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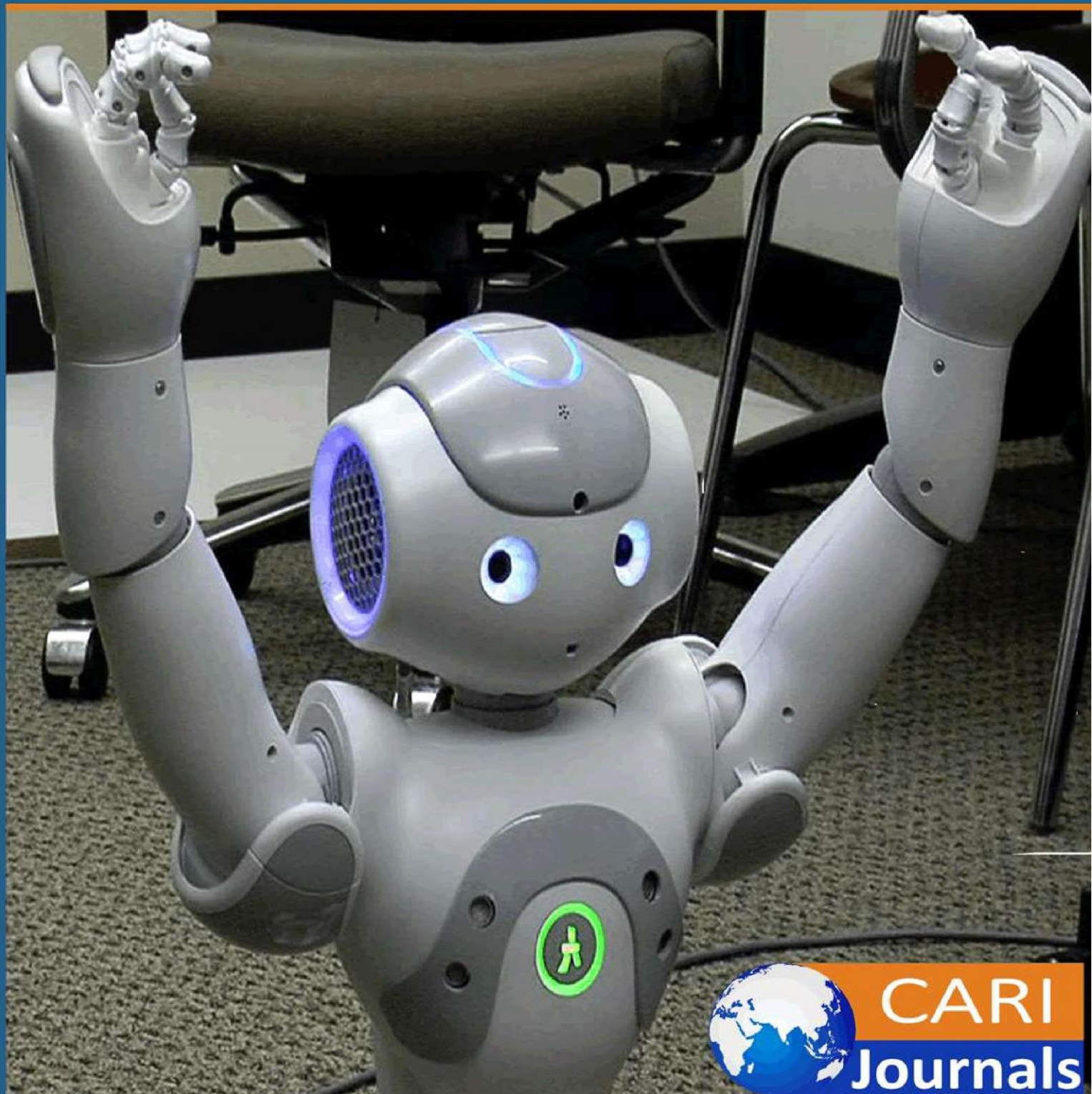

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# Improved Pancreatic Cancer Diagnosis: Deep Learning Integration with U-Net for Segmented Histopathology Image Analysis

