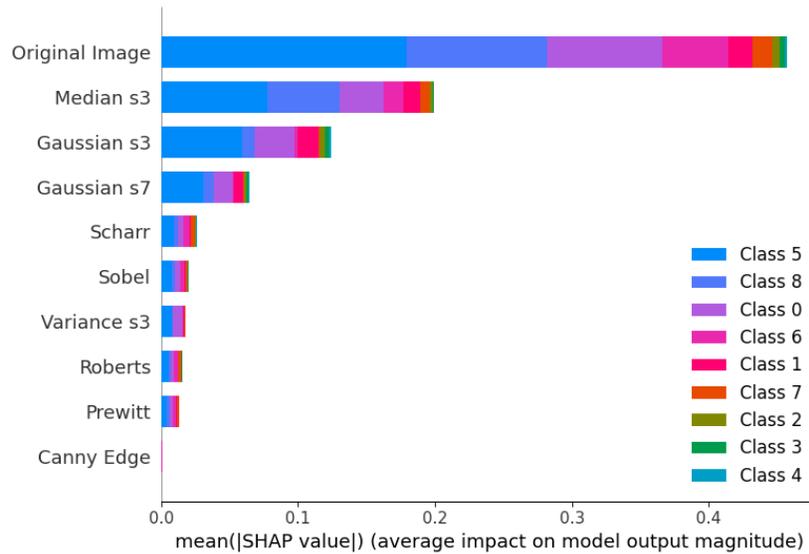


Figure 5: Implementing XGBoost for segmentation with different feature extractors: The feature importance graph demonstrates which feature extractor extracts the most important features in predicting the target variable. The original image was the best, and Canny Edge was the least. The original image is the cropped image. Accuracy can be improved by adding more feature extractors.

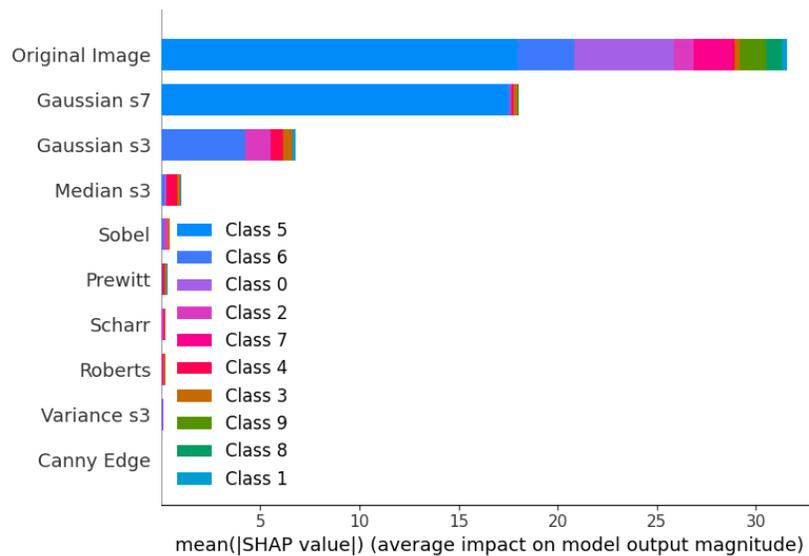


Figure 6: Implementing RandomForest for segmentation with different feature extractors: The feature importance graph demonstrates which feature extractor extracts the most important features in predicting the target variable. The original image was the best, and Canny Edge was the least. The original image is the cropped image. Accuracy can be improved by adding more feature extractors.

increasing the load on the model without improving accuracy. As shown in FIGURE: 7, when using thirty features, the cumulative variance will be below 0.9, which is low. It will be slightly above 0.9 when using one hundred features but shows signs of increasing. When using eight hundred features, the graph line started to be constant when the number of components was above two hundred, so two hundred components were used as the graph shows cumulative variance above 0.95.

