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DEEP LEARNING TECHNIQUES FOR PANCREATIC CANCER IMAGE CLASSIFICATION

Jasmine Chhikara[1], Dr. Swati Malik[2]
[1]Department of Electronics and communication engineering, [2]Department of Computer Science and Engineering
Aff: [1,2]Maharaja Surajmal Institute of Technology, Delhi, India
Aff: [1]Indira Gandhi Delhi Technical University for Women, Delhi, India

Abstract

The identification and therapy of pancreatic cancer are limited by its high fatality rate and extended course of development. The survival rate of pancreatic cancer can be increased through early detection and appropriate classification. Using picture categorization of pancreatic cancer, deep learning increases detection accuracy. Research on pancreatic malignancies, including adenocarcinoma and neuroendocrine tumors, stays under progress after following standard nodal involvement, metastases, and size using the TNM staging approach. From CT, MRI, and histomorphology slides, deep learning—especially CNNs—are altering the medical picture interpretation. Transfer learning accelerates training and releases data limitations. This research uses pre-trained models to handle tasks particular to a domain. Knowledge of feature extraction and classification calls for research of fully connected, pooling, and convolutional layers. The presentation discusses weight decay, dropout, sigmoid, and ReLU activation functions to maximize models and reduce overfitting. New algorithms and domain-specific data-based deep learning detection of pancreatic cancer are presented in this work. Therapeutic outcomes can be improved by early detection and multimodal approaches applied in customized treatment plans.

Keywords: *Pancreatic cancer*, *Deep learning*, *image classification*, *Convolutional neural networks (CNNs)*, *early cancer detection*

1. Introduction

Deep learning provides, depending on big data sets, fresh, real-time recommendations. Deep neural networks help one to change this data. Deep learning, present in convolutional neural networks, drives traffic signals, CNN research images classification, and biological imaging. Deep learning-based popular machine learning methods help to identify images. Targeting some industries, machine learning aims to disturb systems. Autonomous data gathering within deep learning systems Data representation different from hard-coded methods is used in deep learning. Families covering strategies target more forward. Popular deep learning image classification techniques, CNNs examine data without feature extraction. In deep learning, over fitting have consequences for picture classification. This Python project reduces over fitting and increases model efficiency on large datasets by use of deep learning CNN picture grouping. One of the worst diseases, pancreatic cancer is caused by genes altered by unregulated cell development. Once physical examination, MRI, and CT scans fail, biopsy comes next to find malignancy. Pancreatic cancer is microscopically investigated under the guiding idea for therapy planning. Imaging rare diseases related to pancreatic cancer Using deeper learning, Niazi et al. segregate pancreatic neuroendocrine tumours from non-tumours in Ki67-stained data. We aim to count polarity-positive hotspots in tumours. Artificial intelligence fails in pancreatic cancer grade rating. This work uses 14 deep learning (DL) models under transfer learning based on limited artificial intelligence (AI) to evaluate abnormal pancreatic cancer images. Automation helps to lighten the task involved in cancer grading.

2. Theoretical assessment

Infarction or patient variations had no effect on MRI-guided radiation therapy structural changes—including breathing changes. One difficult condition that aggravates once discovered is early pancreatic cancer. Important are early diagnosis, identification, and treatment. Since pancreatic cancer has a very high fatality rate, most studies on this condition focused on diagnosis and treatment. One really relies mostly on visual recognition. Finding adenocarcinomas calls for both feature extraction and selection. Exocrine and endocrine pancreatic cancers are the most terrible, starting with cell enzymes. Exocrine pancreatic cancers are adenocarcinomas. This distinguishes, in terms of phases of cellular malignancy, hormonal tumours from neuroendocrine malignancies. Made hormones and broke down fluids, pancreatic glands created unchecked cell division in abnormal pancreatic cells fuels malignancy. With relation to cancer, this makes logical sense. Apart from the small intestine, cells feed organs and arteries also. A few organs could turn cancerous. Cancer disturbs pancreatic endocrine balance. Apart from others, cancerous cells can develop from pancreatic cells with digestive, abdominal, and hormonal characteristics. Pancreatic cells vary in kind. Adenocarcinoma is the most commonly occurring cancer. An attack on the pancreas could occur from the head, body, or tail in three different directions. Here, exocrine pancreatic tumours rule largely, naturally. To get juice, cells first break down other cells. Of all the exocrine pancreatic tumours, eighty percent are adenocarcinomas developed from pancreatic duct cells.