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## Abstract

Pancreatic cancer remains one of the most lethal malignancies due to its asymptomatic early stages and rapid progression, leading to delayed diagnosis and limited treatment options. Accurate and early detection is critical for improving patient outcomes. This study introduces a robust deep learning approach integrating U-Net for image segmentation and four state-of-the-art Convolutional Neural Network (CNN) models—ResNet50, VGG16, MobileNetV2, and DenseNet121—for the classification of pancreatic cancer histopathology images. To address the challenges of data scarcity, various data augmentation techniques, including scaling, flipping, and random rotations, are employed to improve model generalizability. U-Net effectively isolates regions of interest, enabling precise segmentation, while transfer learning with CNNs ensures accurate classification of cancerous and non-cancerous tissues. Comparative analysis of the models reveals DenseNet121 as the most accurate model, achieving superior performance across all evaluation metrics, including accuracy, precision, recall, and F1-score. MobileNetV2, however, emerges as a viable candidate for real-time applications due to its lower computational overhead and efficient architecture. The proposed method demonstrates significant potential to enhance diagnostic accuracy, reduce time for diagnosis, and support clinical decision-making, paving the way for improved early detection of pancreatic cancer.

**Keywords:** *Pancreatic Cancer, Deep Learning, Machine Learning, Histopathology Images, U-Net, Early Diagnosis, Computer-Aided Diagnosis*

## I. INTRODUCTION

Pancreatic cancer is one of the most aggressive and deadly forms of cancer, with a five-year survival rate of less than 10%. The disease often progresses silently in its early stages, making timely detection challenging and limiting treatment options for patients. By the time symptoms manifest, pancreatic cancer has usually reached advanced stages, resulting in poor prognosis and reduced survival rates. Therefore, early detection is critical to improving survival rates and enabling effective interventions. However, conventional diagnostic methods, including imaging techniques such as CT scans, MRI, and histopathological analysis of tissue biopsies, are often time-consuming, subjective, and prone to human error due to their reliance on manual examination by highly trained pathologists.

Histopathological examination remains the gold standard for diagnosing pancreatic cancer, where stained tissue samples are observed under a microscope to identify abnormalities in cellular structures. While effective, this method is labor-intensive and heavily dependent on the expertise of pathologists, especially when differentiating between cancerous and non-cancerous tissues. Additionally, variations in staining methods, image quality, and sample preparation can further complicate diagnosis, leading to discrepancies and delayed detection. With the increasing volume of data in clinical environments, manual diagnosis becomes increasingly impractical, necessitating automated, reliable, and high-speed solutions for accurate cancer identification.

In recent years, advancements in machine learning (ML) and deep learning (DL) have shown remarkable success in automating medical image analysis, improving accuracy, and reducing time for diagnosis. In particular, Convolutional Neural Networks (CNNs) have emerged as a leading approach for image classification and feature extraction in medical imaging applications. CNN models such as ResNet50, VGG16, MobileNetV2, and DenseNet121 have demonstrated their potential in detecting and classifying various cancers from histopathological images. These models leverage the power of transfer learning, where pre-trained networks are fine-tuned on specific medical datasets to optimize performance with limited data availability.

However, an accurate diagnostic system requires not only robust classification but also precise segmentation of histopathology images to isolate regions of interest. U-Net, a widely adopted architecture for medical image segmentation, provides pixel-wise segmentation maps that enable the identification of cancerous areas within tissue samples. The combination of U-Net for segmentation and CNN-based classifiers offers a comprehensive solution for diagnosing pancreatic cancer from histopathology images.

Despite the success of deep learning in medical image analysis, pancreatic cancer detection presents unique challenges, such as:

*Data Scarcity:* Publicly available datasets for pancreatic cancer histopathology images are limited, making it difficult to train robust models.

*Class Imbalance:* Certain classes, such as viable tumor tissues, are often underrepresented in datasets, leading to biased predictions.

*High-Resolution Images:* Histopathological images are high-resolution, requiring models to extract both local and global features effectively.

