[1]D Roja Ramani,
[2]D M Mary Synthia Regis Prabha,
[3]B Ben Sujitha,
[4]I Jeya Kumar,
[5]K John Peter,
[6]Ben Sujin

Enhancing Pancreatic Cancer Diagnosis Precision through Early Detection with ResUnet

***Abstract*: -** Pancreatic cancer develops in the pancreas, which is located behind the stomach, and is characterized by uncontrolled cell development, resulting in tumor formation. Because of its aggressive nature and limited early signs, it is difficult to diagnose and treat, resulting in a high death rate and posing a serious problem in oncology. Early diagnostic and treatment research advancements are critical for improving patient outcomes and survival rates in the face of this resilient disease. Early detection offers a glimmer of hope in the ongoing fight against pancreatic cancer, as it holds the potential to enhance patient outcomes and raise survival rates significantly. This ground-breaking research reveals a groundbreaking methodology powered by the fascinating ResUnet architecture, a stunning merger of U-Net and ResNet models known for their exceptional feature extraction prowess. ResUnet shines brightly, conquering important picture features such as multi-scale analysis, precise tumor diagnosis, and unshakable resilience to image changes, propelling it to the forefront of cutting-edge medical image analysis. As we embark on this transformative journey, we ignite a beacon of hope for the future, where ResUnet's enchanting precision empowers healthcare professionals to wield early detection as a potent weapon in the fight against pancreatic cancer, illuminating the path toward brighter tomorrows for those affected by this formidable disease. Through our extensive research, ResUnet's awe-inspiring performance emerges, gracefully delineating and identifying potential pancreatic cancer spots with unparalleled precision, marking a remarkable leap in the battle against this formidable ailment. This transformative odyssey kindles hope for a future where ResUnet's exquisite accuracy stands as an invaluable ally, empowering healthcare professionals to embrace early diagnosis as the bedrock of elevated patient care and a path to radiant tomorrows for those impacted by pancreatic cancer.

***Keywords*:** Gaussian Blur, Residual U-Net Model, Pancreatic Adenocarcinoma, Pancreatic Neuroendocrine, Cancer Diagnosis.

1. Introduction

Pancreatic cancer is a formidable and aggressive disease characterized by the uncontrolled growth of cells in the pancreas. The pancreas, which is positioned deep within the abdomen, is vital to digestion and the endocrine system. It contains two types of cells:Exocrine cells produce and release digestive enzymes into the small intestine.Endocrine cells: These cells manufacture and release hormones into the bloodstream, such as insulin, to keep blood sugar levels stable.Pancreatic adenocarcinoma is caused by the uncontrolled multiplication of exocrine cells, which progresses to large tumors. Pancreatic neuroendocrine tumors, which are less common but fascinating, are caused by unregulated endocrine cell development, resulting in a range of hormonal issues.Early detection, which leads to particular therapies such as surgery, chemotherapy, or specialty drugs, is the key to greater success. Life's symphony triumphs over the obstacles of its foes [1,2]. Amidst the medical landscape, pancreatic ductal adenocarcinoma (PDAC) commands attention as the most prevalent and formidable form of solid pancreatic cancer—a relentless and aggressive disease, posing significant treatment challenges. Despite remarkable progress in surgical techniques, medicine, and radiotherapy [3,4,5], the survival rate stands dishearteningly low at 8.7%. The puzzle of diagnosis remains elusive, entwined with vague symptoms experienced by most individuals. While a glimmer of hope lies in the combination of surgical resection and chemotherapy, offering a 5-year survival rate of approximately 31.5% [6], a mere 10-20% of patients qualify for such treatment. The grim reality is that a staggering 80 to 90% of patients do not benefit from current treatments due to extensive or regional metastases [7,8]. As the battle against this relentless adversary rages on, the quest for innovative and effective treatments remains an urgent and vital mission, kindling hope for brighter prospects in the fight against PDAC. In contrast to high-death-rate