Pancreatic Tumor Types

There are number of pancreatic cancers which can be detected through the experimental work which has been reviewed in this section.

The types of exocrine pancreatic cancer include:

- *Cystic Tumors:* Cystic tumours produce a cyst or fluid-filled sac in the pancreas. While some pancreatic cysts are cancerous—malignant—most are benign, non-cancerous. Cystic tumours usually exhibit better prognosis than other types of exocrine pancreatic cancer.
- *Cancer of the Acinar Cells:* The acinar cells occupy the extremes of the ducts, producing pancreatic secretions. Generally speaking, patients with these cancers are younger than those with adenocarcinomas. Usually sluggish growing, they have a better temperament.
- *Endocrine Pancreatic Tumors:* Living on the extremes of the ducts, the acinar cells release pancreatic secretions. Patients with these tumours are often younger than those with adenocarcinomas generally. Often sluggish growing, their attitude is better.

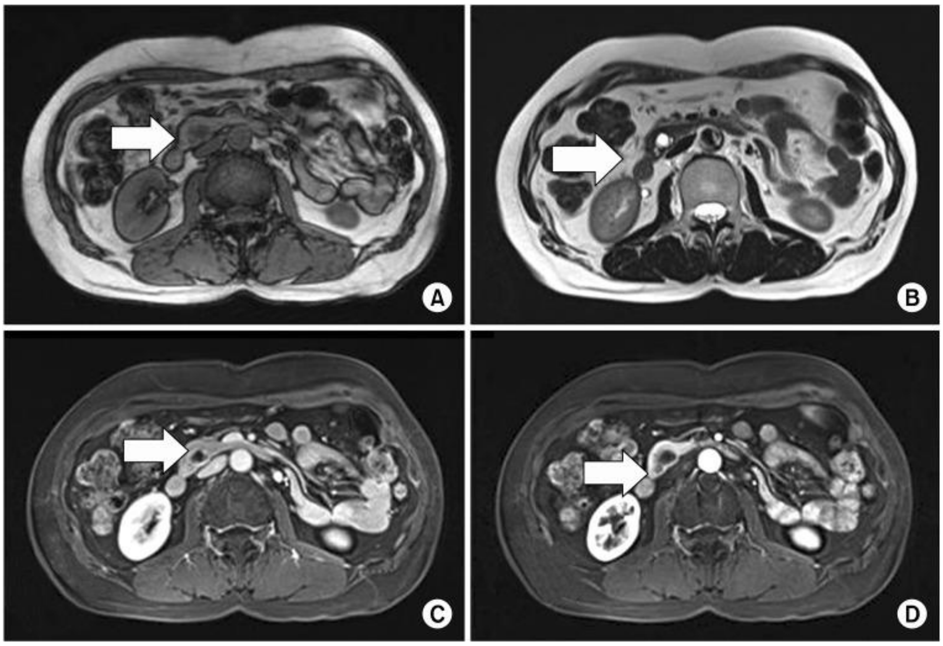
Other Types of Pancreatic Tumors

The pancreas is also affected by certain rare types of cancer. Their treatment differs from that of more often occurring forms of pancreatic cancer.

- *Pancreatoblastoma:* Mostly affecting youth, these are rare cancers. Sometimes rare genetic disorders known as Beckwith-Wiedemann syndrome and familial adenomatous polyposis (FAP) are connected to them.
- *Sarcomas of the Pancreas:* These are tumors of the connective tissue, which bind pancreatic cells together. One comes across them rather rarely.
- *Lymphoma:* Among lymphatic system cancers is lymphoma. Wherever the lymphatic system crosses the body, these tumors could flourish.

The pancreatic caners and its types as found in figure 1 where MRI of pancreatic cancers has been seen in it. From the figure 1, we found the diagnosis of the pancreatic cancers after surgical resection.

