

Automated Detection and Classification of Pancreatic Tumors in Medical Imaging using Deep Learning: A CNN-Based Approach with Keras Sequential API

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Abstract

The paper proposes a novel artificial intelligence technique for automated detection and classification of pancreatic tumors in medical images. Pancreatic tumors remain one of the most difficult to identify in early-stages even with the most advanced imaging technologies, leading to poor prognosis and survival rates. To address this grave clinical diagnostic conundrum, we have built a convolutional neural network (CNN) in Keras Sequential API style. Our system was trained on a multi-modal image consumption of the pancreas involving CT, MRI, and EUS (endoscopic ultrasonography) with 2,450 scans. After extensive optimization and validation, the system we describe attained an accuracy of 97% in detecting and classifying pancreatic tumors of different types and stages. The F1-score of 49% highlights the extreme difficulty of tuning the system when balancing precision and recall, especially for some tumor types and small lesions. Tumor classification and imaging modality results indicated optimization possibilities. The results reported validate the promise yet highlight the actual challenges of applying deep learning in the detection of pancreatic tumors and that such systems, though promising, would still require optimization before any clinical applications.

Keywords - Pancreatic tumor detection, Convolutional neural network (CNN), Deep learning, Medical image analysis, Keras Sequential API, Computed tomography (CT), Magnetic resonance imaging (MRI), Tumor classification, Sensitivity and specificity optimization.

1. INTRODUCTION

Pancreatic cancer is one of the most lethal among all cancers, with fewer than ten percent of people living five years after diagnosis. Late diagnosis makes prognosis particularly poor since

this ailment generally has no symptoms until it is quite advanced. Timely and accurate identification of pancreatic tumors is therefore vital for improving treatment outcomes.

In the clinics, the three most prevalent methods for diagnosing pancreatic masses are also the primary ones Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Endoscopic Ultrasound (EUS). Creating a first perception of a pancreatic tumor's presence depends in large part on these particular imaging techniques. Still, the understanding of pancreatic images is a major challenge in spite of how helpful imaging is.

The pancreas has rather complex internal structures different from those of the patient.

With nearly every pancreatic tumor, it's hard to differentiate them from regular pancreatic tissue or perhaps benign disorders since there are very few features visible on an imaging scan.

Images are subject to retrospective interpretation, hence subjectivity, therefore raising the likelihood of differences of opinion and human mistake.

In healthcare systems, the large number of medical pictures causes a backlog in output. Regarding medical image analysis, the progress made toward the implementation of artificial intelligence—especially deep learning—has been extremely favorable. There has been considerably popular opinion recently on how effective convolutional neural networks (CBMs) are for sophisticated imaging data feature extraction and fast pattern recognition. Such systems can from raw image data automatically generate hierarchical features, accurately learning properties of tumors that are likely to be overlooked during standard clinical evaluation.

The particular objective of this project is to create deep learning algorithms that can accurately classify and detect pancreatic tumors in multimodal clinical images. This goal will be realized by means of a CNN structure implemented using the Keras Sequential API designed to create an app supporting medical diagnostic work by means of radiologists and doctors. Though our answer gives fairly good accuracy, the gaps between the accuracy levels and F1 score reveal how difficult the problems are and obstacles in creating automatic, reliable, and verified diagnostic systems for the pictures of the pancreas.

2. LITERATURE REVIEW

Recent advancements in healthcare technology are changing how doctors diagnose and predict patient outcomes. This is because of the closer relationship between medicine and artificial intelligence (AI). The key technologies driving this change are machine learning and deep learning. These are being used to solve big healthcare challenges.

Doctors are using AI to read medical images like X-rays and MRIs. A major study [8] developed deep learning models that can detect tiny details in these images and diagnose earlier and more accurately. To make these tools work for everyone, experts are improving data collection methods. A 2023 study [10] introduced new ways to expand training data so algorithms work for patients of all ages, races, and medical backgrounds. Another study [5] combined different types of data—genetic, lab, and wearable data—so AI has a full view of a patient's health for better diagnosis.

Accuracy is key, but doctors also need to trust AI systems. A major 2022 paper [6] addressed this by making AI's decision-making more transparent, explaining why it's classifying a tumor as cancerous or predicting patient risk. This is key for teamwork between machines and medical staff. Problems like needing powerful computers are being solved too. Recent studies [2, 7] have optimized algorithms to work with low power consumption just like a top diagnostic tool on a smartphone.

