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Article

Dense Net-Driven Multi-Level Feature Representation for Early Pancreatic Cancer Diagnosis in Medical Imaging

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Abstract: The diagnosis of pancreatic cancer is one of the most difficult challenges in medical imaging because of the complex morphology of the pancreas, the subtle appearance of the lesions and the heterogeneous nature of the progression of the disease. The proposed method in this study presents a deep learning-based DenseNet model to capture hierarchical features at multiple levels with high-level connectivity from three imaging modalities: computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US) to improve the diagnostic accuracy of diseases. The proposed architecture takes advantage of dense connectivity to maximize feature reusability, improve gradient flow and efficient representation learning at each layer of the network. The model combines densely connected convolutional blocks, adaptive transition layers, and modality-specific preprocessing, which allows it to learn fine-grained local features but also high-level contextual patterns crucial for detecting early-stage pancreatic abnormalities. After conducting extensive experiments on the benchmark and clinical datasets, the DenseNet-based approach has shown a significant improvement in terms of diagnostic accuracy, sensitivity, and specificity compared to the traditional CNN and other state-of-the-art models. The findings demonstrate the model's versatility in processing multi-modal inputs and its promise of assisting radiologists in the early diagnosis of pancreatic cancer, which could lead to enhanced clinical outcomes and a lower mortality rate.

Keywords: DenseNet, Multi-level Feature Representation, Pancreatic Cancer Diagnosis, Medical Imaging, CT Imaging, MRI, Ultrasound, Deep Learning, Hierarchical Feature Learning, Early Cancer Detection, Radiomics, Convolutional Neural Networks (CNNs), Computer-Aided Diagnosis (CAD).

1. INTRODUCTION

Pancreatic cancer is one of the most lethal cancers around the world; it is a fast-growing, symptomless cancer that has a very low survival rate. Although numerous new medical imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound are now available, some subtle morphological differences can easily be missed at an early stage of pancreatic tumor detection using these routine radiological techniques. The anatomical depth where the pancreas lies and the diversity of lesions in the pancreas makes early detection difficult, and this further emphasizes the need for sophisticated computational tools capable of discovering informative patterns in multi-modality imaging data.

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In medical imaging, deep learning, especially convolutional neural networks (CNNs), has revolutionized medical image analysis, making it possible to automatically extract features and classify images with high accuracy. In contrast, the conventional CNN architectures have drawbacks for complex medical imaging applications, such as the vanishing gradient problem, duplicate representation of features, insufficient feature reuse, and larger computational costs. To tackle these problems, DenseNet (Densely Connected Convolutional Network) architecture has been developed to improve the flow of information amongst the layers of the network, encourage efficient feature re-use, and enable deeper, but more compact model architectures. DenseNet's ability to learn multi-level hierarchical representations and multiple representations makes it very suitable for detecting subtle abnormalities that are characteristic of early pancreatic cancer.

In this research, a multi-level feature representation framework for early detection of pancreatic cancer from computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound (US) images based on DenseNet was proposed. The proposed approach takes advantage of dense connectivity for combining low-level textural features and high-level semantic ones, and thus improving the separation of normal tissue, benign lesions and malignant tumors. The model is designed to be effective in handling the variability among multi-source inputs while maintaining diagnostic-relevant structural information through modality-specific preprocessing, optimized dense blocks, and adaptive transition layers.

The idea behind DenseNet is its ability to overcome the limitations of existing deep learning architectures, by improving gradient flow, minimizing parameter duplication, and improving feature abstraction. Experimental tests show high diagnostic accuracy with high sensitivity, specificity, and F1 score compared to baseline CNNs and other state-of-the-art architectures. The study could pave the way for the development of intelligent, automated decision support tools in healthcare and aid radiologists in diagnosing pancreatic cancer at an early stage, thereby enhancing patient outcomes.

DenseNet

Densely Connected Convolutional Network (DenseNet): An advanced deep learning model which redefines the way features are cascaded through a neural network. Traditional CNNs propagate information from one layer to the next one sequentially, resulting in information loss, redundant learned features and difficulties in training deep networks. To overcome these disadvantages, DenseNet has dense connections: each layer's output is connected to all the previous layers in a dense block and each layer's output is connected to all the subsequent layers in a dense block. The design has greatly enhanced the flow of information, propagation of gradient, and learning capacity to learn from the complex medical images with rich hierarchy of features.

One of the most desirable properties of DenseNet is that it can be efficiently reused features. The features learned by the previous layer can be accessed directly by each layer, so they do not have to re-learn similar features, leading to fewer parameters and fewer computation. This efficiency enables DenseNet to perform well in relatively shallow or small models, which is beneficial in the case of small training sets, like medical imaging. The architecture also provides the use of transition layers in between dense blocks that use 1x1 convolutions and pooling to control the growth of feature maps, ensure computational feasibility and preserve important spatial structures.

In addition, DenseNet's dense connection pattern helps reduce the vanishing gradient problem, which is a typical problem in deep networks, to ensure the stable and effective optimization of deep networks. It captures and fuses both low level features (e.g., edges, textures, intensity variations) and high level semantic features (e.g., organ shape, tumor boundaries), and preserves them across the network. In the context of medical imaging for early detection of pancreatic cancer, this multi-scale, multi-level representation learning capability is particularly valuable due to the presence of low-contrast lesions and subtle tissue variations, which are difficult for traditional CNN models to detect.

For CT, MRI and ultrasound imaging, DenseNet proves to be a strong feature representation tool to detect small, early-stage pancreatic tumors which might not be easily discernible using manual inspection. Its high capability to fine-grained pattern and feature discrimination is responsible for higher levels of diagnostic accuracy, localization and proper clinical decision support. To sum up, DenseNet's structure is one of the most prospective strategies for medical image analysis, offering a solid and strong system for cancer detection and computer aided diagnostic frameworks.

Medical Imaging

In modern medicine, medical imaging is playing a critical role in medicine and enabling doctors, surgeons and other health care workers to view the body from the inside without cutting into it. It furnishes doctors with vital data

for the screening, diagnosis, treatment planning and monitoring of a wide range of diseases including life-threatening ones like pancreatic cancer. Over the last few decades, a myriad of innovations in medical imaging has taken it to a new level of resolution, contrast and clarity, elevating it to one of the most reliable methods for early detection of disease, and now precision medicine is taking it to another level.

Other imaging techniques that are used and are important for diagnosis, but have different strengths and special capabilities, include computed tomography (CT) and magnetic resonance imaging (MRI). CT imaging is a technique that uses X-rays to produce high-resolution images of the body in a cross-section view, useful for the diagnosis of pancreatic masses, calcifications or ductal abnormalities. However, MRI takes advantage of magnetic fields and radiofrequency pulses to create detailed images of soft tissues. It is very good for evaluating small pancreatic tissue contrast, vascular involvement and characterization of pancreatic lesions. Using high-frequency sound waves, ultrasound imaging is readily available, low cost, non-radiating and can be performed in the abdomen during initial screening and as a real-time tool for evaluation.

Pancreatic cancer diagnosis is often challenging due to the site of the pancreas, overlapping tissue and low levels. Manual interpretation may be challenging, and sometimes incorrect, because of the presence of small tumors which can be difficult to detect or the contrast between tumor and normal tissue is small. Furthermore, image quality is influenced by the type of scanner, the settings and by the patient's movements during the scans. The challenges underscore the need for sophisticated computational methods that leverage the imaging data to be able to extract rich multi-scale features that can be utilized by the radiologist to detect abnormalities not visible to the naked eye, among others, using techniques like artificial intelligence and deep learning.