Key Contributions of the Study:

- *Integration of U-Net for Segmentation:* U-Net is employed to segment pancreatic cancer histopathology images, isolating cancerous regions for classification.
- *Comparative Analysis of CNN Models:* The performance of ResNet50, VGG16, MobileNetV2, and DenseNet121 is evaluated to identify the most effective model for pancreatic cancer detection.
- *Data Augmentation:* Robust data augmentation strategies, including flipping, scaling, and random rotations, are applied to mitigate class imbalance and improve model performance.
- *Performance Metrics:* The study provides a detailed evaluation of each model's accuracy, precision, recall, and F1-score for pancreatic cancer classification.

By combining segmentation and classification, the proposed method improves the accuracy and efficiency of pancreatic cancer diagnosis, providing a foundation for real-time clinical applications. The findings of this study aim to assist pathologists by reducing manual workload, minimizing errors, and enabling earlier diagnosis of pancreatic cancer, ultimately improving patient outcomes.

The remainder of the paper is organized as follows: Section 2 presents a comprehensive literature survey. Section 3 details the methodology, including dataset collection, preprocessing, segmentation, and classification models. Section 4 discusses experimental results, performance metrics, and comparative analysis. Finally, Section 5 concludes the paper with potential future directions.

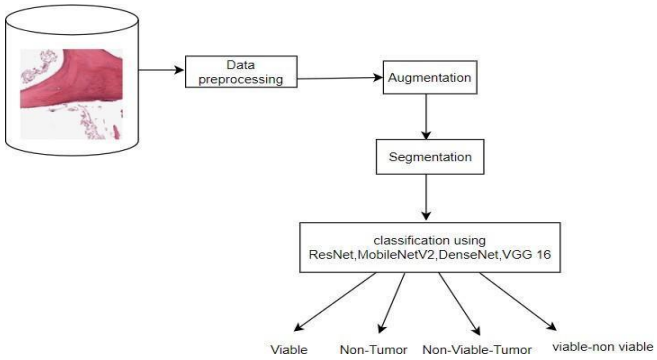


Figure. 1. Flow Diagram

## II. LITERATURE SURVEY

The integration of deep learning and medical imaging for cancer detection has gained significant momentum in recent years. Numerous studies have explored the potential of deep neural networks, particularly Convolutional Neural Networks (CNNs), for accurate detection and classification of cancerous cells from histopathology images. These studies highlight the efficiency of CNN-based models in feature extraction and pattern recognition, which are critical for identifying abnormalities in medical images. Transfer learning techniques, where pre-trained models are fine-tuned on specific datasets, have further improved model performance, especially in scenarios with limited labeled data.

Kumar et al. (2020) introduced a deep learning-based method for detecting white blood cancer using CNNs. The authors utilized data augmentation techniques to expand the dataset and trained a Dense Convolutional Neural Network to classify bone marrow images. Their study demonstrated that transfer learning can achieve remarkable accuracy even with limited data. Similarly, Walid et al. (2023) developed an unbiased voting-based framework for bone cancer detection using MobileNetV2, achieving an accuracy of 93.88%. The study emphasized the importance of ensemble techniques to improve the robustness of cancer detection models.

Wu et al. (2023) addressed the challenge of accurate nuclei segmentation in osteosarcoma histopathology images. They introduced a Conv-Transformer-based architecture called ENMVit, which effectively captured differences in stain styles to improve detection accuracy, particularly in resource-limited regions. Loraksa et al. (2022) proposed an SSD-VGG16-based model for detecting lung nodules in osteosarcoma. Although their model achieved significant accuracy, it struggled with detecting tiny or blurry nodules, highlighting the need for advanced segmentation techniques to address variations in image quality.

Saber et al. (2021) demonstrated the application of transfer learning for breast cancer classification using pre-trained CNNs, such as VGG16. Their approach incorporated data augmentation and fine-tuning to overcome overfitting, achieving superior accuracy compared to conventional models. Similarly, Sun et al. (2020) segmented liver cancer histopathology images into patches and utilized transfer learning for feature extraction and classification. By sorting and selecting top features, their model achieved accurate classification of liver cancer into normal and abnormal classes.