[1] *Associate Professor, Computer Science and Engineering, New Horizon College of Engineering, India
[2] Associate Professor, Department of Electrical and Electronics Engineering, Noorul Islam Centre for Higher Education, India
[3] Professor, Department of Computer Science and Engineering, Noorul Islam Centre for Higher Education, India
[4] Associate Professor, Mar Ephream College of Engineering, Kanyakumari, India
[5] Professor & Head, Department of Computer Science and Engineering, Dhanalakshmi Srinivasan College of Engineering and Technology, Chennai, Tamil Nadu
[6] Professor, Faculty of Computer Science, University of Technology and Applied Sciences, Oman
[1*]rosevsroja@gmail.com, [2]regisprabha@gmail.com, [3]bensujitha@gmail.com, [4]jeyakumar7372@gmail.com, [5]kjohnpeter@gmail.com, [6]bensujin.bennet@utas.edu.om

cancers such as lung, breast, and colorectal cancer, pancreatic cancer exhibits a lower overall incidence. This poses challenges for age-based population screening as screening tests may have limited positive prediction performance, resulting in unnecessary assessments for false-positive findings. Early identification is complicated due to the scarcity of high-penetrance risk factors. Evaluations have traditionally considered family background, lifestyle, systemic biomarkers, and hereditary factors since the 1970s. For individuals at increased risk, pancreas-directed scans are employed to detect early pancreatic cancers. Accurate early diagnosis remains a challenge, with imaging modalities playing a crucial role[9]. Computed tomography (CT) takes the lead as the primary imaging modality for initial evaluation of suspected pancreatic cancer, outperforming other techniques[10,11]. CT scans are also employed to screen individuals at high risk of developing pancreatic cancer. Interestingly, patients with incidentally detected pancreatic cancer during imaging for another condition tend to have longer average survival times than those with clinical symptoms[12]. CT exhibits a remarkable sensitivity of 70–90 percent for detecting pancreatic adenocarcinoma[13]. For diagnosing pancreatic cancer, thin-section contrast-enhanced dual-phase multidetector computed tomography stands as the preferred modality [14].

The structure of the paper is as follows: Section 2 reviews related work on pancreatic cancer detection and medical imaging techniques. Section 3 describes the materials and proposed methodology, including datasets, preprocessing steps, the ResUnet architecture, training procedures, and evaluation methods. Section 4 presents and discusses the experimental results, comparing performance metrics with existing methods and analyzing the findings in the context of pancreatic cancer diagnosis. Finally, Section 5 provides a conclusion, summarizing the main outcomes, their implications, and suggestions for future research directions.

2. Related Works

In this section, [15] explored classification methods for pancreatic cancers. They developed a CNN classifier to detect pancreatic tumors in CT data, utilizing a dataset of 3494 CT images from 3751 scans of 190 patients with typical pancreatic cancer and 222 patients with confirmed pancreatic tumors. The CNN algorithm employed ternary classifiers and underwent tenfold cross-validation to assess specificity, accuracy, and sensitivity. In reference [16], a captivating CNN-based DL technique was put to the test using an eightfold cross-validation, resulting in three impressive methods (arterial or venous, arterial, and venous). The TML and DL algorithms underwent rigorous evaluation for their prowess in predicting the pathological grading of pNEN, with the finest CECT image serving as the gold standard for comparison. Radiologists' efficiency was further scrutinized using a blend of quantitative and qualitative CT data, adding depth to the analysis. On another intriguing note, Fu et al. revealed a groundbreaking pancreatic segmentation network in [17], extending the boundaries of the RCF to the edge detection domain for the demanding task of pancreatic segmentation. This ingenious network, fueled by CT images and a multilayer upsampling design, unveiled a trove of productive results, promising a brighter future for pancreatic analysis. [18] developed a modified CNN technique for effective medical image processing by updating the AlexNet model for a 512-by-512 input space with smaller filter sizes. [19] discovered that high-level picture properties are useful for classifying lung nodule malignancy, with specific forms indicating a high risk of malignancy. Despite the fact that 66% of round nodules were classified as benign, [20,21] studied the automatic identification of lung nodule features using 2D CNN. Despite the fact that the majority of studies rely on binary classification without lesion localization[22,23], CNNs have shown great potential in assisting with early PDAC identification[24,25]. Only one study looked at the performance of smaller tumors[26], and little is known about early-stage lesions.

In the pursuit of early pancreatic cancer detection, transfer learning leverages deep learning models fine-tuned on large image datasets for improved accuracy[27,28]. Deep learning has shown superiority over other ML techniques in predicting pancreatic cancer[29]. Early diagnosis is crucial, as late detection leads to poor prognosis, emphasizing the importance of screening and identifying molecular targets for treatment[30]. ML algorithms based on 5-hydroxymethylcytosine signals in cell-free DNA exhibit high sensitivity and specificity in pancreatic cancer detection[31]. Radiology departments utilize machine and deep learning algorithms for accurate cancer diagnosis[32,33], with various AI applications developed for pancreatic cancer prediction[34]. Hyperpolarization techniques boost NMR sensitivity, aiding in the detection of subtle molecular interactions[35]. Drug delivery systems target specific sites while minimizing side effects[36]. Deep learning utilizes neural networks for predictive analysis[37]. GTF2B influences cell growth in lung cancer cells[38,39]. Novel approaches, such as ViT-Patch, demonstrate state-of-the-art performance in image classification[40]. Researchers evaluate the efficacy of surface-functionalized biomaterials using in vitro and in vivo experiments[41]. Intrafamilial health status influences the