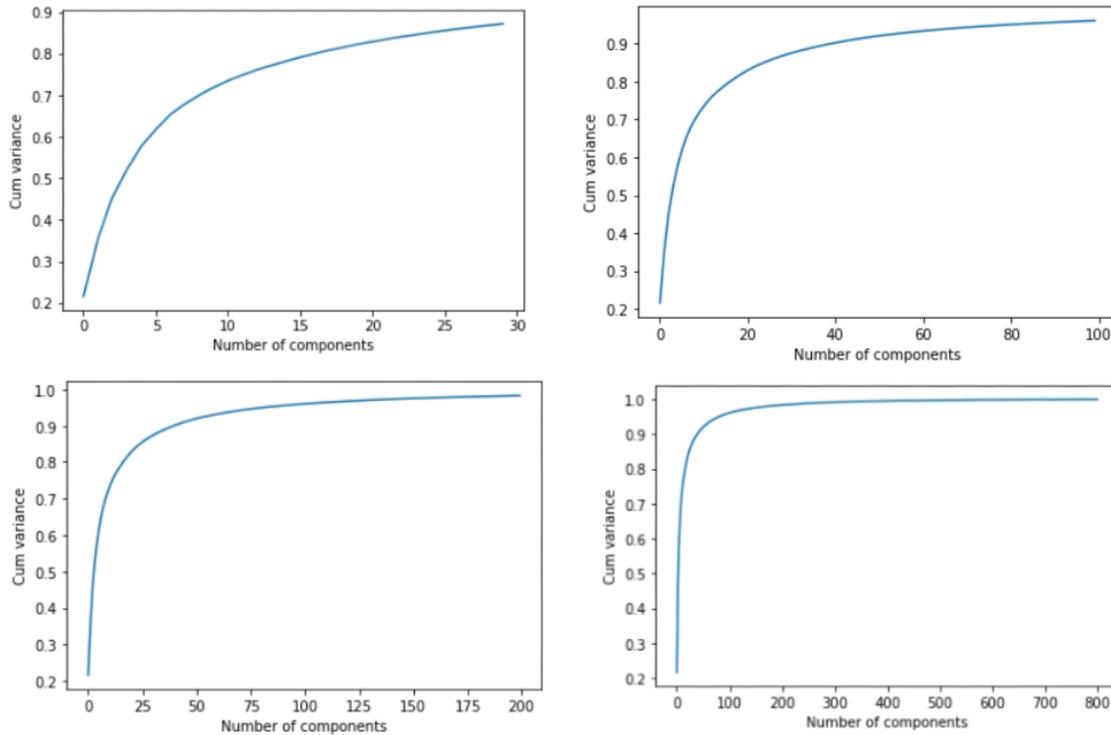


Figure 7: Graph to analyse the best cumulative variance against the number of components using PCA.

7.2 Segmented Images

FIGURE: 8 depicts a sample of original images segmented using the LGBM, XGBoost and Random Forest, and features extracted using traditional methods from the TCIA dataset. The algorithm first identifies regions in the image most likely to contain the desired objects and then examines these regions at increasing resolutions. The ground truth is the true and accurate segmentation to compare with our segmented images to test the accuracy of automated image analysis processes.

8. DISCUSSION

Segmentation’s primary objective is to assist in identifying and characterising the pancreas and its pathogenic characteristics. The comprehension of the main pancreatic diseases, like the size cyst,