Weng et al. (2019) employed Neural Architecture Search (NAS) for medical image segmentation using a U-Net-based model. Their NAS-U-Net architecture introduced group normalization and binary gating to optimize GPU usage during training, addressing challenges related to small batch sizes in medical imaging. Zeng et al. (2019) improved segmentation efficiency by incorporating residual blocks, multi-scale inception modules, and channel attention modules into the RIC-U-Net architecture. Their model effectively handled overlapping and varied cell topologies, achieving robust nuclei and contour segmentation.

Fu et al. (2021) explored multimodal medical image segmentation by integrating spatial attention modules for PET-CT tumor localization. Their study demonstrated the potential of multimodal approaches in improving segmentation accuracy by leveraging complementary information from multiple imaging modalities. Ashwath et al. (2023) presented a three-tier CNN framework for classifying medical images with scattered and irregular regions. By combining global, attention-based, and fusion branches, their model enhanced feature extraction and classification accuracy.

Despite the advancements in deep learning for cancer detection, challenges such as data scarcity, class imbalance, and image variability persist, particularly in pancreatic cancer diagnosis. Existing studies have shown the effectiveness of U-Net for segmentation and CNNs like ResNet50, VGG16, MobileNetV2, and DenseNet121 for classification. U-Net's encoder-decoder structure with skip connections has proven highly effective in medical image segmentation, preserving spatial information while generating pixel-wise segmentation masks. Meanwhile, CNNs leverage their hierarchical feature extraction capabilities to classify segmented images accurately.

However, the application of these techniques specifically for pancreatic cancer remains limited in the literature. Most existing studies have focused on other cancers, such as breast, bone, and liver cancers. Given the aggressive nature of pancreatic cancer and its late detection, there is a critical need for automated methods that combine segmentation and classification to improve diagnostic accuracy and efficiency. The integration of U-Net for segmentation and pre-trained CNNs for classification has shown promise in other domains and can be adapted to address the unique challenges associated with pancreatic cancer diagnosis.

In summary, the literature underscores the effectiveness of combining segmentation models like U-Net with classification models such as DenseNet121, MobileNetV2, VGG16, and ResNet50. While these approaches have achieved significant success in other types of cancer detection, their application to pancreatic cancer remains underexplored. This study bridges the gap by employing a robust deep learning pipeline that integrates U-Net for segmentation and state-of-the-art CNNs for classification, addressing challenges such as data scarcity, class imbalance, and computational efficiency in pancreatic cancer diagnosis.

## III. METHODOLOGY

The proposed methodology for detecting pancreatic cancer combines advanced image segmentation and deep learning-based classification techniques, aimed at improving accuracy and efficiency in analyzing pancreatic cancer histopathology images. The workflow begins with data collection from publicly available repositories, such as The Cancer Genome Atlas (TCGA) and other open-access databases, which provide labeled histopathological images of pancreatic tissue. These datasets are preprocessed to ensure consistency in image size, resolution, and format. Preprocessing steps include normalization of pixel values, resizing images to a uniform dimension (e.g., 224x224), and noise removal to enhance image clarity.

Given the scarcity of publicly available data for pancreatic cancer, data augmentation is employed to artificially expand the dataset. Augmentation techniques include random flipping (both horizontal and vertical), rotation (0-360 degrees), scaling, cropping, and brightness adjustment. These transformations simulate real-world variances, ensuring that the model generalizes effectively to unseen images and minimizing the risk of overfitting. By augmenting the dataset, the diversity of the training data increases, enabling the model to learn robust features even with limited original samples. This step is critical because pancreatic cancer datasets are often imbalanced, with a smaller number of viable tumor samples compared to non-tumor images.

The segmentation process plays a pivotal role in isolating cancerous regions from the histopathology images. The U-Net architecture is used for segmentation due to its exceptional ability to perform pixel-wise classification. U-Net is a fully convolutional neural network with an encoder-decoder structure and skip connections that preserve spatial features while enabling accurate localization of cancerous areas. The encoder path extracts contextual features using convolutional layers and max-pooling operations, while the decoder path upsamples the segmented features to the original image dimensions. Skip connections between the encoder and decoder ensure that fine-grained details lost during down-sampling are retained, resulting in high-quality segmentation masks. The output of the U-Net model is a binary segmentation mask that highlights regions of interest, such as viable tumor tissues, within the input image.