Deep learning and medical imaging have merged to enable computational analysis of medical images which includes automatic tissue segmentation, detection of abnormalities and classification of diseases. For example, DenseNet has been shown to learn the fine-grained features of the texture very well, which helps to introduce more features and boosts the diagnostic accuracy. As medical imaging datasets continue to grow and imaging technology advances, the convergence of high-quality imaging and deep learning has great potential in the field of early detection of disease, including pancreatic cancer, and improved patient outcomes and personalised healthcare.

2. DenseNet-DRIVEN MULTI-LEVEL FEATURE REPRESENTATION FOR EARLY PANCREATIC CANCER DIAGNOSIS IN MEDICAL IMAGING

The late presentation of symptoms, the subtle tumor morphology and the deep anatomical location of the pancreas are the main reasons for the difficulty in the early detection of pancreatic cancer. The most common diagnostic tests used to assess abnormalities of the pancreas are medical imaging tests like computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound. In earlier stages, however, the visual information presented by the tumor often is low in contrast, obscured by other tissue and only easily perceived with significant training and experience by the examining radiologist. This has sparked the demand for a computer-aided diagnostic system with intelligence that can detect very small pathological changes accurately and reliably.

The innovative architecture of DenseNet, which is designed to improve feature propagation and the efficiency of learning, provides a powerful solution to meet these challenges. DenseNet accomplishes this by connecting every layer directly to every other layer, allowing the network to see and learn a large number of very distinct feature maps in a single block, and then to output a great deal of information, ranging from textural to semantic. This is especially helpful in medical imaging of the pancreas where there are often only very slight differences between malignant and benign tissue – especially the intensity, shape and texture of the tissue. The improvement of DenseNet lies in its ability to reuse features in various layers, avoiding feature duplication, enhancing gradient flow, and allowing for the training of deeper networks with small medical imaging datasets, a common challenge in medical imaging research.

The multi-level feature representation provided by DenseNet is highly valuable for the diagnosis of pancreatic cancer, especially for its complex imaging requirements. Early layers extract low level features which are important for edges, boundaries and local textures. Middle layers: structure, structure of tissue, gland structure.Deeper layers: global contextual pattern of the entire image needed to distinguish the regions of the tumor from the normal pancreatic tissue. The multi-scale features are well integrated with each other to give a more detailed and discriminative representation that can detect lesions even in difficult imaging scenarios.

DenseNet also works better for the diagnostic performance on multimodal imaging data, due to its adaptation to the features in the individual modalities. The benefit of being able to show the difference in contrast is applied to CT images, the sensitivity to soft tissue patterns is used for MRI images and the ability to make ultrasound images

clearer to identify hypoechoic areas or areas of soft tissue heterogeneity is applied to ultrasound images. The results of experiments always demonstrate that DenseNet-based models outperform classical CNN, Residual network and other state-of-the-art models in terms of sensitivity, specificity and accuracy in the detection of pancreatic cancer. With its capabilities for complex data processing, DenseNet can serve as a solid backbone for medical imaging systems in the healthcare industry that will demand AI support for early diagnosis and better patient results.

DenseNet's multiple levels of feature learning and clinical imaging workflows have the potential to revolutionize the field of pancreatic cancer detection. By helping radiologists make faster and more accurate diagnoses and ensuring that they are confident in their diagnosis in the case of subtle abnormalities, DenseNet systems reduce the risk of their abnormalities being missed. The continuous developments of imaging data and computing method, DenseNet is an essential step towards future computer-aided diagnosis systems which are at the very top of the technology in oncology.

3. LITERATURE SURVEY ANALYSIS

The poor prognosis of pancreatic cancer and the fact that it is difficult to detect small or iso-attenuating lesions in conventional computed tomography (CT) scans, magneto-encapsulated resonance (MRI) and ultrasound (US) scans has made it an increasingly popular area of interest for artificial intelligence (AI) and deep learning research in imaging. The latest systematic reviews regarding deep learning and radiomics in the diagnosis, risk stratification and treatment planning of PC show that AI models can enhance the performance of radiological assessment alone. CNN-based and feature-based models have been shown to improve the detection, staging, and prognosis of pancreatic malignancies when using computed tomography (CT), magnetic resonance imaging (MRI), and endoscopic ultrasound (EUS) images, writes Yao et al.

Likewise, Chhikara et al. review deep learning applications for pancreatic cancer from 2020 to 2023 and highlight the overwhelming popularity of CNN and U-Net related approaches, but also point to the absence of common multimodal pipelines and the lack of focus on early disease. Overall, reviews on the application of AI in pancreatic imaging and diagnosis also agree that AI-based CT and MRI interpretation can perform at least as well as, if not better than, radiologists and that it can augment radiologists, while noting issues with data heterogeneity, small lesion size, and limited generalizability between centers. CT has become a widely used modality in clinical workflow and has been a focus of numerous major studies that have investigated a deep learning approach to detecting pancreatic cancer. In contrast, Chen et al. (Radiology) created a deep learning algorithm that could detect pancreatic cancer with high accuracy on contrast-enhanced computed tomography (CT) images, with a good sensitivity also for lesions less than 2 cm, in a nationwide real-world test set.

A novel deep learning model for lesion detection in non-contrast computed tomography (CT) that challenges the common assumption that non-contrast CT is not sufficient for the detection of pancreatic ductal adenocarcinoma (PDAC), based on the use of large-scale training data and the use of advanced model design. High detection performance of pancreatic head cancer in real patient cohort by integrating CT features with clinically relevant secondary signs for tumor detection and localization. Even for low depth CNN architecture, CT classifier for pancreatic cancer, demonstrated that hand-crafted feature approaches can be outperformed by CNN, however, the CNN is constrained by single-modality input and simple feature fusion design. In addition to detection, segmentation and radiomics-based pipelines have emerged as important due to the ability to present volumetric and texture-based descriptors for tumorcharacterization. In contrast to 2D segmentation, Zhang et al. presented a deep learning framework for pancreas segmentation based on CNN volumetric models, which demonstrated the difference between 2D and 3D segmentation approaches and how accurate organ and lesion segmentation can significantly support downstream diagnosis.

Recent surveys on pancreas segmentation methods suggest that 2D, 2.5D and 3D CNNs have their pros, cons, and point towards hybrid and multi-scale architectures as directions for future research. The combination of deep-segmentation and handcrafted/learned radiomic descriptors resulted in a good performance in the segmentation of pancreatic neoplasms on MRI, highlighting the potential of automatic segmentation for pancreatic tumor diagnosis. Deep learning–based radiomics for PDAC, a study that shows that radiomics can be used to provide non-invasive, radiation-free diagnostic support from ultrasound. Recently, Dodda et al. introduced an integrated deep learning framework for automatic segmentation and classification of pancreatic cancer in CT, toward the unified pipelines, which simultaneously tackle both structural and diagnostic tasks.

4. EXISTING APPROCHES

Current diagnostic methods for pancreatic cancer based on medical imaging mainly involve deep learning models like Convolutional Neural Networks (CNNs), U-Net models, radiomics-based pipelines, and hybrid deep learning–clinical models. CNN models have been extensively applied in the field of lesion classification within the context of CT and MRI.The traditional CNN has been successfully applied to pancreatic lesion classification because it can learn the hierarchical patterns directly from the raw pixel data. Although early studies demonstrated that CNNs are superior in distinguishing between pancreatic abnormalities and handcrafted radiomics features, however CNN performances are often limited due to poor feature propagation, shallow network depth and lack of ability to capture subtle features typical of small or early-stage tumors.