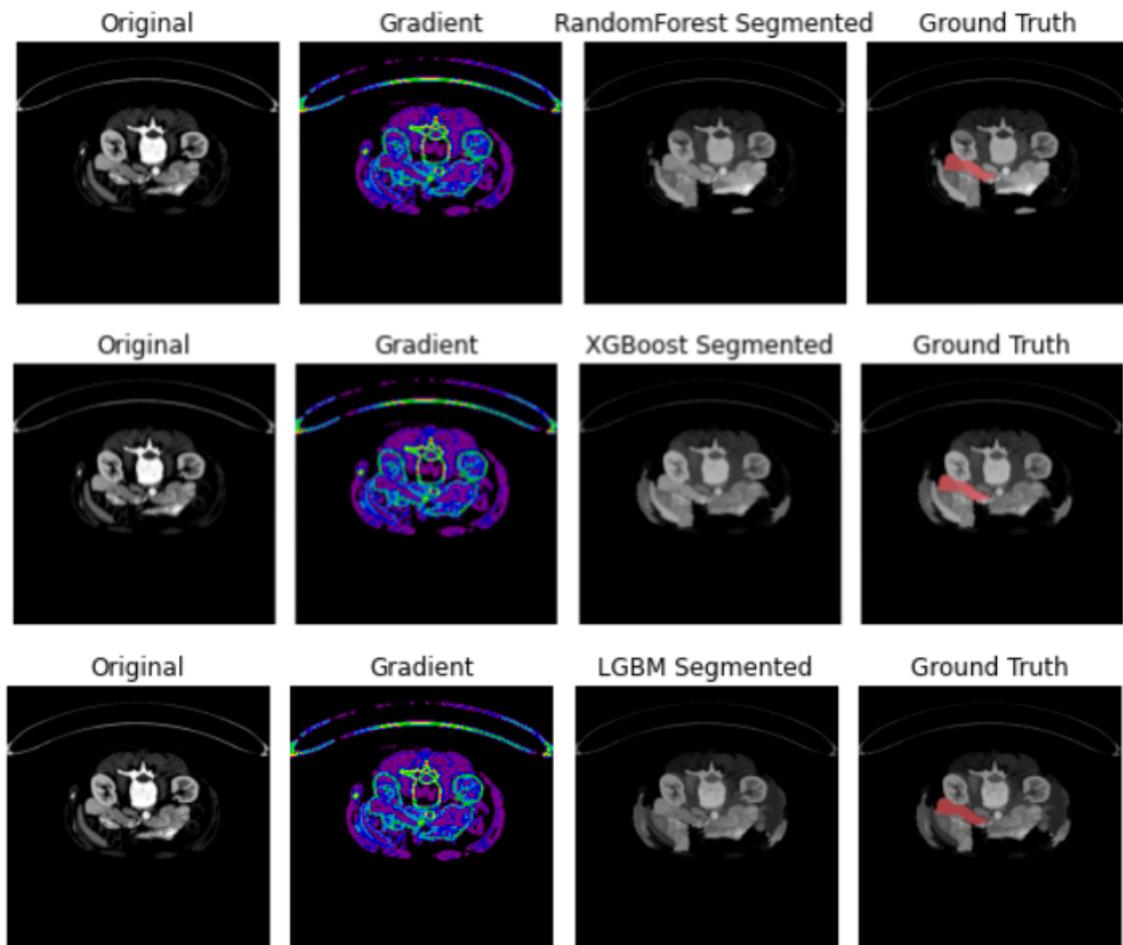


Figure 8: Original images from the dataset, with each row showing the local gradient, segmented and ground truth images for each original image. The pancreas is shown in red for the ground truth, and images are segmented using LGBM, XGBoost and Random Forest.

may be enhanced by quantitative data obtained utilising segmentation techniques [47]. To decide on surgery and treatment, it is crucial to use segmentation algorithms to obtain the quantitative volumetric measures of the pancreatic lesion.

Publicly accessible datasets are crucial for the research community and evaluating the benefits and drawbacks of segmentation techniques since assessing the precision of various segmentation techniques using the same dataset is more useful. It is necessary to use the same standardised dataset and to develop methods for reducing the large degree of variation in image parameters between imaging facilities [48]. Additionally, most of the data only includes CT images; MRI images are few.

The absence of publicly accessible datasets containing matching labelled images has hampered the development of pancreatic segmentation algorithms [49]. The NIH datasets, the first to be utilised

publically, contain the most thorough hand labelled/annotated atlases; however, they are deficient in basic patient data necessary for preprocessing, such as atlas selection. TCIA is designed to foster increased public availability of high-quality cancer imaging data sets for research. F.A.I.R. (Findable, Accessible, Interoperable, and Reproducible) criteria for data release are strictly followed, making data accessible.

The largest research material studies pancreatic segmentation based on atlas and neural network segmentation methods. The equipment operating speed has increased, and the segmentation accuracy is primarily considered reasonably high. These two approaches are crucial directions for future growth. Future research will also include a significant amount of work on novel methodologies and hybrid technologies [50]. Although the pancreas only takes up a very small portion (e.g., 0.5% of the total CT volume), it is well known that it frequently exhibits substantial variability in form, size, and position. Therefore, segmenting the pancreas is still a complex and challenging task.