Fig.1. MRI of Pancreatic Tumor a (b) Head of Pancreatic Tumor (c), Body of Pancreatic Tumor (d)



SOURCE: Pancreatic hamartoma diagnosed after surgical resection

3. Objective

- **To Develop an Accurate image Classification System for detection of pancreatic cancer**
- **To improve Diagnostic Accuracy and its practical Applicability for Cancer Image Classification**

4. Methodology

This work investigates deep learning approaches for the diagnosis of pancreatic cancer using four pre-trained models: Xception, ResNet50V2, InceptionV3, and DenseNet. Having been trained on the DL model, the images were assessed in line with it all through model development.

5. Results & Discussions

In this section we have discussed about the different types of techniques being used for the detection of pancreatic cancers as discussed below:

Convolutional Neural Networks (CNNs)

Deep learning enables numerous processing layers to teach computers data representations with various abstractions. Vision, voice, detection, identification, genetics, pharmacology, and discovery are forward-looking technologies. Deep learning transforms the fundamental characteristics of the machine so that, using back propagation, every layer can obtain its representation from the one before it. This helps one to recognise complicated structures found in large data sets. Recurrent networks evaluate text and voice; deep convolutional networks handle images, videos, and audio. CNN in image processing sharpens the machine learning accuracy. Model derived from deep learning CNN is strong and energetic. CNN's policies define deep learning. Wang and colleagues studied the CNN model and hybrid technique under pre-training or fine-tuning. The network generates two executive images and extracts traits using patches before the last category. CNN's design is incredibly difficult. Artificial neural networks consist of several layers of input-output. CNN secret layers usually find their place here. These are softmax, convolutional, pooling, and absolutely entirely linked layers.

Development models

A deep CNN system helped to classify pancreatic cancer images which have been discussed in this part.

DenseNet: Deep neural networks, well-known for their numerous hidden layers between the input and output layers, often lose knowledge along this lengthy path. DenseNet solves the vanishing imaging problem, therefore improving accuracy more than other basic CNNs and linking every layer.

ResNet: ResNets have enhanced accuracy and performance, but their densely linked character demands enormous processing capacity to generate the best results. Residual networks gained prominence due to their incorporation of a novel channel known as skip connections. ResNets have a lower computational cost than DenseNets; however, earlier studies validate their performance to be equivalent to DenseNets.

Inception-V3: Originally Inception-v1, Inception-V3 is an upgraded variant featuring 1x1 convolutional layers added to lower dimension count, hence improving accuracy and compute performance. Other enhancements of Inception-V3 include the reduction of parameters and the factorization of large convolutions into smaller, asymmetric convolves.

Xception: Google developed its Xception model on an extreme interpretation of the Inception model, drawing inspiration from its design that includes separable and depth-dependent convolutional layers. These depth-wise separable convolutions "factorize" the convolution layer so that it may be repeated with reduced parameters. Separable convolution also resolves cross-depth and 2D components independently.

DenseNet can reduce ResNet representation, minimize the identity shortcut, and stabilize ResNet training through multi-layer feature concatenation. Dense concatenation crosses GPU memory and training intervals. CNN-based inception systems struggle with rotation and scaling, lacking translation invariance and data augmentation. The complexity of the Xception model makes it difficult to confidently project results. Combining several models helps reduce bias and improve variance.

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Transfer-learning

Developing the best model for pancreatic cancer, we fused four ImageNet CNN pre-trained models from the Keras API with 1000 classes. Apart from the proposed pre-training models and photo input forms of the original model, the tables indicate top-1 accuracy on the ImageNet validation set.

Fine-tuning: A flattening layer creates a 1D, completely connected layer; a dense layer with 256 nodes and a ReLU activation function; a dropout layer with a rate of 0.4 helps regularize the network; and a last dense layer with four nodes and a SoftMax activation function pulls features from pathological images.