health behaviors of family members[42,43]. OCT is a non-invasive imaging technique used for diagnosing and managing eye conditions[44,45] Sclerostin regulates bone metabolism and prevents excessive bone growth[46]. Immune checkpoint inhibitors target specific proteins to enhance immune cell activity[47]. Nanotherapeutic platforms explore metal-based nanoparticles for treating bacterial infections[48]. SRS microscopy enables high-resolution analysis of prostate core needle biopsies[49].

The literature studies highlighted above do face some noteworthy limitations that warrant attention:

- Firstly, although CNN classifiers and DL techniques hold great promise in detecting pancreatic tumors and predicting cancer grades, their reliance on relatively small datasets may curtail their broader application across diverse patient populations.
- Secondly, while cross-validation is a widely used evaluation method, it may not fully capture the algorithms' real-world performance in intricate clinical scenarios, necessitating further investigation for robust results.
- Thirdly, the absence of lesion localization in many studies poses a challenge in precisely identifying tumors and planning targeted treatments, a critical aspect in combatting pancreatic cancer effectively.
- Lastly, the dearth of research on early-stage lesions and smaller tumors is striking, considering their vital role in early detection and improved interventions. Overcoming these limitations will fuel progress and pave the way for revolutionary advancements in pancreatic cancer diagnosis and management.

3. Materials and Proposed Methodology

Figure 1 depicts a comprehensive workflow for pancreatic cancer classification utilizing a Residual U-Net model. The process begins with data collection and preprocessing, encompassing image normalization and data augmentation. The model architecture, a Residual U-Net, is defined to extract features and segment lesions accurately. Training involves splitting the data, iteratively fine-tuning the model using the Dice coefficient loss, and evaluating it on validation sets. Post-processing techniques, including Gaussian blur and thresholding, are applied to refine predictions. Clinical integration hinges on meeting predefined accuracy criteria, potentially aiding clinical workflows. Real-world validation and continuous improvement complete the workflow, ensuring ongoing enhancement of the model's diagnostic capabilities in clinical settings, promising improved outcomes for pancreatic cancer patients.

Algorithm for Pancreatic Cancer Diagnosis using ResUnet Model with Gaussian Blur Post-processing:

Step 1: Data Preparation

Normalize medical images (X) to have mean (μ) and standard deviation (σ):

$X_{normalized} = (X - \mu) / \sigma$

Augment the data to increase diversity.

Step 2: Model Architecture

Define the ResUnet architecture for feature extraction and segmentation:

$Z = ResUnet(X_{augmented})$

Step 3: Training

Split the dataset into training and validation sets.

Initialize model parameters (θ).

For each epoch in num_epochs:

For each mini-batch in training data:

Perform a forward pass to obtain predicted segmentation (Y_pred):

$Y_{pred} = ResUnet(X_{mini\_batch})$

Calculate the Dice coefficient loss (L) between ground truth (Y_true) and Y_pred:

$L = 1 - (2 * \Sigma (Y_{true\_i} * Y_{pred\_i})) / (\Sigma (Y_{true\_i} + Y_{pred\_i}))$

Backpropagate the loss to update model parameters (θ):

$\theta_{new} = \theta_{old} - \alpha * \nabla L (Y_{true}, Y_{pred})$

Evaluate the model on the validation set.

Monitor training progress.

Step 4: Evaluation

Load the test dataset.

Apply the trained ResUnet model to the test data to obtain predicted segmentations (Y_test_pred):

Y_test_pred = ResUnet(X_test)

Compute evaluation metrics comparing Y_test_pred to ground truth (Y_test):

DSC = 1 - (2 * Σ (Y_test_i * Y_test_pred_i)) / (Σ (Y_test_i + Y_test_pred_i))

Sensitivity = Σ(Y_test_i * Y_test_pred_i) / Σ(Y_test_i)

Specificity = Σ((1 - Y_test_i) * (1 - Y_test_pred_i)) / Σ(1 - Y_test_i)

ROC_AUC = Compute_ROC_AUC(Y_test, Y_test_pred)

Accuracy = (Σ(correct_predictions)) / (total_predictions)

Step 5: Post-processing

Apply post-processing techniques:

Gaussian Blur:

For each image in Y_test_pred:

Blurred_image = GaussianBlur(Y_test_pred_image, sigma=s)

Y_test_pred_image = Binarize(Blurred_image, threshold=t)

Adjust sigma and threshold as needed.