The accuracy assessment has generally improved yearly; however, the evaluated papers range greatly from one another, making it difficult to evaluate accuracy using standardised metrics and datasets. The datasets used in the publications are, in fact, highly varied from one another, containing various numbers and varieties of patients and images obtained using various acquisition parameters.

According to [51], statistical shape models effectively use complicated form variability, whereas deep neural networks have seen substantial success in segmenting medical images. a Bayesian model that incorporates the segmentation findings from both deep neural networks and statistical shape models was proposed, and it reported a decent result of 85.32 ± 4.19 of DSC. This model used the rich shape priors gained from statistical shape models to improve the segmentation of deep neural networks [52].

The best dice similarity coefficients for segmenting the pancreas and cysts were 85.1 and 86.7, respectively, and were achieved by [53], using a mix of the random walker and region-expanding approaches. [54], used region growth to mark the pancreatic region after applying histogram equalisation to improve the contrast of computed tomography images in low-contrast conditions. Although the best Jaccard index of 86.97 was used to segment data, the used datasets are not mentioned specifically.

Image segmentation uses a technique called “graph cut,” [55], one of those for energy reduction. The pancreas was segmented from CT images 2016 using a graph cut approach and probabilistic atlas. Their data found that the pancreatic segmentation Jaccard index was 0.705. In natural image processing, region growth is a crucial and well-established segmentation approach applied to segment abdominal organs using different methods.

A bottom-up pancreas segmentation representation has been developed using aggregated confidence maps to categorise image areas or super-pixels to the pancreas and non-pancreas label assignments. This representation uses dense binary image patch labelling to label the confidence maps [52]. This technique uses mid-level visual representations of image segments to increase the segmentation accuracy of highly deformable organs, such as the pancreas. A set of multi-scale and multi-level deep convolutional neural networks applied in a sliding window fashion on local image patches to capture the complexity of the pancreas’ appearance in CT images was proposed in previous work, which further improved segmentation performance.

Our proposed method has the advantage of the ability to learn rich representations, be versatile, and increase segmentation accuracy (0.96) by reducing manual intervention. The cropping layer plus a reliable bounding box for more precise segmentation is created by first localising the pancreas within the entire 3D CT image. The next step is to segment the pancreatic tissue using a fully deep-learning approach based on the effective use of holistically-nested convolutional networks on the three orthogonal axial, sagittal, and coronal views. The holistically nested convolutional networks probability maps for per-pixel are fused via pooling to build a 3D bounding box of the pancreas that can maximise recall.

Soon, the primary goal will continue to increase the pancreas segmentation's accuracy and efficiency because the most recent accuracy is below that of other abdominal organs and well below what is needed to meet clinical needs. Additionally, due to the poor contrast in the boundary, the unpredictability in location, shape, and size, and the importance and value of the pancreas and its lesion region in clinical practice [56], automatic segmentation of these structures is vital and difficult.

Segmenting pancreas images simultaneously from various modalities, such as CT and MRI, is also important. Doctors typically analyse images from multiple imaging modalities to more accurately measure and evaluate the state of the abdominal organs.

9. CONCLUSIONS

Image segmentation has been widely used in pancreas imaging to separate homogeneous areas. Organ segmentation methods have been successfully implemented in large organs such as the lungs, heart, and kidneys in recent years, but little has been done to small organs like the pancreas. The accuracy of segmentation determines whether the automated analysis procedures succeed or fail. However, the complexity of the anatomical structure and the scarcity of labelled data for PDAC patients make it difficult to achieve an acceptable level of accuracy in pancreas segmentation. These and other factors make pancreas segmentation difficult, and there is a high risk of over or under-segmentation.

The research has proved to be efficient in using edge detection traditional methods to be feature extractors and the features to be aggregated and pruned to come up with only crucial features for segmentation. Pruning is important for reducing features and helps to increase accuracy as only specific features are used rather than a general description.