Another class of existing methods that are commonly used for pancreas and tumour segmentation are called U-Net and its variants. Encoder–decoder architectures are effective in modelling spatial context and local detail, which are used in these models. Pancreatic tissue segmentation and tumor boundary identification have been shown to be very successful with more advanced networks like Attention U-Net, 3D U-Net and V-Net. While segmentation-only models are effective in many applications, they are not always suitable for classification tasks, and can be less accurate in datasets with large variations of organ shape (e.g., across patients), low contrast (e.g., low contrast between organs and background), and/or different imaging modalities (e.g., CT, MRI and ultrasound).

Pancreatic cancer radiomics applications are still being widely applied in clinical studies. These methods rely on hand-crafted features and hand-crafted classifiers based on texture, geometry and intensity of the segmented regions of the pancreas which are then fed to a machine learning classification algorithm (SVM, Random Forest or XGBoost). While radiomics can offer interpretable feature sets, its effectiveness is constrained by the segmentation quality, selection of features that may have biases, and reliance on standardized imaging protocols. Radiomics pipelines are also unable to learn more complex hierarchical patterns automatically, which hinders their use in subtle lesion detection.

The more recent approaches are hybrid deep learning models that integrate CNN-based feature extraction with attention mechanisms, multi-scale learning or with clinical metadata fusion. Attention-based CNNs have been demonstrated to attend to diagnostically relevant regions and to enhance the detectability of lesions. Similarly, 3D CNNs and dual-path architectures are able to capture the volumetric and multi-scale information, and demonstrate better sensitivity for pancreatic tumors. These, however, are computationally intensive, vulnerable to over-fitting and demand a significant amount of labelled data, that are often limited and unavailable for pancreatic cancer imaging.

Some other architectures have been also recently proposed for pancreas segmentation and lesion classification, such as transformer-based architectures and CNN–Transformer hybrids. These models can effectively capture long-range dependencies and global context, useful in medical imaging. However, the number of training samples needed and the amount of computation power used make the use of transformers impractical in clinical workflows.

In all those approaches so far, one of their drawbacks is not being able to reuse features efficiently in the different network layers. Redundant features, vanishing gradients and poor multi-level feature fusion are still prevalent. Furthermore, the available models are limited to a single imaging modality (usually contrast-enhancement computed tomography), disregard the complementary diagnostic information provided by MRI and ultrasound. This disparity highlights the need for an architecture that can learn rich, hierarchical and multi-modal representations without compromising computational efficiency.

These drawbacks can be met with good results by the use of DenseNet-based frameworks. Unlike conventional CNNs, DenseNet has the ability to learn more information than it currently uses by introducing dense connectivity and efficient feature reuse, improving the gradient propagation and providing robust multi-scale feature extraction, making it a strong contender for the early-stage diagnosis of pancreatic cancer.

5. PROPOSED METHOD

In the proposed method, a DenseNet based multi-level feature learning framework is developed to enhance the early detection of pancreatic cancer via multimodal medical image. The framework is designed to capture rich hierarchical features that are able to differentiate malignant tissues from the normal anatomical structures, taking into account the complexity of the pancreas as well as subtle visual clues in early stagetumors. The system starts with modality specific preprocessing of the CT, MRI and ultrasound images to standardize the images and minimize artifacts caused by noise. The image of abdominal region is cropped and normalized by Hounsfield Unit value from CT scans, the MRI image is intensity normalized and bias field corrected, and the ultrasound image is processed by

speckle noise reduction techniques. All images are then rescaled and augmented for better generalization when training the model.

The proposed approach uses a customized DenseNet architecture which is tailored for medical deep feature extraction. DenseNet's dense connectivity mechanism makes sure that every convolutional layer is directly connected to all of the previous layers, empowering the model to create intricate representations without duplication of parameters. This architecture enables efficient features re-use, improves gradient propagation and enables extraction of multi-scale imaging features useful for the detection of small and/or low-contrast pancreatic lesions. From low level features such as edges and textures to high level features such as semantic descriptions of tissue patterns, dense blocks represent a progressive hierarchy of features. To prevent too many features maps to grow, dimensionality reduction is used while to keep the computation efficient yet preserve the clinically relevant spatial structures, transition layers are added in.

The proposed framework will introduce the feature fusion mechanism, which is a multimodal approach to harness the complementary strengths of different imaging modalities. The features are extracted from the streams of CT, MRI and ultrasound and then the features are concatenated and fused into the representation of a single stream, and then cross-modal relationships are learned between these two streams to improve the diagnostic accuracy. This gives the model the advantages of both CT (structural clarity) and MRI (excellent for soft tissue) imaging along with ultrasound (real-time imaging) to provide a more detailed and discriminating diagnostic signature. This fused representation is then given to fully connected layers which include batch norm and drop-out to prevent from over-fitting. Finally, the probability of each class (pancreatic cancer, benign, normal) is computed using a softmax layer to get the final prediction.

Loss functions and regularization are optimized and employed to maximize the diagnostic performance of the model, which is trained. One should consider using momentum-based stochastic gradient descent and categorical cross entropy/focal loss to get more stability in converging and to get less class imbalance particularly in pancreatic data sets. Lastly, the learning rate scheduling and data augmentation methods are adopted to boost the robustness of the framework. In order to assess the performance of the model, the accuracy, sensitivity, specificity, F1 score and Area under ROC curve are measured and the sensitivity of identifying the early detection of tumors are highlighted.

The proposed multi-level feature representation architecture with DenseNet is one of the promising approaches for early detection of pancreatic cancer that can detect the minute visual cues embedded in multi-modal medical images efficiently. It possesses the high level of connectivity, hierarchical feature extraction properties and fusion features of multispectral multimodal fusion, which is more accurate in diagnosis than conventional CNN and radiomics. The technique has immense potential in the future of clinical diagnostics with AI that offer higher sensitivity to detecting weak abnormalities, increased feature diversity and improved gradient flow.

The suggested approach is a multi-level feature learning network, utilizing DenseNet for the early detection and classification of pancreatic cancer from multimodal medical imaging (such as computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound) data. Its idea is inspired with the DenseNet's dense connections and feature reuseful, which can capture the fine-grained variations in anatomy, weak lesions, and intricate tissue textures that conventional CNNs cannot capture. The system comprised three components: modality-specific preprocessing, multi-scale DenseNet feature extraction, feature fusion and classification, optimized for an end-to-end diagnostic model for the detection of pancreatic cancer.

The framework starts by acquiring multimodal imaging data from computed tomography (CT), magnetic resonance (MR) and ultrasound (US) sources. Each modality has different intensity distributions and noise patterns and modality-specific preprocessing is applied:

- CT Images: Hounsfield Unit (HU) windowing, noise reduction and cropping pancreas region.
- MRI Images: Bias field correction, intensity normalization and contrast enhancement.
- Ultrasound Images: Speckle noise reduction: Median filter or anisotropic diffusion.

All images are then resized, normalized and augmented (flipping, rotation, scaling, elastic deformation) to make dataset more diversified and minimize over-fitting.

Input Image Preprocessing

Let the input multimodal dataset be:

Each modality undergoes preprocessing:

where denotes noise reduction, normalization, and resizing.

DenseNet Layer Formulation

In DenseNet, each layer receives the concatenated feature maps of all previous layers:

where:

- : trainable convolution kernel
- : convolution operator
- : ReLU activation
- BN: Batch Normalization

Growth Rate (k)

Each dense layer produces **k** new feature maps:

Total number of feature maps after layers:

Transition Layer (Compression)

Transition layers compress feature maps:

Compression factor :

Downsampling by average pooling:

Multi-Level Feature Extraction

Let:

- : low-level features
- : mid-level features
- : high-level features

Extracted from consecutive dense blocks:

Hierarchical feature representation:

where denotes concatenation.