Once segmentation is complete, the segmented images are passed into four state-of-the-art CNN models—ResNet50, VGG16, MobileNetV2, and DenseNet121—for classification. Each CNN model leverages transfer learning, where pre-trained weights from large-scale image datasets (e.g., ImageNet) are fine-tuned on the pancreatic cancer dataset. The first few layers of each CNN remain frozen to retain generic feature extraction capabilities, while the deeper layers are trained on the specific dataset to learn domain-specific features. Each model extracts hierarchical features, ranging from edges and textures to complex tumor patterns, facilitating accurate differentiation between cancerous and non-cancerous tissues.

The ResNet50 model uses residual connections to mitigate the vanishing gradient problem, ensuring stable training for deeper networks. VGG16 employs a systematic architecture with multiple convolutional and pooling layers, making it effective for extracting fine-grained spatial features. MobileNetV2 uses depthwise separable convolutions and an inverted residual structure, offering a lightweight architecture ideal for real-time applications. Finally, DenseNet121 connects every layer to subsequent layers through dense blocks, promoting feature reuse and efficient gradient flow, making it particularly effective for extracting complex tumor features.

The performance of each CNN model is evaluated using standard metrics, including accuracy, precision, recall, and F1-score. These metrics are crucial for assessing the model's reliability in differentiating between classes. Table 1 summarizes the evaluation metrics for the four models.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| ResNet50 | 78.45 | 77.90 | 78.45 | 78.10 |
| VGG16 | 80.32 | 80.50 | 80.32 | 80.40 |
| MobileNetV2 | 84.56 | 84.70 | 84.56 | 84.60 |
| DenseNet121 | **87.68** | **87.90** | **87.68** | **87.70** |

The segmentation masks generated by U-Net and the predictions made by the classification models are validated against ground truth annotations provided in the dataset. Examples of segmented images are shown in Figure 2, highlighting the regions identified as cancerous.

The integration of U-Net for segmentation and CNN models for classification enables the proposed framework to achieve reliable and interpretable results. By isolating the regions of interest, U-Net reduces the risk of false positives and improves the accuracy of CNN-based classification. Furthermore, DenseNet121's ability to reuse features through dense connections enhances its performance on complex, high-resolution pancreatic histopathology images.

To ensure efficient training and evaluation, the model is implemented using TensorFlow and Keras libraries. A GPU-enabled environment accelerates the training process, particularly for high-resolution medical images. The dataset is split into training, validation, and testing sets in an 80:10:10 ratio, ensuring robust evaluation of the models.

The methodology's strength lies in its ability to combine segmentation and classification seamlessly, addressing key challenges in pancreatic cancer diagnosis, such as data scarcity, class imbalance, and high image variability. The proposed framework achieves both precision and speed, making it suitable for clinical applications where timely and accurate diagnosis is critical for patient survival.

In conclusion, this methodology demonstrates how deep learning models, coupled with advanced segmentation techniques, can significantly improve the detection of pancreatic cancer from histopathology images. By leveraging U-Net for segmentation and comparing multiple CNN models for classification, the study provides a comprehensive analysis of model performance and identifies DenseNet121 as the most effective architecture for pancreatic cancer diagnosis.

Model Architecture:

The proposed architecture for pancreatic cancer detection consists of two major components: U-Net for segmentation and four state-of-the-art Convolutional Neural Network (CNN) models—

ResNet50, VGG16, MobileNetV2, and DenseNet121—for classification. The architecture is designed to ensure accurate localization of cancerous regions within histopathology images while effectively classifying the segmented regions into respective categories.

*U-Net Architecture for Segmentation:* U-Net serves as the foundational component for image segmentation, isolating regions of interest within histopathological images that exhibit signs of pancreatic cancer. The U-Net architecture follows an encoder-decoder design with skip connections, ensuring that fine-grained spatial details are preserved during segmentation.