Table 1. Pre-trained ImageNet models

Pre-trained models	**Input shape**	**Top-1 accuracy**
Xception	298 * 298	0.810
ResNet50V2	223 * 223	0.850
InceptionV3	298 * 298	0.789
DenseNet	225 * 225	0.850

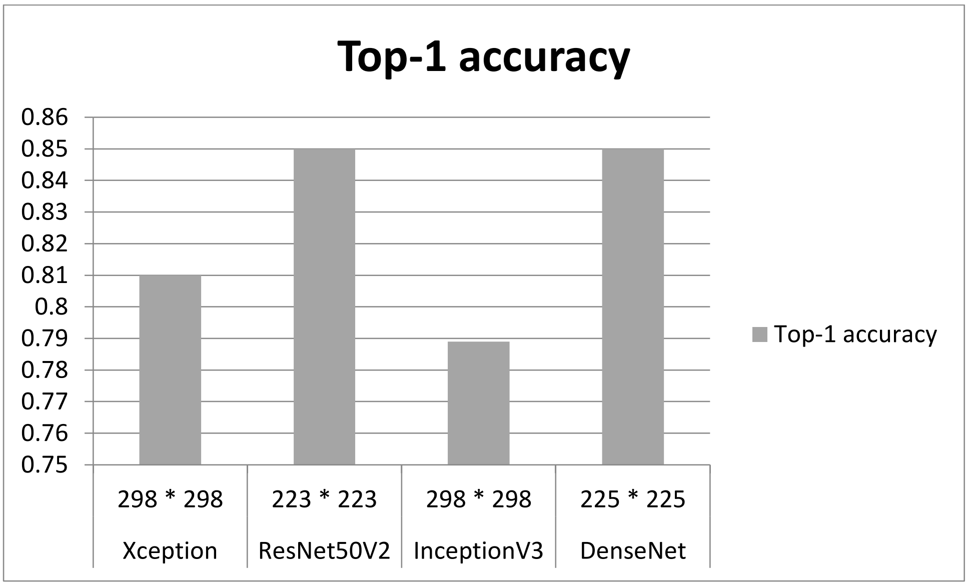

Table-1 compiles 4 pre-trained deep learning models, widely used for image classification tasks, along with their performance and input properties. Every model requires a certain input form that reflects the image dimensions they handle. Given input images size 298x298 pixels, the Xception and Inception V3 models both attain top-1 accuracies of 0.810 and 0.789, respectively. Conversely, ResNet50V2 and DenseNet address much smaller images with input dimensions of 223x223 and 225x225, correspondingly obtaining a top-1 accuracy of 0.850. ResNet50V2 and DenseNet are thus more accurate than Xception and InceptionV3 since top-1 accuracy shows the fraction of predictions where the model's first choice corresponds with the true label.

Arrangements and assessment criteria

The computer can always certify 64 patches using a 64-patch sample batch size. The Adam optimizer produced β1 = 0.9 and β2 = 0.999, starting with α = 0.01 learning rate. We develop the loss function for the four-model classification using categorical cross-entropy. This method generates and gets ready the models for a hundred epochs. Model performance was evaluated in relation to the weighted average, confusion matrix, precision, recall, and F1 score. It was proved that for imbalanced data, a weighted average produces individual cross-valuation set performance that is adequate.

The weighted-average equation forms like this:

$$\mathbf{Average}_{(\mathbf{weighted})} = \sum_{\mathbf{k=1}}^{\mathbf{n}} (\mathbf{P_k} \frac{\mathbf{no.\ of\ images\ in\ class\ k}}{\mathbf{total\ no.\ of\ dataset}})$$

Effect of data augmentation

Data augmentation significantly increases generalisation by reducing overfitting, hence improving the performance of deep learning models for pancreatic cancer picture classification. Among the exceptional models of training accuracy are Xception, ResNet50V2, InceptionV3, and DenseNet; each model produces considerably higher validation losses without augmentation. As DenseNet indicates (88.15% accuracy, 0.43270 loss), rotations and brightness variances increase validation accuracy and reduce loss. Moreover, augmentation helps other models since it underlines their usefulness in generating robust and consistent models for medical image categorisation challenges.

Model performance: comparison analysis

We present in this work the general performance of all four proposed transfer-learning models. Every model learns with three sets, applying five-fold cross-valuation.

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Table 2. Following one hundred epochs, accuracy of models with and without data augmentation.