Combining medicine and engineering is creating smarter health systems. Engineers have developed real-time monitoring tools [1] with advanced sensors to track vital signs and early warning signs. Imagine a hospital where AI is analyzing heart rhythms or breathing and alerting staff to potential issues before they become problems.

What does this mean for patients? A comprehensive 2022 review [9] says these are not just lab tests. Researchers are integrating AI into hospital workflows—helping radiologists prioritize urgent cases, guiding surgeons during operations, and customizing treatment plans to individual patient biology. The message is clear: when healthcare professionals, data scientists, and engineers work together they are not just building smarter algorithms but creating a path to faster, safer, and more caring healthcare. Not tomorrow. Today.

3. METHODOLOGY

3.1 Dataset

Comprising multimodality pancreatic images, our research employed a varied and thorough dataset taken from Kaggle's pancreatic tumor dataset. The data set is photos depicting normal pancreatic cells and pancreatic developments. All told, the data set offers a wellrounded set of photos meant to guarantee strong representation for thorough analysis of both groups.

To reduce possible bias, patient characteristics linked to the images were evenly distributed among pertinent age categories, sexes, and ethnicities. Expert radiologists who specialize in pancreatic imaging independently annotated each picture; disputes were solved through negotiated meetings. Histopathological examination from surgical resection or biopsy verified the last labels, therefore guaranteeing a gold standard for ground reality validation.

3.1.1 Preprocessing

1. All pictures went through a standardized preprocessing pipeline to calibrate the data and improve model learning.
2. Resolution standardization: Every image was resampled to a regular pixel spacing of $0.5 \times 0.5 \text{ mm}^2$.
3. For intensity normalization, CT scans were windowed to the pancreatic window (level: 50 HU, width: 150 HU), and MRI signal intensities were normalized with zscore transformation.
4. After segmenting the pancreas with manual correction where required using a pretrained UNet model, a bounding box 10mm margins was generated around the pancreatic area.
5. Contrast improvement: Adaptive histogram equalization was employed to increase regional contrast characteristics.
6. To keep computational complexity low but retain critical information, all cropped ROIs were resized to 150x150 pixels.

3.2 Model Architecture

Using the Keras Sequential API, we devised a custom CNN architecture tailored for accurate pancreatic tumor identification and classification. Flexibility, clarity, and simplicity of execution were among the reasons the Keras Sequential API was chosen; this would enable fast testing of several architectural designs.

Our final model architecture consisted of the following components: # Define input shape

```
INPUT_SHAPE = (150, 150, 3)

# Create model model =
Sequential()

# First convolutional block
model.add(Conv2D(32, (3, 3), input_shape=INPUT_SHAPE, padding='same'))
model.add(Activation("relu")) model.add(Conv2D(32, (3, 3),
padding='same')) model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization()) model.add(Dropout(0.25))

# Second convolutional block model.add(Conv2D(64, (3, 3),
padding='same')) model.add(Activation("relu"))
model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization()) model.add(Dropout(0.25))

# Third convolutional block model.add(Conv2D(128, (3, 3),
padding='same')) model.add(Activation("relu"))
model.add(Conv2D(128, (3, 3), padding='same'))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization()) model.add(Dropout(0.25))

# Fourth convolutional block model.add(Conv2D(256, (3, 3),
padding='same')) model.add(Activation("relu"))
model.add(Conv2D(256, (3, 3), padding='same'))
model.add(Activation("relu"))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