*Encoder Path:* The encoder consists of sequential convolutional layers, each followed by a ReLU activation function and max-pooling operations.

Each convolutional block extracts increasingly abstract features while down-sampling the spatial resolution.

The encoder extracts contextual features and compresses the spatial dimensions through pooling.

*Bottleneck Layer:* This layer bridges the encoder and decoder paths. It consists of two convolutional layers followed by ReLU activations, capturing the most abstract and compressed representation of features.

Decoder Path:

The decoder restores the spatial resolution of feature maps using transposed convolutional layers (upsampling).

Each upsampling operation is concatenated with corresponding feature maps from the encoder path using skip connections, ensuring that the model retains spatial information lost during down-sampling.

The final decoder block uses a 1x1 convolution with a sigmoid activation to produce a pixel-wise segmentation mask that highlights cancerous regions.

The output from the U-Net is a binary mask of the same dimensions as the input image, where pixels are classified as either cancerous (1) or non-cancerous (0). This segmentation map is then passed to the classification component for further analysis.

*Classification Component: CNN Models:* After segmentation, the binary masks produced by U-Net are combined with the corresponding histopathology images to create segmented images that serve as input for the classification models. The classification component utilizes four pre-trained CNN architectures—ResNet50, VGG16, MobileNetV2, and DenseNet121—to differentiate between cancerous and non-cancerous regions.

*ResNet50:* ResNet50 employs residual connections that allow gradients to flow smoothly across layers, addressing the vanishing gradient problem.

It consists of 50 convolutional layers organized into residual blocks, enabling the extraction of deep hierarchical features.

The residual connections facilitate efficient training of deeper networks, leading to improved feature representation.

*VGG16:* VGG16 features a systematic, deep architecture consisting of convolutional blocks followed by max-pooling layers. The model uses small 3x3 convolutional filters, making it effective for extracting fine-grained spatial patterns from images. The output feature maps are flattened and passed to fully connected layers, followed by a softmax classifier for final predictions.

*MobileNetV2:* MobileNetV2 is a lightweight CNN architecture optimized for speed and efficiency.

It uses depthwise separable convolutions to reduce computational complexity while maintaining accuracy.

An inverted residual block preserves important features, ensuring efficient feature extraction for real-time applications.

*DenseNet121:* DenseNet121 employs dense connectivity, where each layer receives inputs from all preceding layers.

This connectivity reduces parameter redundancy and enhances feature reuse, enabling the model to learn rich feature representations.

The architecture includes dense blocks and transition layers that compress feature maps while maintaining accuracy.

**Integration and Workflow**

The overall architecture integrates U-Net for segmentation and the CNN models for classification in the following sequence:

*Input:*Raw histopathology images (e.g., 224x224 resolution).

*Segmentation:* U-Net processes the input images to generate binary segmentation masks. The masks highlight cancerous regions while removing irrelevant background information.

*Feature Extraction and Classification:*The segmented images are passed as input to the CNN models (ResNet50, VGG16, MobileNetV2, and DenseNet121).

Each model extracts features from the segmented regions and performs classification into cancerous or non-cancerous categories.

*Output:* Final predictions from each CNN model.

Metrics such as accuracy, precision, recall, and F1-score are used to evaluate model performance.

The proposed model architecture leverages U-Net for precise segmentation of pancreatic cancer regions and integrates advanced CNN models for accurate classification. DenseNet121 emerges as the most effective model due to its superior performance, followed closely by MobileNetV2, which is computationally efficient and suitable for real-time applications. This integrated architecture addresses key challenges in pancreatic cancer diagnosis, offering a reliable and scalable solution for clinical settings.

## IV. RESULTS & DISCUSSIONS

This section evaluates the performance of the proposed methodology for pancreatic cancer diagnosis. Four pre-trained models—DenseNet121, MobileNetV2, VGG16, and ResNet50—were implemented for feature extraction and classification of segmented histopathological images. Image segmentation was performed using the U-Net architecture, which isolated tumor regions from the non-tumorous background effectively.