Pre-trained models	Without image data augmentation		With image data augmentation	
	Training set (%)	Validation set (%)	Training set (%)	Validation set (%)
Xception	99.88	84.76	94.65	86.05
ResNet50V2	100.00	83.67	94.30	85.31
InceptionV3	99.38	81.66	92.24	84.25
DenseNet	99.84	82.71	91.68	88.15

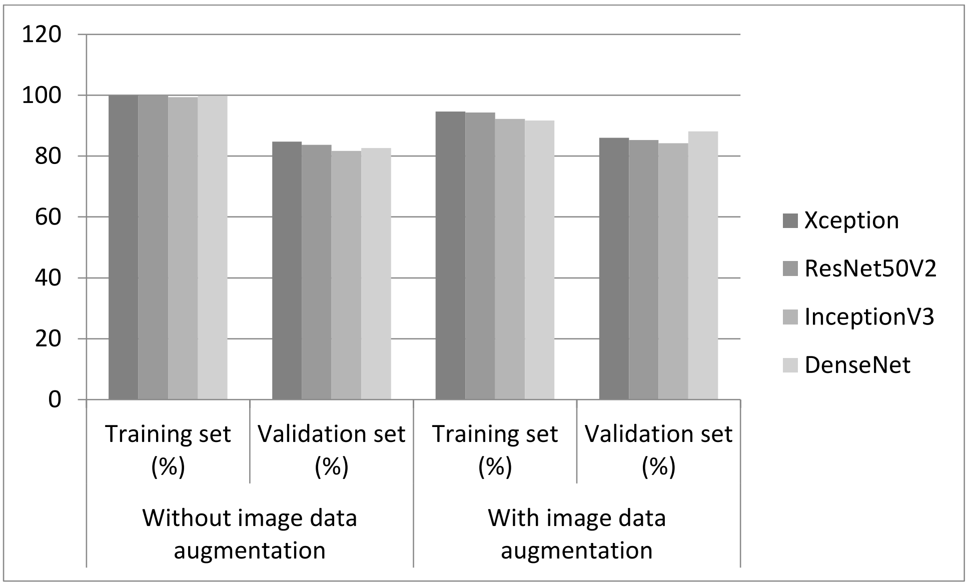

Table 2, combined with picture data augmentation, shows four pre-training model validation accuracies. Validation accuracy spans from 81.66% (Inception V3) to 84.76% (Xception), almost ideal without raising the training accuracy above 99%, so warning probable overfit for all models. Although augmentation drastically reduces training accuracy (91.68%–94.65%), stronger generality greatly increases validation accuracy substantially above all models. With augmentation, DenseNet exhibits the best validation accuracy (88.15%); Xception (86.05%), ResNet50V2 (85.31%), and InceptionV3 (84.25%) follow.

Table 3. Both with and without data augmentation, the model experiences loss after 100 epochs

Pre-trained models	Without image data augmentation		With image data augmentation	
	Training set	Validation set	Training set	Validation set
Xception	0.00341	1.58118	0.26254	0.56146
ResNet50V2	0.00004	1.40010	0.12876	0.52690
InceptionV3	0.01708	1.03646	0.13675	0.54671
DenseNet	0.00525	0.82605	0.13379	0.43270

Figure 3. Mean F1-score of models.