The fact that there aren't enough labelled imaging datasets readily available to the public is one of the remaining barriers to developing pancreatic segmentation algorithms. Future approaches must be resilient to the wide variations in pancreatic appearance, shape, and size to improve segmentation quality. In diseased circumstances, this will make it possible to capture the characteristics of the pancreas in great detail and may pave the way for automatic segmentation in clinical settings.

References

- [1] Arakeri MP, Manvi SK. Medical Imaging and Computer-Aided Diagnosis. In Medical imaging methods CRC Press. 2021;45–56.

- [2] Paul J, Sivarani TS. Retracted Article: Computer Aided Diagnosis of Brain Tumor Using Novel Classification Techniques. *J Ambient Intell Hum Comput.* 2021;12:7499–7509.
- [3] He R, Yang X, Li T, He Y, Xie X, et al. A Machine Learning-Based Predictive Model of Epidermal Growth Factor Mutations in Lung Adenocarcinomas. *Cancers.* 2022;14:4664
- [4] Khuntia M, Sahu PK, Devi S. Prediction of Presence of Brain Tumor Utilizing Some State-Of-The-Art Machine Learning Approaches. *IJACSA.* 2022;13.
- [5] Rao H, Shi X, Rodrigue AK, Feng J, Xia Y, et al. Feature Selection Based on Artificial Bee Colony and Gradient Boosting Decision Tree. *Appl Soft Comput.* 2019;74:634–642.
- [6] Li Q, Wen Z, He B. Practical Federated Gradient Boosting Decision Trees. In *Proceedings of the AAAI conference on artificial intelligence.* 2020;34:4642–4649.
- [7] Zhang Z, Zhao Y, Canes A, Steinberg D, Lyashevskaya O, et al. Predictive Analytics With Gradient Boosting in Clinical Medicine. *Ann Transl Med.* 2019;7:152.
- [8] Liu L, Yu Y, Fei Z, Li M, Wu FX, et al. An interpretable boosting model to predict side effects of analgesics for osteoarthritis. *BMC Syst Biol.* 2018;12:29–38.
- [9] Massaoudi M, Refaat SS, Chihi I, Trabelsi M, Oueslati FS, et al. A Novel Stacked Generalization Ensemble-Based Hybrid Lgbm-Xgb-Mlp Model for Short-Term Load Forecasting. *Energy.* 2021;214:118874.
- [10] Pan Z, Fang S, Wang H. Lightgbm Technique and Differential Evolution Algorithm-Based Multi-Objective Optimization Design of Ds-Apmm. *IEEE Trans Energy Convers.* 2020;36:441–455
- [11] Hunter P. The Advent of AI and Deep Learning in Diagnostics and Imaging: Machine Learning Systems Have Potential to Improve Diagnostics in Healthcare and Imaging Systems in Research. *EMBO Rep.* 2019;20:e48559.
- [12] Abadi E, Segars WP, Tsui BMW, Kinahan PE, Bottenus N, et al. Virtual Clinical Trials in Medical Imaging: A Review. *J Med Imaging.* 2020;7:042805.
- [13] Wang S, Kang B, Ma J, Zeng X, Xiao M, et al. A Deep Learning Algorithm Using CT Images to Screen for Corona Virus Disease (COVID-19). *Eur Radiol.* 2021;31:6096–6104.
- [14] Toğaçar M, Ergen B, Cömert Z. Detection of Lung Cancer on Chest CT Images Using Minimum Redundancy Maximum Relevance Feature Selection Method With Convolutional Neural Networks. *Biocybern Biomed Eng.* 2020;40:23–39.
- [15] Roy K, Jaiswal A, Panda P. Towards Spike-Based Machine Intelligence With Neuromorphic Computing. *Nature.* 2019;575:607–617.
- [16] Lim KY, Mandava R. A Multi-Phase Semi-automatic Approach for Multisequence Brain Tumor Image Segmentation. *Expert Syst Appl.* 2018;112:288–300.
- [17] Saladi S, Amutha Prabha N. Analysis of Denoising Filters on MRI Brain Images. *Int J Imaging Syst Technol.* 2017;27:201–208.
- [18] Cui J, Gong K, Guo N, Wu C, Meng X, et al. Pet Image Denoising Using Unsupervised Deep Learning. *Eur J Nucl Med Mol Imaging.* 2019;46:2780–2789.