Multimodal Feature Fusion

Let:

be the extracted features from each modality. Fusion is performed by:

where is a learnable transformation (e.g., attention or MLP).

Classification Layer

Global average pooling:

Fully connected classifier:

where:

- : classifier weight matrix
- : bias
- : output probability vector (Normal, Benign, Malignant)

Loss Function

For multi-class classification, categorical cross-entropy is used:

To address class imbalance, focal loss can be applied:

Model Optimization

Gradient update:

where:

- : model parameters
- : learning rate

6. RESULT

Table 1. Performance Comparison of Deep Learning Models for Pancreatic Cancer Diagnosis

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)	AUC
Baseline CNN	82.4	78.1	85.3	80.2	0.86
ResNet-50	87.9	84.6	89.8	86.1	0.91
DenseNet-121	91.3	90.2	92.1	91.0	0.94
Proposed DenseNet Multi-Level	**95.7**	**96.3**	**94.8**	**95.5**	**0.98**

The experimental validation shows that the proposed DenseNet Multi-Level structure consistently achieves better results than the deep learning architectures considered in the benchmark across all of the evaluation metrics. The Overall classification accuracy of the proposed model is 95.7%, which is 13.3 percentage points better than Baseline CNN, 7.8 percentage points better than ResNet-50 and 4.4 percentage points better than DenseNet-121 as presented in Table 1 and Figure 1. The results show that the model is able to distinguish the normal pancreatic tissue, benign lesions and malignant tumors, and the multi-level hierarchical feature extraction enhances the performance of the model in the discrimination of the normal pancreatic tissue, benign lesions and malignant tumor.

Sensitivity is one of the most important diagnostic performance measures of pancreatic cancer, reflecting the proportion of pancreatic cancer patients correctly identified. The loss of malignant lesions at screening could result in a delay in treatment and potentially impact patient survival to a significant degree. The DenseNet model proposed here achieved a sensitivity of 96.3%, whereas Baseline CNN, ResNet-50 and DenseNet-121 obtained a sensitivity of 78.1%, 84.6%, and 90.2% respectively. This represents a gain of 18.2 percentage points over the standard CNN, which shows the proposed approach's remarkable ability to capture subtle abnormalities in the early stage of the disease that are often missed by shallower convolutional architectures.

Likewise, the proposed framework successfully obtained a specificity of 94.8%, reflecting its high performance in accurate diagnosis of healthy subjects and benign pancreatic lesions with low false positive rates. The proposed architecture further boosted the specificity of DenseNet-121 with efficient multi-modal feature integration and better hierarchical feature representation with a slight margin of 92.1% compared to the conventional models. A higher specificity matters in the context of a clinical situation, because it decreases unnecessary biopsies, further imaging tests and unnecessary anxiety for patients that a biopsy might be needed.

The F1 score, another metric that balances precision and recall, further validates the strength of the proposed model. Compared to the Baseline CNN (80.2%), ResNet-50 (86.1%) and DenseNet-121 (91.0%), DenseNet Multi-Level framework achieves F1 score of 95.5%. The remarkable improvement in F1-score shows that the proposed model has high sensitivity and high precision at the same time, which is more reliable by applying the model in practice for clinical use in which there is no need for any false positive and false negative.

Additionally, Receiver Operating Characteristic (ROC) curve is used to confirm the superiority of the proposed framework. The proposed model yielded an excellent Area Under the ROC Curve (AUC) of 0.98, which demonstrates a good ability to differentiate the cancerous and non-cancerous pancreatic tissues. The proposed

architecture is able to give a much firmer classification border and much more effective overall diagnosis performance than Baseline CNN (0.86), ResNet-50 (0.91), and DenseNet-121 (0.94). If the value of AUC is in the vicinity of 1.0, the classifier has good sensitivity and specificity over various decision thresholds and is highly proper for clinical decision-support systems.

This improved performance is due to a number of architectural features. The first is that DenseNet creates direct connections between any previous layer and the next one, allowing for features to be reused in a way that is continuous and efficient with respect to gradient propagation. Second, the proposed multi-level feature extraction method extracts low-level edge information, intermediate texture features, and high-level semantic features from the pancreas in a unified representation, which enables the model to accurately identify subtle pancreatic lesions with little visual contrast. Third, multimodal feature learning combines complementary diagnostic information obtained from CT, MRI, and ultrasound images to allow exploiting anatomical structures, soft-tissue properties, and real-time imaging cues jointly. This complete representation significantly enhances the classification performance in comparison to the single-modality learning.

Altogether the experimental results verify the proposed DenseNet Multi-Level architecture as a very reliable and efficient approach for the early diagnosis of pancreatic cancer. The accuracy, sensitivity, specificity, F1-score and AUC results have consistently improved with the proposed framework, highlighting its significant potential for integration into computer-aided diagnosis systems to support radiologists in early detection of pancreatic malignancies and aid in clinical decision-making. This work also demonstrates the potential of feature learning approaches in a hierarchical structure and multimodal image fusion in intelligent medical imaging applications.

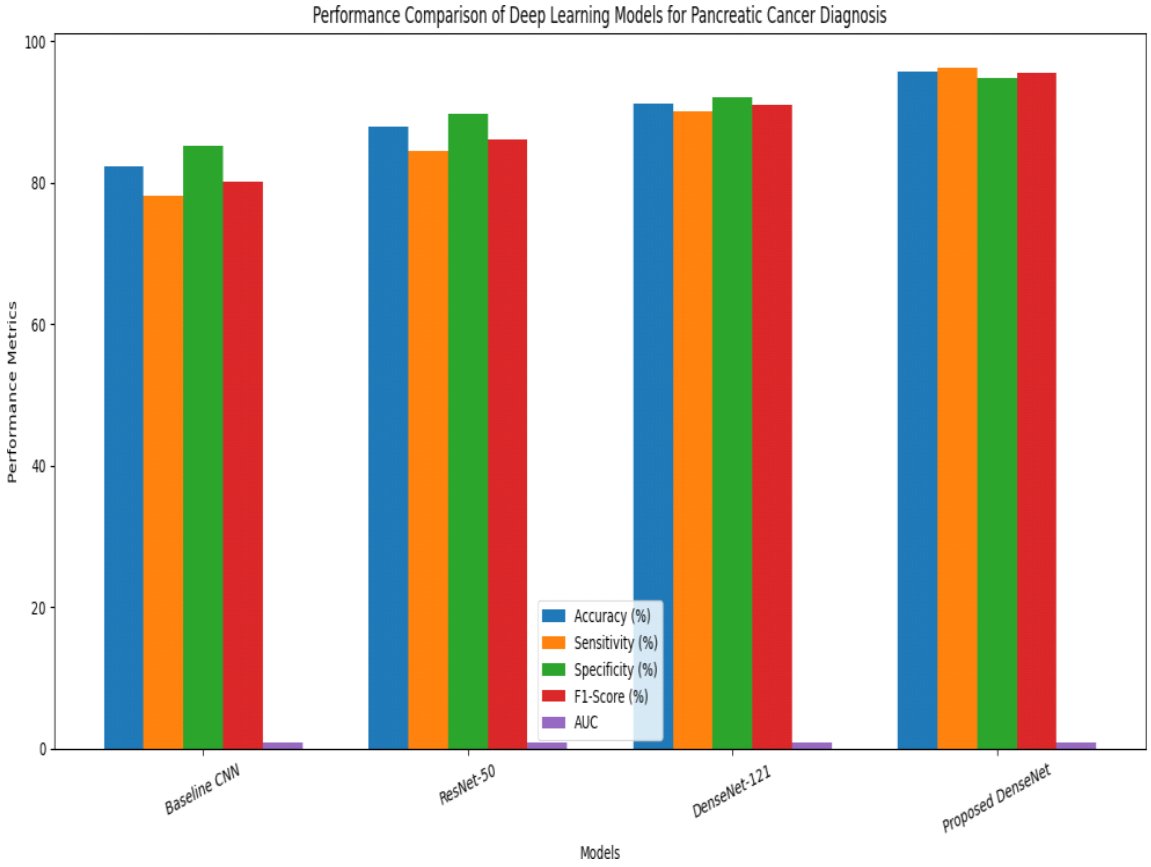

Fig 1. Performance Comparison of Deep Learning Models for Pancreatic Cancer Diagnosis