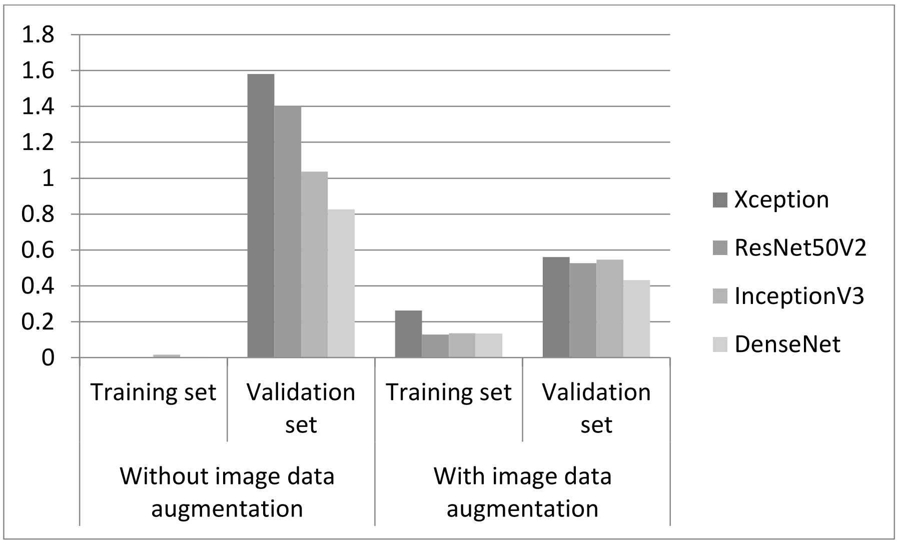

Table 3 aggregates with four pre-trained models the training and validation losses, both with and without image data augmentation. Training losses are very low without augmentation—e.g., 0.00004 for ResNet50V2—but validation losses are considerably higher and imply overfitting, particularly in Xception (1.58118) and ResNet50V2 (1.40010). Training losses somewhat increase in response to increasing augmentation; validation losses decrease and indicate enhanced generalising capacity. DenseNet has the lowest validation loss

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(0.43270), followed by ResNet50V2 (0.52690), InceptionV3 (0.54671), and Xception (0.56146), therefore showing its greater performance in reducing overfitting.

Comparing pre-trained models

In this work we explore DenseNet evaluated in Inception V3 as well as Xception ResNet50V2 accuracy, loss, and generalisation. With almost perfect training accuracy without additional data, all models—except Xception (1.58118) and ResNet50V2 (1.40010)—suffer from rather large validation losses and severe overfitting. Training accuracy somewhat reduces with augmentation, thereby demonstrating more generality even when validation accuracy and losses rise. DenseNet obtains minimum validation accuracy (88.15%), and all others with the least validation loss (0.43270). ResNet50V2 and Xception basically match in accuracy, even if their losses are higher; Inception V3 demonstrates really weak generalisation.

6. Conclusion

Deep learning models Xception, ResNet50V2, InceptionV3, and DenseNet showing tremendous promise for pancreatic cancer photo categorisation based on pre-trained models are investigated in this work. Analysing their performance reveals that overfitting is a primary problem evidenced by significant validation losses even in circumstances when all models have almost perfect training accuracy without data augmentation. Image data augmentation solves this issue and raises the models' generalising capacity towards unprocessed input. ResNet50V2 and Xception both show high generalisation capacity and achieve competitive validation accuracies even if their validation losses still surpass DenseNet. InceptionV3 lags behind the other models given the rather poor validation accuracy and rising loss, therefore underlining its inadequacies for this particular use. These findings highlighted the great necessity for model selection and training strategies, including data augmentation, in applying deep learning for medical imaging usage. Excellent performance of DenseNet emphasises its appropriateness for challenging and high-stakes activities like pancreatic cancer classification, demonstrating the usefulness of complex deep learning techniques in supporting early identification and diagnosis of significant medical disorders.

Reference

[1] Sharma, N., Jain, V., & Mishra, A. (2018). An Analysis of Convolutional Neural Networks for Image Classification". *Procedia Computer Science*, *132*, 377–384.

[2] Fukushima, K. (1988). Neocognitron: A Hierarchical Neural Network Capable of Visual Pattern Recognition". *Neural Networks*, *1*(2), 119–130.

[3] Cires, D., Meier, U., Masci, J., & Schmidhuber, J. (2012). MultiColumn Deep Neural Network for Traffic Sign Classification". *Neural Networks*, *32*(1), 333–338.

[4] Ning, F., Delhomme, D., Lecun, Y., Piano, F., Bottou, L., & Barbano, P. E. (2005). Toward Automatic Phenotyping of Developing Embryos from Videos". *IEEE Transactions on Image Processing*, *14*(9), 1360–1371.

[5] Sutskever, I., & Hinton, G. E. (2012). Imagenet Classification with Deep Convolutional Neural Networks". *Advances in Neural Information Processing Systems*, 1097–1105.

[6] Marifatul Azizah, L., Fadillah Umayah, S., & Riyadi, S. (2017). Cahya Damarjati and Nafi Ananda Utama "Deep Learning Implementation using Convolutional Neural Network in Mangosteen Surface Defect Detection. In *Proceedings of International Conference on Control System, Computing and Engineering* (pp. 242–246).