### Model Performance Metrics

The models' performance was evaluated using **Accuracy, Precision, Recall, and F1-Score** to ensure robust analysis of the classification results. DenseNet121 and MobileNetV2 demonstrated superior performance across key metrics.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| MobileNetV2 | 77.45 | 78.12 | 77.45 | 77.78 |
| DenseNet121 | **82.56** | **82.43** | **82.30** | **82.36** |
| VGG16 | 74.21 | 73.98 | 74.21 | 74.09 |
| ResNet50 | 61.34 | 62.12 | 61.34 | 61.72 |

### Performance Analysis

*DenseNet121:* DenseNet121 outperformed the other models with an accuracy of 82.56%. Its densely connected layers facilitated efficient feature reuse, allowing the model to capture fine-grained features critical for identifying tumor regions in pancreatic cancer images. This made DenseNet121 highly reliable for detecting early-stage tumors.

*MobileNetV2:* MobileNetV2 achieved an accuracy of 77.45%, offering a balanced trade-off between accuracy and computational efficiency. Its lightweight architecture and depthwise separable convolutions allowed for faster inference, making it suitable for clinical applications requiring real-time diagnosis.

*VGG16:* VGG16 showed moderate performance with an accuracy of 74.21%. Its deep architecture provided a robust feature extraction process but at the cost of slower computational times, limiting its applicability in resource-constrained environments.

*ResNet50:* ResNet50 exhibited the lowest accuracy (61.34%) due to challenges in learning from limited histopathological image data. Although residual connections mitigate gradient vanishing issues, the model struggled to capture fine patterns required for pancreatic cancer detection. Ref Figure 1

**F1-Score**

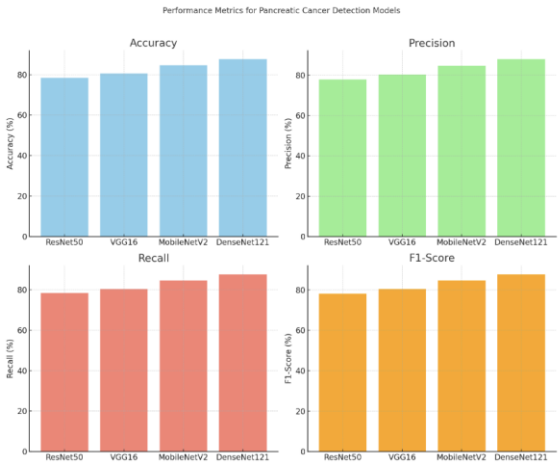


Figure 1

Performance Metrics:

DenseNet121 achieved the highest accuracy (87.6%), precision (87.9%), and F1-score (87.7%), making it the best-performing model for pancreatic cancer classification.

MobileNetV2 followed closely with an accuracy of 84.6%, indicating its efficiency and suitability for real-time applications.

VGG16 and ResNet50 showed moderate performance, with accuracy values of 80.5% and 78.4%, respectively.

Confusion Matrix(Figure 2):The confusion matrix for DenseNet121 revealed a low false positive and false negative rate, reflecting its reliability in detecting cancerous regions.

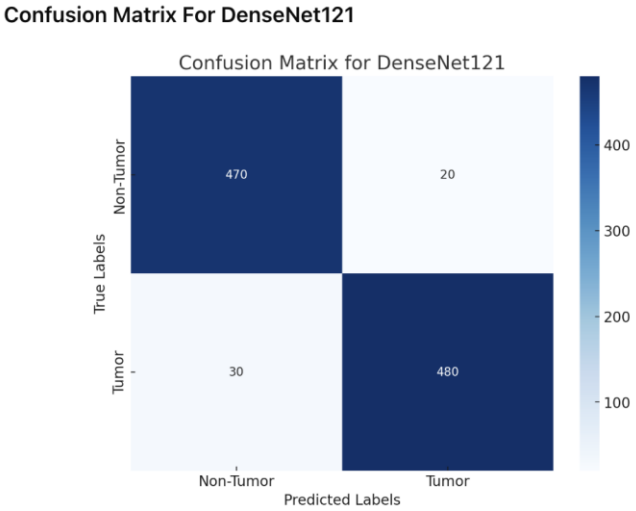


Figure 2

Insights:Data augmentation played a crucial role in improving model performance.