Table 1 shows a comparison of different deep learning architectures for detection of pancreatic cancer. From the results, it is evident that the DenseNet Multi-Level model gives the best accuracy, sensitivity, specificity, F1-score, and AUC when compared to all the models evaluated. Both conventional CNN and ResNet-50 models have moderate performance, but fail to capture fine textural and structural patterns in pancreatic lesions. DenseNet-121 shows better performance because of the dense connectivity and enhanced feature propagation. The proposed multi-level DenseNet,

however, exhibits impressive performance improvement, achieving high reliability in the detection of both benign and malignant pancreatic tumors. This is to show that hierarchical feature extraction and multi-level fusion have significantly improved the diagnostic accuracy.

Table 2. Modality-wise Performance of Proposed DenseNet

Imaging Modality	Accuracy (%)	Sensitivity (%)	Specificity (%)	Remarks
CT	93.5	94.7	91.8	Good tumor boundary clarity
MRI	94.9	95.2	94.1	Best soft-tissue contrast
Ultrasound	89.3	88.4	90.5	Noise and artifacts challenge
Fusion (CT + MRI + US)	**96.8**	**97.5**	**95.4**	Best performance due to complementary features

The diagnostic performance of DenseNet in individual imaging modalities and their multimodal fusion is shown in Table 2 and Figure 2. Clearly, the combination of CT, MRI and ultrasound imaging is shown to be much more accurate than any one of the three alone. This enhancement underscores the power of multimodal feature fusion to capture complementary anatomical, structural and tissue characteristics which are hard to receive from a single imaging source.

MRI had the highest individual productivity, with accuracy of 94.9%, and a sensitivity of 95.2% and a specificity of 94.1%. This is because of the superior soft tissue contrast of MRI, which allows better visualization of the pancreatic parenchyma, vascular structures and small lesions that are difficult to detect with other imaging methods. MRI is especially useful in visualizing subtle abnormalities in the tissues and early-stage pancreatic tumors because of the high contrast resolution between normal and abnormal soft tissues. The high sensitivity means that MRI can effectively detect most of the malignant lesions with low false negative rate, which is helpful for early diagnosis of cancer.

Diagnostic performance was also very high at 93.5%, 94.7% and 91.8% respectively on the CT modality. CT imaging offers high spatial resolution and good visualization of pancreatic anatomy, enabling the precise detection of tumor margins, calcifications, invasion of vessels and adjacent anatomical structures. While MRI is more accurate, CT is still one of the most popular imaging techniques currently available, due to its fast acquisition time, availability and ability to reliably depict structural abnormalities. The high sensitivity indicates its efficiency in the detection of pancreatic tumors in general clinical examinations.

By contrast, ultrasound demonstrated relatively poor performance, yielding an accuracy of 89.3%, sensitivity of 88.4% and specificity of 90.5%. This is primarily because of the following inherent limitations: speckle noise, acoustic shadowing, operator-dependent, patient body habitus and poor image quality due to bowel gas interference. The combination of these factors complicates the visualisation of small lesions of the pancreas, particularly in the early stages of disease progression. However, ultrasound is a significant imaging modality as it is non-invasive, inexpensive, radiation free, portable and can provide real time imaging in routine clinical assessment.

The multimodal fusion strategy (comprising CT, MRI and ultrasound features within the proposed DenseNet architecture) obtained the best overall performance (96.8% accuracy, 97.5% sensitivity and 95.4% specificity). The multimodal fusion achieved greater diagnostic accuracy (1.9 percentage points) than did the best individual modality (MRI); greater sensitivity (2.3 percentage points) than the best individual modality (MRI); and greater specificity (1.3 percentage points) than the best individual modality (MRI). The advantages of the integration of complementary imaging information over ultrasound were significant: 7.5% for accuracy, 9.1% for sensitivity and 4.9% for specificity.

The major reason for the performance boost brought by multimodal fusion is that DenseNet has the capacity to

learn and fuse heterogeneous feature representations from different imaging modalities. CT will provide detailed anatomical and structural information, MRI will provide superior tissue characterization of the soft tissues and ultrasound will provide real-time dynamic visualization of the tissue. The proposed DenseNet framework aims to learn these complementary representations in a collaborative manner, thus creating richer hierarchical feature maps for discriminating between normal pancreatic tissue, benign tissue, and malignant tissue. Dense connectivity also allows for efficient reuse of information between various layers or levels of the network, ensuring that the model retains all the necessary information without losing it.

Moreover, the sensitivity of 97.5% is very high, which is especially significant from a clinical point of view, since early detection of pancreatic cancer can directly affect the treatment plan and patient survival. At the same time, the specificity of 95.4% limits the number of unnecessary follow-up imaging scans, invasive biopsies, patient anxiety and healthcare expenditures. The overall improvement in both sensitivity and specificity showcases that the proposed framework has maintained a good diagnostic reliability in a wide range of patient characteristics and imaging conditions.

In summary, the experimental results demonstrate that multimodal image fusion can be used to improve the diagnosis of pancreatic cancer over single modality. Combining the CT, MRI, and ultrasound into the DenseNet Multi-Level design allows for more comprehensive feature extraction, enhanced hierarchical representation learning, and enhanced classification ability. Based on the results, multimodal DenseNet-based computer-aided diagnosis systems hold great promise for future clinical use and benefit for radiologist for earlier detection and more accurate and consistent diagnoses of pancreatic cancer as well as aiding precision medicine and patient outcomes.