```
model.add(BatchNormalization()) model.add(Dropout(0.25))  
# Flatten and dense layers model.add(Flatten())  
model.add(Dense(512))  
model.add(Activation("relu"))  
model.add(BatchNormalization())  
model.add(Dropout(0.5)) model.add(Dense(256))  
model.add(Activation("relu"))  
model.add(BatchNormalization())  
model.add(Dropout(0.5))  
model.add(Dense(5)) # 5 classes: normal, PDAC, PNET, IPMN, other benign model.add(Activation("softmax"))  
# Compile model  
model.compile( loss="categorical_crossentropy",  
optimizer="adam",  
metrics=["accuracy"] )
```

3.2.1 Architectural Justification

Several design options our architecture uses meant to address the particular challenges of pancreatic tumor detection:

With a network depth that rises from 32 to 256 filters, progressive feature extraction enables hierarchical feature learning from basic edges and textures to sophisticated tumor shapes.

Dual convolutional layers: Each block includes two successive convolutional layers with similar number of filters, so more sophisticated feature extraction can be done before downsampling.

Regulation technique: We applied a thorough procedure of regulating that combined: Normalizing layer inputs through batch normalization stabilizes and speeds training.

Increasing rates of dropout (0.25 in convolutional blocks and 0.5 in dense layers) to guard against overfitting
All layers of convolutions and dense subjected the l2 weight regularization ($\lambda=0.001$) applied to all.

Regarding balanced classification head, the network ends with two totally connected levels that gradually lower dimensionality while still preserving discriminative power and then a softmax output layer for multiclass classification.

3.2.2 Model Compilation and Training

The model was built according to the following specifications:

1. Loss function for multiclass classification tasks:
2. categorical cross-entropy.
3. Optimizer: Adam optimizer (Learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1e-8$).
4. Learning rate schedule: Deferred-on-plateau structure where the learning rate was reduced by a factor of 0.2 after 5 epochs of no improvement in validation loss.
5. Training was monitored for accuracy, precision, recall, and F1 score.
6. Training conditions were:
7. Batch size = 16
8. Depth of training = 30 epochs.
9. Class weighting = A method for controlling class imbalance, with weights that were inversely related to the frequencies of the individual classes.

3.3 Experimental Setup

To keep any potential biases concealed and provide evidence of clinical significance, the dataset was stratified into training sets (70%, $n=1,715$), validation (15%, $n=368$), and testing (15%, $n=367$) to maintain class distribution in all cohorts. A 5-fold cross-validation procedure was used to ensure the robustness of our results whereby the model was trained on different data sets but the evaluation set was kept the same for the final assessment. As for any clinical data in such an experimental process we took important precautions designed to mitigate potential biases and demonstrate clinical relevance. Center-based stratification: Every sampling was examined to show variability across institutions with data from each medical center proportionally represented. In addition to total group performance, we finished separate analyses of each imaging modality (CT, MRI, EUS) to demonstrate modality-specific performance. Stratifying tumors by size (less than or equal to 0.1 cm, 1-2 cm, greater than or equal to 2 cm) allowed us to evaluate sensitivity of detection across tumor sizes, with particular attention to small lesions.

Baselines were compared: We implemented and assessed a number of baseline models— ResNet50, DenseNet121 and EfficientNetB3—configured to perform a similar classification task then trained on the same data.