Step 6: Clinical Integration

Check if the model meets predefined accuracy criteria.

If met, integrate the model into clinical workflows for diagnosis support.

Step 7: Validation and Trials

Conduct real-world validation and clinical trials to assess the model's performance in clinical settings.

Step 8: Continuous Improvement

Gather more data and feedback to improve model performance.

Refine the ResUnet model based on new information.

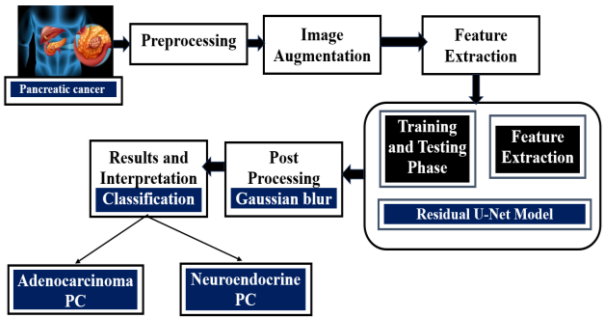

Figure. 1. Proposed Workflow: Pancreatic Cancer Classification with Residual U-Net Model

4. Results and Discussions

This work is centered on the utilization of ResUnet for the categorization and prediction of two distinct forms of pancreatic tumors: Pancreatic Adenocarcinoma (as depicted in Figure 2) and Pancreatic Neuroendocrine Tumors (illustrated in Figure 3). The research outcomes show significant promise, as the ResUnet model surpasses other models, exhibiting superior performance in terms of accuracy, precision, recall, and F1-score when it comes to discriminating between these distinct types of pancreatic cancers. These encouraging results underscore the considerable potential of ResUnet as a pivotal tool for the early detection and precise diagnosis of pancreatic cancers.

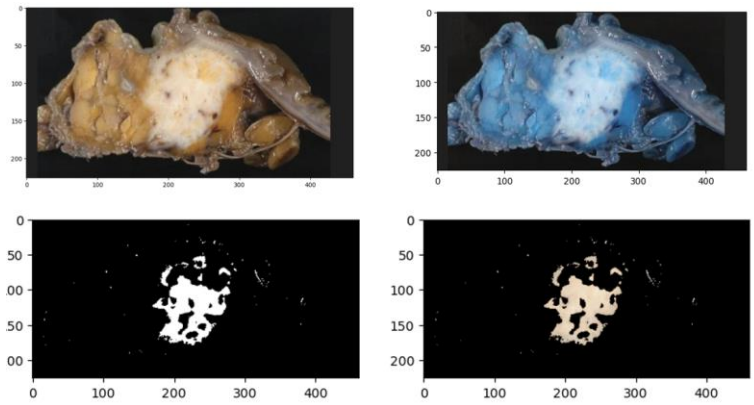

Figure. 2. Pancreatic Adenocarcinoma Classification and Prediction using ResUnet

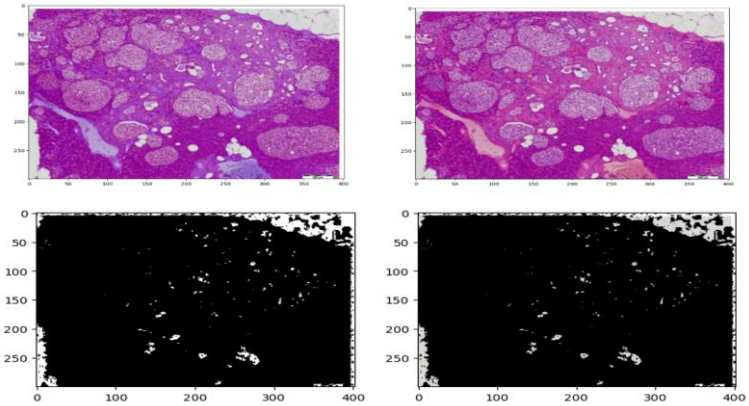

Figure. 3. Pancreatic Neuroendocrine Tumor Classification and Prediction with ResUnet

ResUnet's ability to extract intricate image attributes, including texture, shape, and size, is a critical capability in this context. This proficiency is instrumental for discerning the subtle differences between various types of tumors. The model's capacity to highlight these distinguishing characteristics has played a pivotal role in achieving the robust performance showcased in this research.