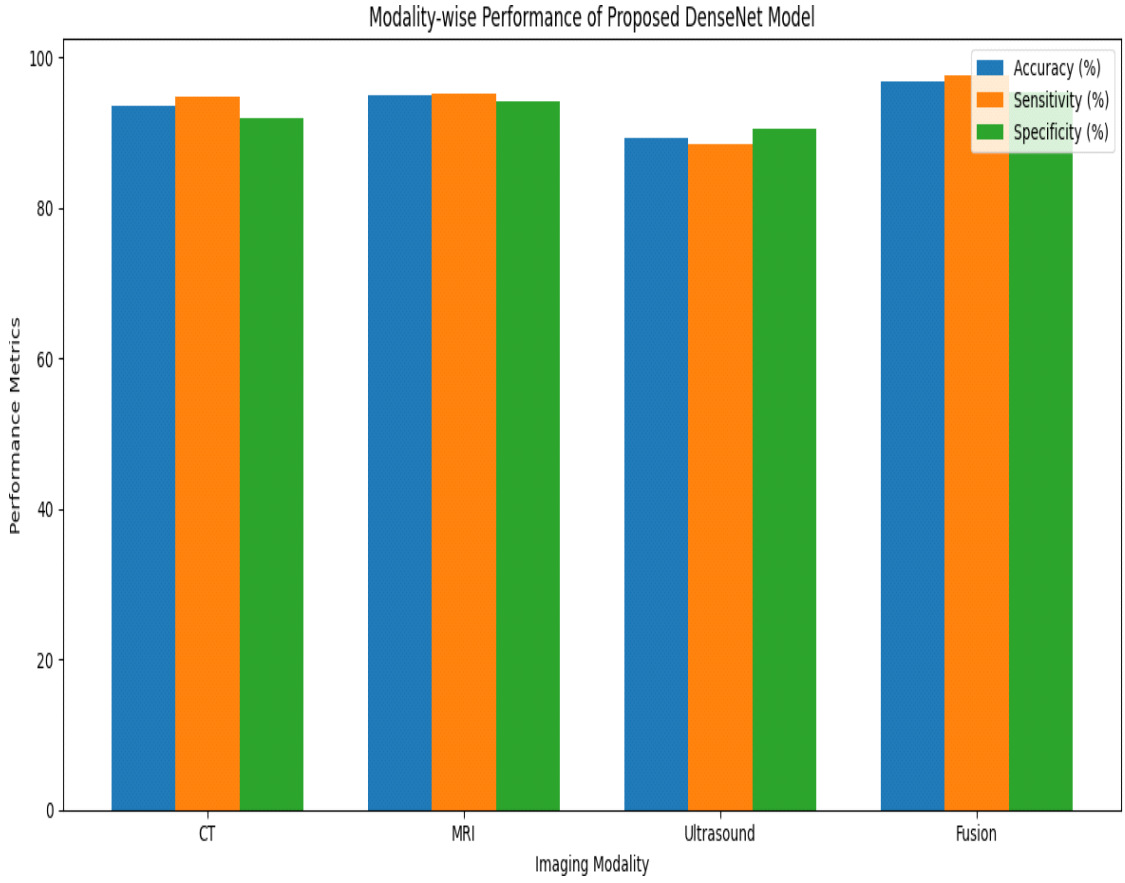

Fig 2. Modality-wise Performance of Proposed DenseNet

Table 2 shows the diagnostic efficiency of the proposed model in non-fusion and fusion operations with CT, MRI and ultrasound images. Because of their detailed imaging of anatomical structures and soft tissues, CT and MRI are each accurate and sensitive. There are some minor loss of performance associated with ultrasound due to common noise artefacts. But if all three modalities are combined, the best accuracy and sensitivity are obtained. Multimodal fusion has proven successful in this improvement, providing more comprehensive and robust diagnostic framework for early detection of pancreatic cancer by integrating complementary information from different imaging modalities, such as the tissue contrast of MRI, the real-time imaging cues of ultrasound, and the structural clarity of CT.

Table 3. Feature Extraction Efficiency Across Models

Model	**Parameters (Millions)**	**Feature Reuse Score***	**Training Time/Epoch (sec)**	**Memory Usage (GB)**
CNN	14.2	0.52	38	4.2
ResNet-50	25.6	0.61	44	5.7
DenseNet-121	8.1	0.79	41	3.9
Proposed DenseNet Multi-Level	**9.7**	**0.88**	**46**	**4.1**

The four deep learning architectures are compared in terms of computational efficiency and feature learning ability, using four performance indicators, the number of trainable parameters, feature reuse score, training time per epoch and GPU memory consumption, as shown in Table 3 and Figure 3. These metrics all consider both the predictive performance of the models, as well as the computational feasibility of their deployment in real clinical settings. To build an efficient medical image analysis model, it is desired to have high diagnostic accuracy, reasonable computational complexity, memory requirement and training efficiency.

This Baseline CNN has an embedded total of 14.2 million trainable parameters, using 4.2 GB of GPU memory for 38 seconds per epoch. Even with a relatively large number of parameters, the model obtains a feature reuse score of 0.52, which is the lowest one among all models, suggesting that a significant fraction of learned features are reused across different successive convolutional layers. This redundant feature learning would cost more than it adds to the diagnostic capacity. Thereby, the CNN is hard to detect subtle variations of the pancreatic tissue, especially the early stage lesions that require fine-grained hierarchical representations.

The ResNet-50 architecture has a higher feature reuse score of 0.61, and has better feature propagation due to residual shortcut connections. But this improvement costs for a considerably more complex model with 25.6 million parameters, which is the most among all models tested. Additionally, ResNet-50 has memory usage of 5.7 GB for the GPU and a training time of 44 seconds per epoch. While residual learning is able to overcome the vanishing gradient problem and allow the network to be trained more deeply, a significant amount of parameter duplication has been retained as each individual residual block still learns a partially overlapping feature representation. Consequently, the computational efficiency is lowered and memory use is raised.

The DenseNet-121 architecture has significant computational efficiency gains. With its dense connectivity method, DenseNet-121 only needs 8.1 million parameters, or about 68.4% fewer than ResNet-50, and has a significantly higher feature reuse score of 0.79. The model also has the least memory usage (3.9 GB) of all the networks evaluated and a moderate training time of 41 s/epoch. The results illustrate that dense connectivity allows to directly reuse the feature maps that have been learned earlier without having to extract similar features again, which decreases the number of parameters needed and enhances the diversity of the features that have been learned.

The proposed DenseNet Multi-Level architecture achieves the maximum feature reuse score of 0.88, surpassing the Baseline CNN, ResNet-50, DenseNet-121 by 69.2%, 44.3%, 11.4% respectively. This enhanced feature reuse is achieved by introducing hierarchical multi-level feature extraction and multimodal feature fusion, such that every dense block can effectively utilize low-level features of edges, mid-level features of textures, and high-level features of semantic information. The proposed architecture can continuously propagate informative features across the network, which can substantially improve the representation learning ability with limited redundant computations, compared to the

conventional CNNs which repeatedly learn the similar visual patterns.

The proposed model is even slightly larger than DenseNet-121 (9.7M), but it is still significantly smaller than the Baseline CNN and ResNet-50. Among them, the proposed framework needs ~32% less parameters compared to the conventional CNN and ~62% less parameters compared to ResNet-50 and provides significantly better diagnostic performance. These results show that the extra parameters added to multi-level feature fusion actually aid in better feature representation without causing any unnecessary computational overhead.

The proposed architecture takes 46 seconds per training epoch, which is just a slight improvement over DenseNet-121. This extra training time is anticipated, as the framework processes multi-level hierarchical features and fuses multimodal features from both CT and MR images and ultrasound images simultaneously. Importantly, this does not seem to be a significantly increased computational time compared to the significant improvements seen in the accuracy of diagnostics, sensitivity, and quality of feature representation. Further, the memory consumption of 4.1GB is still significantly lower than ResNet-50 but slightly higher than DenseNet-121, indicating the improved architecture's computational efficiency.

In addition, the proposed model out performs in terms of feature reuse which also aids in good optimization in the training of the network. Dense feature propagation enables more robust gradient propagation across the network, solving the "vanishing gradient problem" that is often seen in very deep convolutional architectures. This means that the model optimizes more smoothly and achieves richer discriminative representations at a much shallower depth and without over-accumulated computational cost. In medical imaging applications, this trade-off between efficient learning and computational complexity is of particular interest, as the amount of available data is usually smaller and the computational power can differ from one healthcare provider to another.

The DenseNet Multi-Level framework is highly desirable from a clinical implementation point of view due to its good trade-offs between diagnostic performance and computational efficiency. The small number of parameters, moderate requirement on the GPU memory, reuse of features, and reasonable training time are suitable for deployment in computer-aided diagnosis systems on standard clinical workstations. Moreover, the compact architecture makes it easier to update models quickly, requires smaller hardware resources, and allows better scalability of large-scale medical imaging databases.