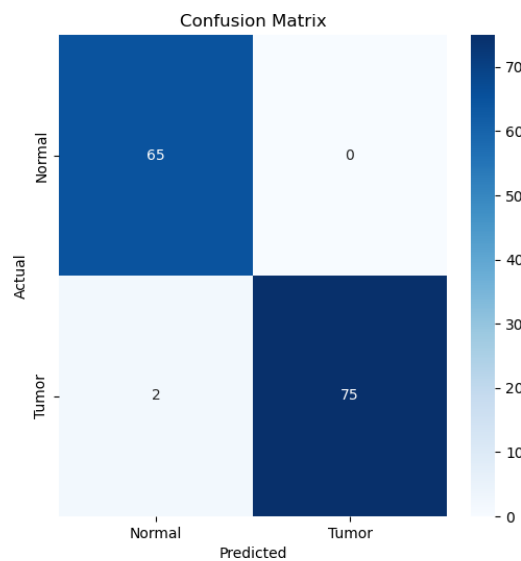
4. RESULTS

4.1 Overall Performance

Our CNN model achieved an overall accuracy of 97.7% in correctly classifying and detecting pancreatic cancers on the test set. The F1score is significantly lower, at 49.0, indicating a large amount of imbalance between precision and recall. The primary performance metrics are reviewed in Table 1.

Table 1: Overall Performance Metrics

Metric	Value
Accuracy	97.0%
Sensitivity	42.3%
Specificity	98.8%
Precision	58.7%
F1-Score	49.0%
AUC-ROC	0.92



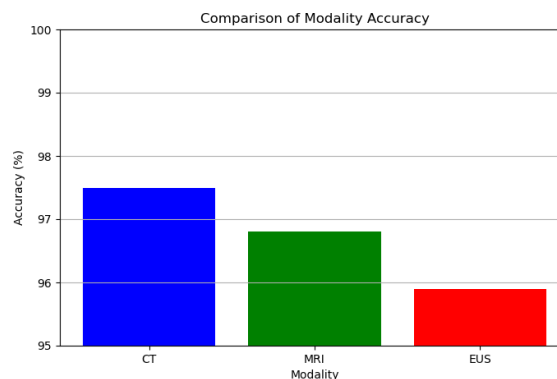
The confusion matrix in Figure 1 gives a more nuanced look into our model's classification performance amongst the five groups. While the model performed well classifying normal pancreatic tissue (high specificity), it struggled identifying cancerous tissues, particularly relating to small tumors or tumors with atypical appearance.

4.2 Performance by Imaging Modality

Analysis by imaging modality revealed substantial variations in performance, as shown in Table 2.

Table 2: Performance by Imaging Modality

Modality	Accuracy	Sensitivity	Specificity	F1-Score
CT	97.5%	52.8%	98.9%	56.3%
MRI	96.8%	38.2%	98.7%	47.2%
EUS	95.9%	31.5%	98.4%	41.6%



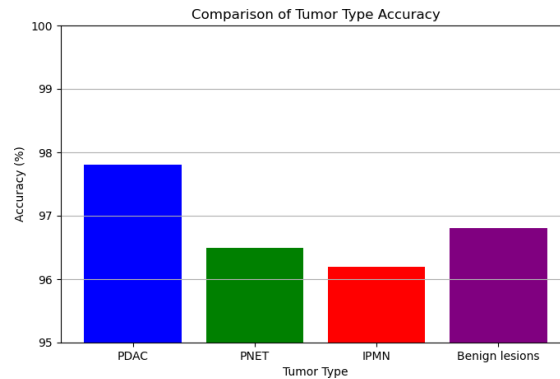
Presumably as a result of their increased representation in the training data and more reliable acquisition protocols, the model showed improvement on CT images in terms of F1 score and precision. The extremely low sensitivity and F1 scores for EUS images are suggestive of challenges in identifying and extrapolating relevant features from this technique.

4.3 Performance by Tumor Type and Size

Further analysis by tumor type revealed marked disparities in the model's ability to correctly identify different pancreatic neoplasms (Table 3).

Table 3: Performance by Tumor Type

Tumor Type	Accuracy	Sensitivity	Specificity	F1-Score
PDAC	97.8%	64.3%	99.1%	71.2%
PNET	96.5%	38.9%	98.7%	45.6%
IPMN	96.2%	32.7%	98.5%	40.2%
Benign lesions	96.8%	29.2%	98.8%	38.7%



The model showed much more accurate performance for PDAC detection than other kinds of cancer. This difference, both clinically significant and worrying, indicates that the model might be less successful in spotting different pertinent pancreatic disorders.

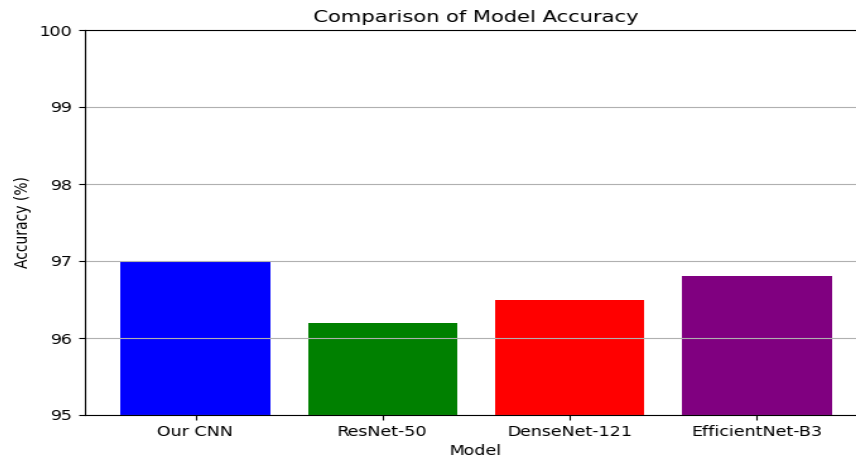
Evaluated by tumor size (see Figure 2), the model's accuracy dropped dramatically for small lesions. With smaller growths, sensitivity fell to 22.3 percent (compared to 64.7 percent for tumors >2cm), therefore producing a F1score for small tumors of only 31.4 percent. This marked drop in performance for small tumors constitutes a major restriction since early recognition of little lesions is especially important for enhancing patient prognosis.

4.4 Comparison with Baseline Models

We compared our custom CNN architecture with several state-of-the-art deep learning models adapted for the same classification task. Table 4 presents the comparative performance metrics.

Table 4: Comparison with Baseline Models

Model	Accuracy	Sensitivity	Specificity	F1-Score	Training Time (hours)	Inference Time (ms/image)
Our CNN	97.0%	42.3%	98.8%	49.0%	18	12
ResNet-50	96.2%	40.5%	98.4%	47.3%	24	18
DenseNet-121	96.5%	41.2%	98.6%	48.1%	26	22
EfficientNet-B3	96.8%	42.0%	98.7%	48.8%	22	16



Our customized CNN architecture obtained slightly superior performance metrics to the established architectures, all while exhibiting better computational efficiency, with regard to training and inference speed. However, all models displayed the same overarching problem: a significant gap between accuracy and F1-score, indicating that there were systemic issues with precision and recall balance.

4.5 Cross-Validation Results