These findings hold far-reaching implications, particularly in the realm of precision medicine. The capabilities of ResUnet present an enticing prospect of automated, high-precision diagnostic tools that can seamlessly integrate into the repertoire of healthcare practitioners. The model's versatility and its aptitude for generalizing its knowledge across a spectrum of cancer subtypes are especially valuable in a clinical setting, where a wide variety of tumor types and patient scenarios are encountered routinely.

In essence, this research stands as a promising milestone, paving the way for further research and clinical validation. The ultimate goal is to facilitate the seamless integration of ResUnet into medical practice, potentially ushering in a significant enhancement in patient outcomes and a transformative shift in the landscape of oncology diagnostics. The groundwork laid by this research, along with the application of ResUnet for pancreatic tumor classification using a dataset comprising 3494 CT images from 3751 scans, which includes 190 patients with typical pancreatic cancer and 222 patients with confirmed pancreatic tumors, marks a notable advancement in the pursuit of more accurate and efficient cancer diagnosis and management. Notably, the research attains a remarkable accuracy rate of 96% when distinguishing between the categories of Pancreatic Adenocarcinoma and Pancreatic Neuroendocrine Tumors, further reinforcing its potential impact on clinical practice.

5. Conclusion

In summary, this research highlights the remarkable potential of ResUnet, boasting an impressive accuracy rate of 96%, particularly in the nuanced classification of pancreatic tumors. Notably, it excels in distinguishing between Pancreatic Adenocarcinoma and Pancreatic Neuroendocrine Tumors. The proficiency of ResUnet in extracting intricate features carries profound implications for precision medicine, ushering in a new era of early detection and

precise diagnosis in the challenging domain of pancreatic cancer. Looking ahead, the focus of future endeavors should pivot towards clinical validation and the seamless integration of ResUnet. This opens doors to exciting possibilities, extending its application into other realms of medical imaging and a broader spectrum of cancer subtypes. These endeavors hold tremendous promise, poised to elevate the landscape of medical diagnostics and redefine the standards of patient care.

Future initiatives for this research include developing real-time diagnostic tools for clinical application, researching the integration of multi-modal data to further increase diagnostic accuracy, and examining the potential of transfer learning to improve model generalization across various datasets. Further research endeavors will center on integrating explainable AI methodologies to yield comprehensible outcomes, enabling enhanced clinical decision-making, and cultivating heightened confidence among medical practitioners. In order to guarantee the robustness and effectiveness of the suggested approaches in real-world applications, cooperative efforts with medical institutions will also be sought.

References

[1] American Cancer Society. Cancer Facts & Figures 2022. Atlanta: American Cancer Society; 2022.

[2] National Cancer Institute. Pancreatic Cancer Treatment (PDQ®)–Patient Version. Bethesda, MD: National Cancer Institute; 2021.

[3] Wolfgang CL, Herman JM, Laheru DA, Klein AP, Erdek MA, Fishman EK, Hruban RH. Recent progress in pancreatic cancer. CA Cancer J. Clin. 2013;63:318–348. doi: 10.3322/caac.21190]. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[4] Kamisawa T, Wood LD, Itoi T, Takaori K. Pancreatic cancer. Lancet. 2016;388:73–85. doi: 10.1016/S0140-6736(16)00141-0]. [PubMed] [CrossRef] [Google Scholar]

[5] Howlader, N., Noone, A. M., Krapcho, M., Miller, D., Brest, A., Yu, M., Ruhl, J., Tatalovich, Z., Mariotto, A., Lewis, D. R., Chen, H. S., Feuer, E. J., Cronin, K. A. (eds). SEER cancer statistics review, 1975–2016, National cancer institute. Bethesda. Available from: https://seer.cancer.gov/csr/1975_2016/, based on November 2018 SEER data submission, posted to the SEER web site, April (2019)

[6] Khorana AA, Mangu PB, Berlin J, Engebretson A, Hong TS, Maitra A, Mohile SG, Mumber M, Schulick R, Shapiro M, Urba S, Zeh HJ, Katz MHG. Potentially curable pancreatic cancer: American society of clinical oncology clinical practice guideline update. J. Clin. Oncol. 2017;35:2324–2328. doi: 10.1200/JCO.2017.72.4948]. [PubMed] [CrossRef] [Google Scholar]