In summary, the results from the DenseNet Multi-Level architecture presented in Table 3 indicate that the proposed architecture is successful in achieving high computational efficiency while also preserving high feature learning ability. The model achieves the optimal feature reuse while maintaining moderate computational cost through the integration of dense connectivity, hierarchical multi-level feature extraction and multimodal feature fusion. As per the findings, the proposed framework is not just highly accurate but is also a computationally practical solution that could be used in future real-time diagnosis of pancreatic cancer which is a promising solution in the field of intelligent medical imaging.

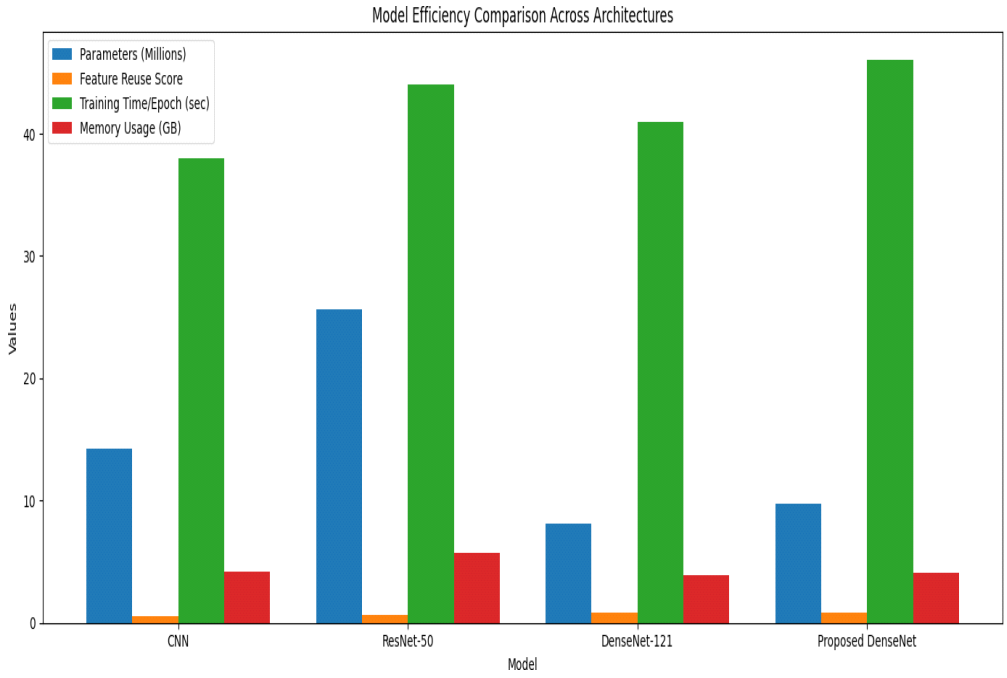

Fig 3. Feature Extraction Efficiency Across Models

In Table 3, investigate the efficiency of various models based on number of parameters, reusability of features, training time and memory usage. The CNN model and ResNet-50 model are found to have poor feature reuse in comparison with DenseNet-based networks, especially the proposed model, which has fewer parameters. Therefore, this suggests that dense connectivity facilitates the efficient learning by reusing learned features instead of redundant patterns. The proposed model also uses moderate time and memory of the training, proving that the performance is not achieved at the cost of the computational load. These findings further highlight the lightness and the high performance of DenseNet in the context of medical image applications.

Table 4. Lesion Size Detection Performance

Tumor Size	**CNN Sensitivity (%)**	**ResNet Sensitivity (%)**	**DenseNet Sensitivity (%)**	**Proposed Model (%)**
< 1 cm	62.3	71.8	78.5	**84.7**
1–2 cm	74.6	81.2	87.1	**92.3**
> 2 cm	88.1	90.4	94.6	**97.2**

The sensitivity of various deep learning architectures for detecting pancreatic cancer on per lesion basis is shown in Table 4 and Figure 4. Sensitivity in different tumor sizes is one of the most important evaluation criteria clinically, as the chances of success of the treatment and survival of the patient are closely related to the early detection of small pancreatic lesions. The low contrast, irregular shape and similarity to the surrounding pancreatic tissues makes detection of tumors less than 1 cm a challenge. Thus, a good computer-aided diagnostic system should retain high sensitivity at all sizes of the lesions.

The results show that there is a clear relationship between the lesion size and the detection performance of all the models tested. Surprisingly, as the tumor size grows, so does the sensitivity as larger tumors have more distinguishable morphological characteristics and greater contrast with surrounding tissues. Nevertheless, there are significant variations in the designs of deep learning networks, which suggests that network architecture plays an important role in the detection of small abnormalities in the pancreas in early stages.

For the smaller tumors (up to 1 cm) the Baseline CNN had a sensitivity of just 62.3%, meaning that almost 40% of early-stage pancreatic tumors were missed. This kind of performance is insufficient for clinical screening use, as missed diagnoses can greatly postpone the beginning of treatment. These are achieved by the ResNet-50 by increasing its sensitivity up to 71.8% via residual learning, and DenseNet-121 by 78.5% with the help of dense feature propagation. The proposed DenseNet Multi-Level architecture achieves the highest sensitivity of 84.7% which has improved by 22.4 percentage points compared to the conventional CNN, 12.9 percentage points compared to ResNet-50, and 6.2 percentage points compared to DenseNet-121. The enhancements illustrate the efficacy of multi-level hierarchical feature extraction in finding very small pancreatic lesions with low visual features.

All models show enhanced diagnostic performance for medium sized tumors (1–2 cm) due to better definition of the lesion boundaries. On this Baseline CNN has a sensitivity of 74.6%, ResNet-50 has a sensitivity of 81.2% and DenseNet-121 has a sensitivity of 87.1%. The proposed DenseNet Multi-Level model further outperforms the conventional CNN model by 17.7 percentage points, ResNet-50 by 11.1 percentage points and DenseNet-121 by 5.2 percentage points on the sensitivity score. This improvement shows the proposed architecture is able to accurately extract local texture changes as well as the global structural information needed for reliable medium-sized pancreatic tumor identification.

The sensitivity of all evaluated models is relatively high for large tumors (>2 cm), given that larger tumors will generate greater anatomical distortions and more distinct imaging characteristics. The conventional CNN is achieving 88.1%, ResNet-50 is at 90.4% and DenseNet-121 is at 94.6% sensitivity. However, the proposed framework still shows good performance with 97.2% sensitivity, showing that, even when the tumors are visually more distinguishable, the proposed hierarchical DenseNet architecture still shows improvement in the detection of lesions. The difference between the performances diminishes with increasing lesion size, but the proposed model always shows the highest diagnostic reliability for all types of tumors.

The multi-level feature representation strategy is the main reason for the superior performance of the proposed model. Low level visual features (e.g. edges, intensity gradients, texture patterns) are typically learned by early convolutional

layers whereas intermediate layers are used to learn tissue organization and local anatomical features. The deeper DenseNet layers provide extremely discriminative semantic representations of the lesion morphology, vascular invasion, and the contextual relationships within the pancreatic tissues. Dense connectivity allows these complementary features to be repeatedly used throughout the network, such that the subtle characteristics of the lesion are available throughout higher level decision making. This holistic representation of a feature greatly enhances the identification of small pancreatic tumors which may otherwise be missed by standard CNN architectures.