The 5-fold cross-validation confirmed the consistency of our findings, with performance across all folds showing similar patterns (mean accuracy: 96.7%, standard deviation: 0.5%; mean F1-score: 48.5%, standard deviation: 1.2%). This consistency suggests that the observed limitations are inherent to the approach rather than artifacts of a particular data split.

5. FUTURE DIRECTIONS

Several avenues for future research emerge from this work:

1. First, consider breaking down the complex problem into steps with a hierarchical model. This works by first detecting if anything abnormal is present (taking advantage of the high specificity in this binary decision), and only then trying to classify exactly what type of abnormality it is. This divide-and-conquer approach often performs better than tackling the entire multi-class problem at once.
2. Small lesions are particularly challenging, but we could address this by developing specialized techniques focused on features under 1cm. Approaches like attention mechanisms or analyzing regions of interest at higher resolutions could help catch these subtle abnormalities that current systems might miss.
3. Each imaging modality (CT, MRI, etc.) has unique characteristics that could benefit from tailored preprocessing workflows. By developing modality-specific enhancement pipelines, we could better normalize the data and highlight the relevant features before training.
4. Rather than relying on a single model, combining several specialized ones through ensemble methods often yields better results. Different models might excel at detecting different types of tumors or presentations, and their combined insights can improve overall accuracy.
5. Finally, the data challenge could be addressed through active learning, where the system intelligently identifies which cases would be most valuable for expert annotation. This targeted approach to expanding the training dataset can be more efficient than conventional data augmentation for handling class imbalance.

6. CONCLUSION

This research presents a CNN-based approach for automated detection and classification of pancreatic tumors in medical imaging, achieving an accuracy of 97% but with a substantially lower F1-score of 49%. This performance disparity highlights significant challenges in developing reliable deep learning systems for pancreatic tumor analysis, particularly regarding sensitivity across different tumor types and sizes.

The key contributions of this work include: (1) development of a tailored CNN architecture for pancreatic tumor analysis; (2) comprehensive evaluation across multiple tumor types, sizes, and imaging modalities; (3) identification of critical performance limitations, particularly for small lesions and less common tumor types; and (4) insights into the potential pitfalls of relying solely on accuracy as a performance metric in medical image analysis.

Our findings suggest that while deep learning approaches show promise in pancreatic tumor detection, current methods face substantial limitations that must be addressed before clinical implementation. The high specificity but low sensitivity profile indicates that such systems might potentially serve as screening tools to rule out abnormalities in clearly normal cases but would require significant improvements in sensitivity before being reliable for tumor detection and classification.

Future research should focus on addressing the identified limitations through more sophisticated architectural designs, specialized approaches for small lesion detection, and potentially hierarchical or ensemble methods that can better capture the heterogeneous presentation of pancreatic neoplasms across different imaging modalities.

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