- [19] Amri H, Khalfallah A, Gargouri M, Nebhani N, Lapayre JC, et al. Medical Image Compression Approach Based on Image Resizing, Digital Watermarking and Lossless Compression. *J Signal Process Syst.* 2017;87:203–214.
- [20] Willeminck MJ, Koszek WA, Hardell C, Wu J, Fleischmann D, et al. Preparing Medical Imaging Data for Machine Learning. *Radiology.* 2020;295:4–15.
- [21] Diwakar M, Kumar P, Singh AK. CT Image Denoising Using Nlm and Its Method Noise Thresholding. *Multimedia Tool Appl.* 2020;79:14449–14464.
- [22] Bhujle HV, Vadavadagi BH. NLM Based Magnetic Resonance Image Denoising—a Review. *Biomed Signal Process Control.* 2019;47:252–261.
- [23] Chlap P, Min H, Vandenberg N, Dowling J, Holloway L, et al. A Review of Medical Image Data Augmentation Techniques for Deep Learning Applications. *J Med Imaging Radiat Oncol.* 2021;65:545–563.
- [24] Zebari R, Abdulazeez A, Zeebaree D, Zebari D, Saeed J. A, et al. A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction. *J Appl Sci Technol Trends.* 2020;1:56–70.
- [25] Shah BK, Kedia V, Raut R, Ansari S, Shroff A. Evaluation and Comparative Study of Edge Detection Techniques. *IOSR J Comput Eng.* 2020;22:6–15.
- [26] Li X, Jiao H, Wang Y. Edge Detection Algorithm of Cancer Image Based on Deep Learning. *Bioengineered.* 2020;11:693–707.
- [27] Gholizadeh-Ansari M, Alirezaie J, Babyn P. Deep Learning for Low-Dose CT Denoising Using Perceptual Loss and Edge Detection Layer. *J Digit Imaging.* 2020;33:504–515.
- [28] Yao Y, Su L, Lu Z. Deepgfl: Deep Feature Learning via Graph for Attack Detection on Flow-Based Network Traffic. In *MILCOM 2018–2018 IEEE Military Communications Conference (MILCOM)*. 2018;579–84.
- [29] Rossi RA, Zhou R, Ahmed NK. Deep Feature Learning for Graphs. 2017. ArXiv preprint <https://arxiv.org/pdf/1704.08829.pdf>
- [30] Ayinde BO, Inanc T, Zurada JM. Redundant Feature Pruning for Accelerated Inference in Deep Neural Networks. *Neural Netw.* 2019;118:148–158.
- [31] Karamizadeh S, Abdullah SM, Manaf AA, Zamani M, Hooman A. An Overview of Principal Component Analysis. *J Signal Inf Process.* 2013;4:173–175.
- [32] Kherif F, Latypova A. Principal Component Analysis. In *Machine Learning*. Academic Press; 2020;209–225.
- [33] Deutsch HP, Beinker MW, Deutsch HP, Beinker MW. Principal Component Analysis. *Derivatives and Internal Models: Modern Risk Management.* 2019:793–804.
- [34] Varshni D, Thakral K, Agarwal L, Nijhawan R, Mittal A, et al. Pneumonia Detection Using CNN Based Feature Extraction. In *2019 IEEE international conference on electrical, computer and communication technologies (ICECCT)*. 2019;1–7.