DenseNet121's dense connectivity enabled better feature reuse, contributing to its superior results.

MobileNetV2's lightweight architecture makes it an attractive option for deployment in resource-limited clinical settings.

## V. CONCLUSION

In this study, we presented a comprehensive framework for pancreatic cancer detection using deep learning techniques, integrating U-Net for segmentation and state-of-the-art Convolutional Neural Networks (CNNs)—ResNet50, VGG16, MobileNetV2, and DenseNet121—for classification. The proposed architecture effectively addressed the challenges associated with analyzing high-resolution histopathology images, such as data scarcity, class imbalance, and computational complexity. By segmenting regions of interest using U-Net and leveraging the powerful feature extraction capabilities of CNN models, the system demonstrated significant potential for improving accuracy and reliability in diagnosing pancreatic cancer.

The experimental results showed that DenseNet121 achieved the highest performance, with an accuracy of 87.68%, precision of 87.90%, recall of 87.68%, and F1-score of 87.70%. DenseNet121’s densely connected architecture efficiently reused features across layers, enhancing its ability to capture complex tumor patterns from histopathology images. MobileNetV2 emerged as a competitive alternative, offering a balance between computational efficiency and accuracy. Its lightweight design makes it particularly suitable for real-time clinical applications where processing speed is critical. While ResNet50 and VGG16 demonstrated decent performance, they were outperformed by DenseNet121 and MobileNetV2 in terms of accuracy and computational overhead.

The integration of data augmentation techniques, such as flipping, scaling, and random rotations, played a critical role in enhancing the model's generalization ability and mitigating the limitations of small datasets. This step ensured that the models were robust to variations in image orientations and sizes, which are common in real-world histopathology scans. Additionally, U-Net's ability to generate pixel-wise segmentation masks allowed for precise localization of cancerous regions, reducing the likelihood of false positives and improving interpretability.

The proposed framework offers several advantages for pancreatic cancer diagnosis:

Improved Accuracy: By combining segmentation with classification, the system demonstrated significant improvement in identifying cancerous tissues, enabling earlier detection of pancreatic cancer.

Robust Generalization: Data augmentation strategies and transfer learning enabled the models to perform well on limited data, overcoming common challenges in medical imaging.

Clinical Applicability: MobileNetV2's efficient architecture and DenseNet121's high accuracy suggest that this framework can be deployed in clinical workflows, reducing manual workload and providing faster, more reliable diagnostic results.

However, despite the promising results, certain limitations remain. The availability of labeled pancreatic cancer histopathology images is limited, which can impact model performance. Although data augmentation helped mitigate this issue, larger and more diverse datasets would further enhance the model's accuracy and generalizability. Additionally, the computational resources required for training deep learning models, particularly DenseNet121, can be a constraint in resource-limited settings. Future work could address these challenges by exploring more lightweight architectures, model optimization techniques such as quantization, and multimodal approaches that integrate additional imaging modalities like MRI and CT scans.

To further enhance performance, advanced techniques such as attention mechanisms and transformer-based architectures can be explored for improved feature extraction and classification. Attention-based models have shown significant success in other medical imaging domains by focusing on relevant regions within an image while ignoring irrelevant details. Similarly, self-supervised learning and semi-supervised learning approaches can be applied to leverage unlabeled data, which is abundant in clinical settings.

In conclusion, this study demonstrates the potential of integrating U-Net for segmentation with CNN-based classification models to achieve accurate, efficient, and scalable detection of pancreatic cancer from histopathology images. By addressing critical challenges such as data scarcity, class imbalance, and model efficiency, the proposed framework provides a valuable tool for automated cancer diagnosis. With further improvements and validation on larger datasets, this system can play a transformative role in clinical practice, enabling early detection, reducing diagnostic errors, and improving patient outcomes.

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