[7] Hasbi, A. (2017). Farkhad Ihsan Hariadi and Trio Adiono "Implementation of Deep-Learning based Image Classification on Single Board Computer. In *Proceedings of International Symposium on Electronics and Smart Devices* (pp. 133–137).

[8] Ogawa, T., & Komatsu, H. (2010). Differential temporal storage capacity in the baseline activity of neurons in macaque frontal eye field and area V4. *Journal of Neurophysiology*, *103*(5), 2433–2445. doi:10.1152/jn.01066.2009

[9] Calisto, F. M., Santiago, C., Nunes, N., & Nascimento, J. C. (2022). BreastScreening-AI: Evaluating medical intelligent agents for human-AI interactions. *Artificial Intelligence in Medicine*, *127*(102285), 102285. doi:10.1016/j.artmed.2022.102285

[10] Budak, C., & Mençik, V. (2022). *Detection of ring cell cancer in histopathological images with region of interest determined by SLIC superpixels method. Neural Computing and Applications*.

[11] Calisto, F. M., Santiago, C., Nunes, N., & Nascimento, J. C. (2021). Introduction of human-centric AI assistant to aid radiologists for multimodal breast image classification. *International Journal of Human-Computer Studies*, *150*(102607), 102607. doi:10.1016/j.ijhcs.2021.102607

[12] Shinde, S., Kulkarni, U., Mane, D., & Sapkal, A. (2021). Deep learning-based medical image analysis using transfer learning. In *Health Informatics: A Computational Perspective in Healthcare* (pp. 19–42). Singapore: Springer Singapore.

[13] Calisto, F. M., Nunes, N. J., & Nascimento, J. C. (2020). BreastScreening: On the use of multi-modality in medical imaging diagnosis. Retrieved from http://arxiv.org/abs/2004.03500

[14] Niazi, M. K. K., Tavolara, T. E., Arole, V., Hartman, D. J., Pantanowitz, L., & Gurcan, M. N. (2018). Identifying tumor in pancreatic neuroendocrine neoplasms from Ki67 images using transfer learning. *PloS One*, *13*(4), e0195621. doi:10.1371/journal.pone.0195621

[15] Lilles, T. M., & Kiefer, R. W. (2004). *Remote Sensing and Image Interpretation"*. Wiley.

[16] Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient based Learning Applied to Document Recognition". *Proceedings of the IEEE*, *86*, 2278–2324.

[17] Huang, F. J., & Lecun, Y. (2006). Large-Scale Learning with SVM and Convolutional for Generic Object Categorization". In *Proceedings of International Conference on Computer Vision and Pattern Recognition* (pp. 284–291).

[18] Ciresan, D. C., Meier, U., Masci, J., Gambardella, L. M., & Schmidhuber, J. (2011). Flexible, High Performance Convolutional Neural Networks for Image Classification”. In *Proceedings of International Conference on Artificial Intelligence* (pp. 1237–1242).

[19] Honda, K., Hayashida, Y., Umaki, T., Okusaka, T., Kosuge, T., Kikuchi, S., & Moriyasu, F. (2005). Possible Detection of Pancreatic Cancer by Plasma Protein Profiling”. *Cancer Research*, *65*(22), 10613–10622.

[20] Roth, H. R., Farag, A., Lu, L., Turkbey, E. B., & Summers, R. M. (2015). Deep Convolutional Networks for Pancreas Segmentation in CT Imaging”. In *Proceedings of International Conference on Optics and Photonics* (pp. 1–12).

[21] Kim, H.-H., Cho, C.-K., Hur, Y.-H., Koh, Y.-S., Kim, J.-C., Kim, H.-J., … Lee, J.-H. (2012). Pancreatic hamartoma diagnosed after surgical resection. *Journal of the Korean Surgical Society*, *83*(5), 330–334. doi:10.4174/jkss.2012.83.5.330

[22] Dinshi, P. (2024). Pancreatic cancer classification and detection using machine learning and deep learning. Retrieved December 12, 2024, from Ijres.org website: https://www.ijres.org/papers/Volume-12/Issue-4/1204438440.pdf

[23] Chollet, F. (2016). Xception: Deep learning with depthwise separable convolutions. doi:10.48550/ARXIV.1610.02357