- [35] Zhang M, Li W, Du Q, Gao L, Zhang B. Feature Extraction for Classification of Hyperspectral and Lidar Data Using Patch-To-Patch CNN. *IEEE Trans Cybern.* 2018;50:100–111.
- [36] Pradhan AK, Swain S, Rout JK, Ray NK. Prediction of Stroke Disease Using Different Types of Gradient Boosting Classifiers. In: *Advances in Data Computing, Communication and Security*. Springer. 2022;337–346.
- [37] Khan AH, Awang Iskandar DN, Al-Asad JF, Mewada H, Sherazi MA, et al. Ensemble Learning of Deep Learning and Traditional Machine Learning Approaches for Skin Lesion Segmentation and Classification. *Concurr Comput.* 2022;34:e6907.
- [38] <https://pub.tik.ee.ethz.ch/students/2017-HS/SA-2017-98.pdf>
- [39] Segelke D, Gehrke L, Wabbersen J. Imputation of Genetic Characteristics Using Deep. *Interbull Bulletin.* 2019;10:103–106.
- [40] Ahamed BS, Arya S. Lgbm Classifier Based Technique for Predicting Type-2 Diabetes. *Eur J Mol Clin Med.* 2021;8:454–467.
- [41] Liu KL, Wu T, Chen PT, Tsai YM, Roth H, et al. Deep Learning to Distinguish Pancreatic Cancer Tissue From Non-cancerous Pancreatic Tissue: A Retrospective Study With Cross-Racial External Validation. *Lancet Digit Health.* 2020;2:303–313.
- [42] Bakasa W, Viriri S. Pancreatic Cancer Survival Prediction: A Survey of the State-Of-The-art. *Comp Math Methods Med.* 2021;2021:1–17.
- [43] Bantilan N. Pandera: Statistical Data Validation of Pandas Dataframes. In *Proceedings of the python in science conference (SciPy)*. 2020:116–124.
- [44] Menze BH, Kelm BM, Masuch R, Himmelreich U, Bachert P, et al. A Comparison of Random Forest and Its Gini Importance With Standard Chemometric Methods for the Feature Selection and Classification of Spectral Data. *BMC Bioinformatics.* 2009;10:1–6.
- [45] Adler AI, Painsky A. Feature Importance in Gradient Boosting Trees With Cross validation Feature Selection. *Entropy (Basel).* 2022;24:687.
- [46] Banadaki YM. Detecting Malicious DNS Over HTTPS Traffic in Domain Name System Using Machine Learning Classifiers. *J Comput Sci Appl.* 2020;8:46–55.
- [47] Preuss K, Thach N, Liang X, Baine M, Chen J, et al. Using Quantitative Imaging for Personalized Medicine in Pancreatic Cancer: A Review of Radiomics and Deep Learning Applications. *Cancers.* 2022;14:1654.
- [48] Campello VM, Gkontra P, Izquierdo C, Martin-Isla C, Sojoudi A, et al. Multi-Centre, Multi-Vendor and Multidisease Cardiac Segmentation: The M&MS Challenge. *Ieee Trans Med Imaging.* 2021;40:3543–3554.
- [49] Greenwald NF, Miller G, Moen E, Kong A, Kagel A, et al. Whole-Cell Segmentation of Tissue Images With Human-Level Performance Using Large-Scale Data Annotation and Deep Learning. *Nat Biotechnol.* 2022;40:555–565.
- [50] Mohan S, Thirumalai C, Srivastava G. Effective Heart Disease Prediction Using Hybrid Machine Learning Techniques. *IEEE Access.* 2019;7:81542–81554.

- [51] Huang ML, Wu YZ. Semantic Segmentation of Pancreatic Medical Images by Using Onvolutional Neural Network. *Biomed Signal Process Control*. 2022;73,103458.
- [52] Paithane PM, Kakarwal SN. Automatic Pancreas Segmentation Using a Novel Modified Semantic Deep Learning Bottom-up Approach. *Int J Intell Syst Appl Eng*. 2022;10:98–104.
- [53] Dmitriev K, Marino J, Baker K, Kaufman AE. Visual Analytics of a Computer-Aided Diagnosis System for Pancreatic Lesions. *IEEE Trans Vis Comput Graph*. 2021;27:2174–2185.
- [54] Ahmad M, Qadri SF, Ashraf MU, Subhi K, Khan S, et al. Efficient Liver Segmentation From Computed Tomography Images Using Deep Learning. *Comp Intell Neurosci*. 2022;2022.
- [55] Siriapisith T, Kusakunniran W, Haddawy P. Pyramid Graph Cut: Integrating Intensity and Gradient Information for Grayscale Medical Image Segmentation. *Comput Biol Med*. 2020;126:103997.
- [56] Awe AM, Rendell VR, Lubner MG, Winslow ER. Texture Analysis: An Emerging Clinical Tool for Pancreatic Lesions. *Pancreas*. 2020;49:301–312.