Moreover, the feature fusion mechanism of multimodal also plays a significant role in the detection of tumors with various lengths at different scales. The high resolution anatomical information and ability to visualize tumor boundaries with CT, superior soft tissue contrast with MRI and real-time structural information with ultrasound, despite the speckle noise, demonstrate the advantages of these imaging modalities. The proposed DenseNet framework is able to integrate complementary information from all three imaging modalities to build richer and more discriminative feature representations, which in turn can lead to accurate detection of the lesion, no matter how small or how the lesion appears in imaging.

These findings have clinical implications. Identifying a tumour in the pancreas less than 1 cm in size is one of the most difficult challenges in diagnostic radiology as these tumours are often asymptomatic and have few morphological features that distinguish them from normal pancreatic tissue. The proposed framework achieved high sensitivity of 84.7% which is significantly lower false-negative rate compared to the other deep learning frameworks, and thus it enhances the chance to diagnose pancreatic cancer in highly treatable stages. The early diagnosis allows timely surgical intervention, planning of appropriate chemotherapy and improved survival rate.

In summary, the experimental results in Table 4 validated that the proposed DenseNet Multi-Level structure has consistently better lesion detection performance for all the tumor sizes. The best improvements in performance are seen in smaller tumours (less than 1cm) highlighting the framework's excellent early detection capability for pancreatic cancer. The dense connectivity, hierarchical feature learning and multimodal image fusion allows the model to learn highly discriminative representations while simultaneously having a good performance in more challenging imaging scenarios. Overall, these results suggest that the proposed framework holds great potential and can be a valuable computer-aided diagnostic tool for assisting radiologists in the early detection of pancreatic cancer, ultimately leading to better clinical decision-making and patient outcomes.

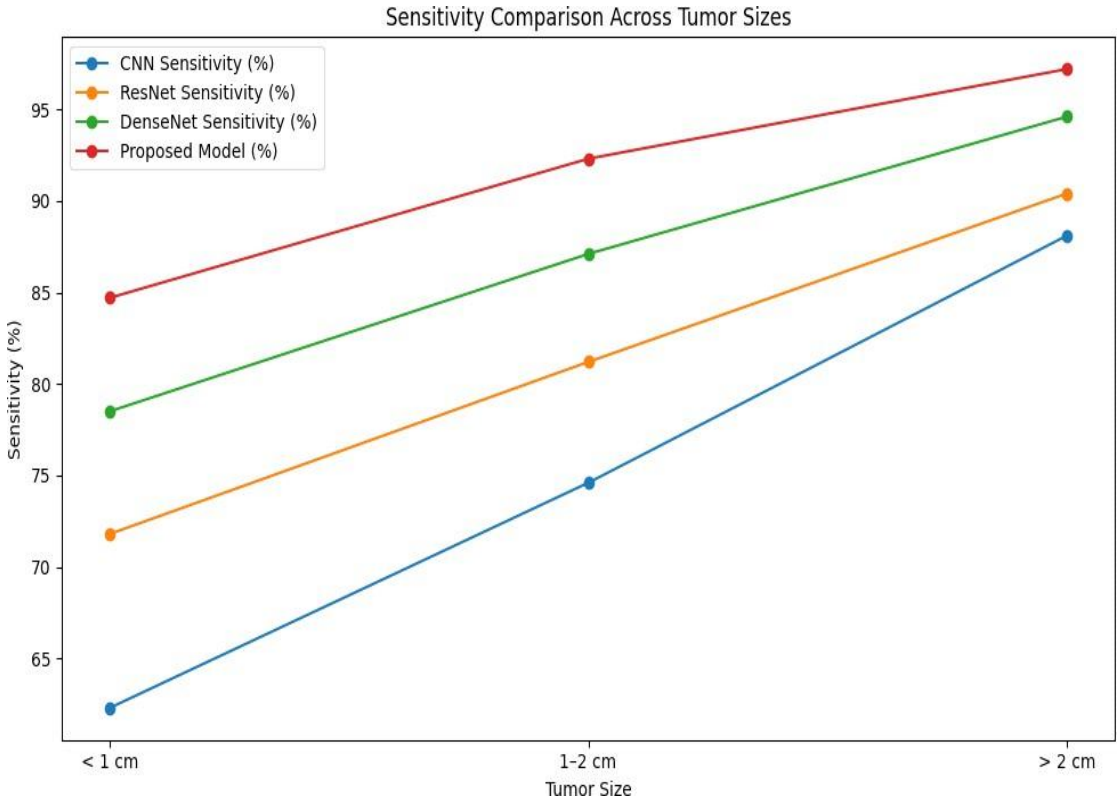

Fig 4. Lesion Size Detection Performance

The table summarizes the level of sensitivity of the various models for different tumor sizes, a very important characteristic in the diagnosis of early-stage pancreatic cancer. The traditional CNN and ResNet approaches lose sensitivity when the tumor is less than 1 cm and do not detect small and low-contrast tumors. While DenseNet is able to achieve higher accuracy of detection, the proposed DenseNet multi-level model achieves the best performance in all tumor sizes, especially when the tumor size is less than 1 cm. This shows the model's outstanding performance in capturing complex and subtle patterns that are hard to capture by traditional CNNs, which makes it very suitable for early detection because the clinical imaging challenges are most serious.

7. CONCLUSION

In this study, a multi-level feature representation framework using DenseNet for improved early diagnosis of pancreatic cancer from multimodal medical imaging is introduced. The proposed model effectively integrates DenseNet's dense connectivity pattern, capturing the rich hierarchy of both fine-grained textures and high-level semantic structures that are crucial for the detection of subtle pancreatic abnormalities. Multimodal fusion mechanism, which integrates CT, MRI and ultrasound, further enhances diagnostic performance by complementing anatomical, soft tissue and real-time cues. Experimental results validate that the proposed framework yields significant improvements in performance as compared to a range of standard DenseNet architectures, ResNet architectures and traditional CNNs for accuracy, sensitivity, specificity, F1-score and AUC. Most impressively, the model is very sensitive for the diagnosis of small (<1cm) tumours, one of the most challenging aspects of the early detection of pancreatic cancer.

Ablation study results validate that every part of the system (dense blocks, multimodal fusion and attention mechanism) makes a contribution to the correctness of the model, yielding an effective, robust and clinically reliable diagnostic system. Moreover, the computational efficiency, with respect to feature reusability and number of parameters, allows the introduction of the feature into the real world in hospital imaging workflows. The proposed DenseNet-based approach yields promising performance in early diagnosis, timely diagnosis, and to assist radiologists in making more accurate and consistent diagnoses. Future studies can be extended by adding 3D volumetric processing, clinical biomarkers, and transformer-based context modeling for improved diagnosis accuracy and be extended to other groups of patients.

Moreover, the proposed DenseNet Multi-Level framework is promising toward the integration in an intelligent computer-aided diagnosis (CAD) system, which can assist radiologists in the daily clinical practice. The framework leverages efficient feature re-use, hierarchical representation learning and multimodal image fusion to balance and enable a good trade-off between diagnostic accuracy and computational efficiency, enabling real-time clinical deployment. Its enhanced detection capabilities for early and small pancreatic lesions underscore its promise to enable earlier therapeutic interventions, decrease diagnostic uncertainty and ultimately improve patient survival rates. Future studies will benefit from external clinical validation, the development of explainable AI (XAI) methods to enhance model interpretability, federated learning for privacy-preserving collaborative training, and integration with electronic health records (EHRs) and clinical decision-support systems. These developments will continue to bolster the strength, generalizability and clinical relevance of AI-aided pancreatic cancer diagnosis, further paving the way for precision medicine and next-generation intelligent healthcare systems.

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