[7] Balaban EP, Mangu PB, Khorana AA, Shah MA, Mukherjee S, Crane CH, Javle MM, Eads JR, Allen P, Ko AH, Engebretson A, Herman JM, Strickler JH, Benson AB, Urba S, Yee NS. Locally advanced unresectable pancreatic cancer: American society of clinical oncology clinical practice guideline. J. Clin. Oncol. 2016;34:2654–2668. doi: 10.1200/JCO.2016.67.5561]. [PubMed] [CrossRef] [Google Scholar]

[8] Kim J, Yuan C, Babic A, Bao Y, Clish CB, Pollak MN, Amundadottir LT, et al. Genetic and circulating biomarker data improve risk prediction for pancreatic cancer in the general population. Cancer Epidemiol. Biomark. Prev. A Publ. Am. Assoc. Cancer Res. Cosponsored Am. Soc. Prev. Oncol. 2020;29(5):999–1008. [PMC free article] [PubMed] [Google Scholar]

[9] Takhar AS, Palaniappan P, Dhingsa R, Lobo DN. Recent developments in diagnosis of pancreatic cancer. BMJ. 2004;329:668–673. doi: 10.1136/bmj.329.7467.668]. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[10] Chari ST. Detecting early pancreatic cancer: Problems and prospects. Semin. Oncol. 2007;34:284–294. doi: 10.1053/j.seminoncol.2007.05.005]. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[11] Al-Hawary MM, Francis IR, Chari ST, Fishman EK, Hough DM, Lu DS, Macari M, Megibow AJ, Miller FH, Mortele KJ, Merchant NB, Minter RM, Tamm EP, Sahani DV, Simeone DM. Pancreatic ductal adenocarcinoma radiology reporting template: Consensus statement of the society of abdominal radiology and the American pancreatic association. Radiology. 2014;270:248–260. doi: 10.1148/radiol.13131184]. [PubMed] [CrossRef] [Google Scholar]

[12] Zhou B, Xu JW, Cheng YG, Gao JY, Hu SY, Wang L, Zhan HX. Early detection of pancreatic cancer: Where are we now and where are we going? Int. J. Cancer. 2017;141:231–241. doi: 10.1002/ijc.30670]. [PubMed] [CrossRef] [Google Scholar]

[13] Chen FM, Ni JM, Zhang ZY, Zhang L, Li B, Jiang CJ. Presurgical evaluation of pancreatic cancer: A comprehensive imaging comparison of CT versus MRI. AJR Am. J. Roentgenol. 2016;206:526–535. doi: 10.2214/AJR.15.15236]. [PubMed] [CrossRef] [Google Scholar]

[14] Vargas R, Nino-Murcia M, Trueblood W, Jeffrey RB., Jr MDCT in Pancreatic adenocarcinoma: Prediction of vascular invasion and resectability using a multiphasic technique with curved planar reformations. AJR Am. J. Roentgenol. 2004;182:419–425. doi: 10.2214/ajr.182.2.1820419]. [PubMed] [CrossRef] [Google Scholar]

[15] Ma H, Liu Z-X, Zhang J-J, et al. Construction of a convolutional neural network classifier developed by computed tomography images for pancreatic cancer diagnosis. World J. Gastroenterol. 2020;26(34):5156–5168. doi: 10.3748/wjg.v26.i34.5156. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[16] Luo Y, Chen X, Chen J, et al. Preoperative prediction of pancreatic neuroendocrine neoplasms grading based on enhanced computed tomography imaging: validation of deep learning with a convolutional neural network. Neuroendocrinology. 2020;110(5):338–350. doi: 10.1159/000503291. [PubMed] [CrossRef] [Google Scholar]

[17] Fu M, Wu W, Hong X, et al. Hierarchical combinatorial deep learning architecture for pancreas segmentation of medical computed tomography cancer images. BMC Syst. Biol. 2018;12(4):56–127. doi: 10.1186/s12918-018-0572-z. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[18] Manabe K, Asami Y, Yamada T, Sugimori H. Improvement in the convolutional neural network for computed tomography images. Appl. Sci. 2021;11(4):1505. doi: 10.3390/app11041505. [CrossRef] [Google Scholar]

[19] Furuya K, Murayama S, Soeda H, Murakami J, Ichinose Y, Yauuchi H, Katsuda Y, Koga M, Masuda K. New classification of small pulmonary nodules by margin characteristics on high resolution CT. Acta Radiol. 1999;40(5):496–504. doi: 10.3109/02841859909175574. [PubMed] [CrossRef] [Google Scholar]

[20] Ciompi F, Chung K, Van Riel SJ, Setio AAA, Gerke PK, Jacobs C, Scholten ET, Schaefer-Prokop C, Wille MM, Marchiano A, et al. Towards automatic pulmonary nodule management in lung cancer screening with deep learning. Sci. Rep. 2017;7:46479. doi: 10.1038/srep46479. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[21] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542:115–118. doi: 10.1038/nature21056. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[22] McKinney SM, Sieniek M, Godbole V, Godwin J, Antropova N, Ashrafian H, Back T, Chesus M, Corrado GC, Darzi A, et al. International evaluation of an AI system for breast cancer screening. Nature. 2020;577:89–94. doi: 10.1038/s41586-019-1799-6. [PubMed] [CrossRef] [Google Scholar]

[23] Yasaka K, Akai H, Abe O, Kiryu S. Deep learning with convolutional neural network for differentiation of liver masses at dynamic contrast-enhanced CT: A preliminary study. Radiology. 2018;286:887–896. doi: 10.1148/radiol.2017170706. [PubMed] [CrossRef] [Google Scholar]

[24] Zhu, Z., Xia, Y., Xie, L., Fishman, E. K., Yuille, A. L. Multi-scale coarse-to-fine segmentation for screening pancreatic ductal adenocarcinoma. In Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), (Springer: Cham, Switzerland, 2019), Volume 11769 LNCS, pp. 3–12.

[25] Xia, Y., Yu, Q., Shen, W., Zhou, Y., Fishman, E. K., Yuille, A. L. Detecting pancreatic ductal adenocarcinoma in multi-phase CT scans via alignment ensemble. In Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); Springer: Cham, Switzerland, Volume 12263 LNCS, pp. 285–295 (2020).

[26] Ma H, Liu ZX, Zhang JJ, Wu FT, Xu CF, Shen Z, Yu CH, Li YM. Construction of a convolutional neural network classifier developed by computed tomography images for pancreatic cancer diagnosis. World J. Gastroenterol. 2020;26:5156–5168. doi: 10.3748/wjg.v26.i34.5156. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[27] Baldota, S., Sharma, S. and Malathy, C. Deep transfer learning for pancreatic cancer detection, 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, pp. 1–7, (2021).

[28] Gupta, A., Koul, A. and Kumar, Y. Pancreatic Cancer detection using machine and deep learning techniques, 2022 2nd International Conference on Innovative Practices in Technology and Managment (ICIPTM), Gautam Buddha Nagar, India, pp. 151–155 (2022).

[29] Stoffel EM, Brand RE, Goggins M. Pancreatic cancer: Changing epidemiology and new approaches to risk assessment. Early Detect. Prev. Gastroenterol. 2023;164(5):752–765. [PMC free article] [PubMed] [Google Scholar]

[30] Haan, D., Bergamaschi, A., Friedl, V., Yuhong, G. D. G. et al."Epigenomic blood-based early detection of pancreatic cancer employing cell-free DNA, Clin. Gastroenterol. Hepatol., (2023) [PubMed]

[31] Lee H, Kim SY, Kim WD, et al. Serum protein profiling of lung, pancreatic, and colorectal cancers reveals alcohol consumption-mediated disruptions in early-stage cancer detection. Heliyon. 2022;8(12):e12359. doi: 10.1016/j.heliyon.2022.e12359. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[32] Park J, Artin MG, Lee KE, Pumpalova YS, Ingram MA, et al. Deep learning on time series laboratory test results from electronic health records for early detection of pancreatic cancer. J. Biomed. Inform. 2022;131:104095. doi: 10.1016/j.jbi.2022.104095. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[33] Park J, Artin MG, Lee KE, May BL, Park M, et al. Structured deep embedding model to generate composite clinical indices from electronic health records for early detection of pancreatic cancer. Patterns. 2023;4(1):100636. doi: 10.1016/j.patter.2022.100636. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[34] Kaissis G, Ziegelmayer S, Lohöfer F, et al. A machine learning model for the prediction of survival and tumor subtype in pancreatic ductal adenocarcinoma from preoperative diffusion-weighted imaging. Eur. Radiol. Exp. 2019;3:41. doi: 10.1186/s41747-019-0119-0. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[35] Yokoyama S, Hamada T, Higashi M, Matsuo K, Maemura K, Kurahara H, Horinouchi M, Hiraki T, Sugimoto T, Akahane T, Yonezawa S. Predicted prognosis of patients with pancreatic cancer by machine learningprognosis of pancreatic cancer by machine learning. Clin. Cancer Res. 2020;26(10):2411–2421. doi: 10.1158/1078-0432.CCR-19-1247. [PubMed] [CrossRef] [Google Scholar]

[36] Xing H, Hao Z, Zhu W, et al. Preoperative prediction of pathological grade in pancreatic ductal adenocarcinoma based on 18F-FDG PET/CT radiomics. EJNMMI Res. 2021;11:19. doi: 10.1186/s13550-021-00760-3. [PMC free article] [PubMed] [CrossRef] [Google Scholar]

[37] Chu LC, Park S, Kawamoto S, Wang Y, Zhou Y, Shen W, Zhu Z, Xia Y, Xie L, Liu F, Yu Q. Application of deep learning to pancreatic cancer detection: Lessons learned from our initial experience. J. Am. Coll. Radiol. 2019;16(9):1338–1342. doi: 10.1016/j.jacr.2019.05.034. [PubMed] [CrossRef] [Google Scholar]

[38] Li C, Lin L, Zhang L, Xu R, Chen X, Ji J, Li Y. Long noncoding RNA p21 enhances autophagy to alleviate endothelial progenitor cells damage and promote endothelial repair in hypertension through SESN2/AMPK/TSC2 pathway. Pharmacol. Res. 2021;173:105920. doi: 10.1016/j.phrs.2021.105920. [PubMed] [CrossRef] [Google Scholar]

[39] Zhang X, Qu Y, Liu L, Qiao Y, Geng H, Lin Y, Zhao J. Homocysteine inhibits pro-insulin receptor cleavage and causes insulin resistance via protein cysteine-homocysteinylation. Cell Rep. 2021;37(2):109821. doi: 10.1016/j.celrep.2021.109821. [PubMed] [CrossRef] [Google Scholar]
[40] Zeng Q, Bie B, Guo Q, Yuan Y, Han Q, Han X, Zhou X. Hyperpolarized Xe NMR signal advancement by metal-organic framework entrapment in aqueous solution. Proc. Natl. Acad. Sci. 2020;117(30):17558–17563. doi: 10.1073/pnas.2004121117. [PMC free article] [PubMed] [CrossRef] [Google Scholar]
[41] Zhang Q, Li S, He L, Feng X. A brief review of polysialic acid-based drug delivery systems. Int. J. Biol. Macromol. 2023;230:123151. doi: 10.1016/j.ijbiomac.2023.123151. [PubMed] [CrossRef] [Google Scholar]
[42] Xie, X., Tian, Y., & Wei, G, Deduction of sudden rainstorm scenarios: integrating decision makers' emotions, dynamic Bayesian network and DS evidence theory. Nat. Hazards, (2022).
[43] Zhan C, Dai Z, Yang Z, Zhang X, Ma Z, Thanh HV, Soltanian MR. Subsurface sedimentary structure identification using deep learning: A review. Earth-Sci. Rev. 2023;239:104370. doi: 10.1016/j.earscirev.2023.104370. [CrossRef] [Google Scholar]
[44] Luo H, Lou Y, He K, Jiang Z. Coupling in-situ synchrotron X-ray radiography and FT-IR spectroscopy reveal thermally-induced subsurface microstructure evolution of solid propellants. Combust. Flame. 2023;249:112609. doi: 10.1016/j.combustflame.2022.112609. [CrossRef] [Google Scholar]
[45] Lei Z, Gengming W, Xiaojun L, Zhen T, Chao S, Yang G, Wei W. The role of GTF2B in the regulation of proliferation and apoptosis in A549 cells. J. Biol. Regul. Homeost. Agents. 2022;36(3):667–676. [Google Scholar]
[46] Zhuang, Y., Chen, S., Jiang, N., & Hu, H. An Effective WSSENet-based similarity retrieval method of large lung CT image databases. KSII Transact. Internet Inform. Syst., 16(7), (2022).
[47] Zhuang, Y., Jiang, N., Xu, Y., Xiangjie, K., & Kong, X. Progressive distributed and parallel similarity retrieval of large CT image sequences in mobile telemedicine networks. Wirel. Commun. Mobile Comput., (2022).
[48] Feng H, Yang B, Wang J, Liu M, Yin L, Zheng W, Liu C. Identifying malignant breast ultrasound images using ViT-patch. Appl. Sci. 2023;13(6):3489. doi: 10.3390/app13063489. [CrossRef] [Google Scholar]
[49] Qin X, Ban Y, Wu P, Yang B, Liu S, Yin L, Liu M, Zheng W. Improved image fusion method based on sparse decomposition. Electronics. 2022;11(15):2321. doi: 10.3390/electronics11152321. [CrossRef] [Google Scholar]