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**Research Article**

# Pancreatic Cancer Classification Based on Deep Learning

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**ABSTRACT**

Due in large part to its early asymptomatic character and the dearth of accurate diagnostic techniques, pancreatic cancer continues to rank among the most difficult cancers to identify and treat. Despite the fact that early and precise pancreatic cancer classification can greatly enhance patient outcomes, traditional diagnostic methods frequently have low sensitivity and specificity. In order to improve diagnostic performance, we provide a unique hybrid deep learning framework in this study for the classification of pancreatic cancer. This framework combines machine learning classifiers with sophisticated convolutional neural networks (CNNs). To identify pertinent anatomical features, the suggested approach starts with thorough preprocessing and segmentation of medical imaging data, such as computed tomography (CT) and magnetic resonance imaging (MRI). Pre-trained deep learning models, such ResNet and EfficientNet, are used for feature extraction. These models have been refined on pancreatic datasets to capture complex patterns linked to cancers. To increase accuracy and generalization by 95%, particularly when data is scarce, these extracted features are fed into conventional classifiers like Support Vector Machines (SVM) and Random Forests (RF) rather than depending exclusively on end-to-end deep learning classification. According to experimental results, the hybrid approach performs better than solo deep learning models in terms of precision, recall, and F1-score, indicating that it has the potential to be a potent tool for clinical decision support in the diagnosis of pancreatic cancer.

**Keywords:** advanced CNN, MRI, ResNet, Efficient Net, SVM and random Forest classifier, deep learning.

## INTRODUCTION

One of the most aggressive and lethal types of cancer, pancreatic cancer has a very poor five-year survival rate and few available therapeutic options when it is first discovered. It is currently the seventh most common cause of cancer-related deaths globally, and its prevalence is continually rising. The disease is insidious and usually asymptomatic in its early stages, which is one of the main causes of its high fatality. Curative treatment is nearly impossible because the cancer has frequently spread to an advanced or metastatic stage by the time clinical symptoms appear. In order to improve prognosis, enable prompt treatment interventions, and eventually increase patient survival rates, early and correct detection of pancreatic cancer is essential.

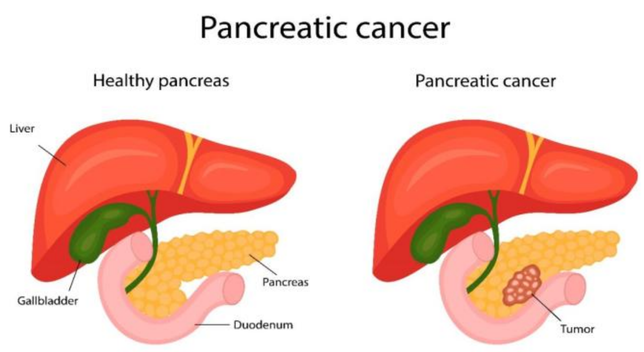


**Figure 1: Overview of pancreatic cancer**

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Figure 1 illustrates that when pancreatic cells undergo mutations and becoming malignant, pancreatic cancer results. Unchecked cell division causes these aberrant cells to develop into a mass, or tumor, which subsequently spreads to other bodily parts. The pancreas is affected by pancreatic cancer, which is difficult to detect in its early stages since it may develop for a while before causing stomach pressure or any pain. The accuracy and specificity of traditional diagnostic techniques are still restricted, even with improvements in imaging modalities including computed tomography (CT), magnetic resonance imaging (MRI), and endoscopic ultrasonography (EUS). Because Convolutional Neural Networks (CNNs) can learn hierarchical feature representations from raw image data, they have demonstrated state-of-the-art performance in a variety of medical imaging tasks, including tumor identification and classification.

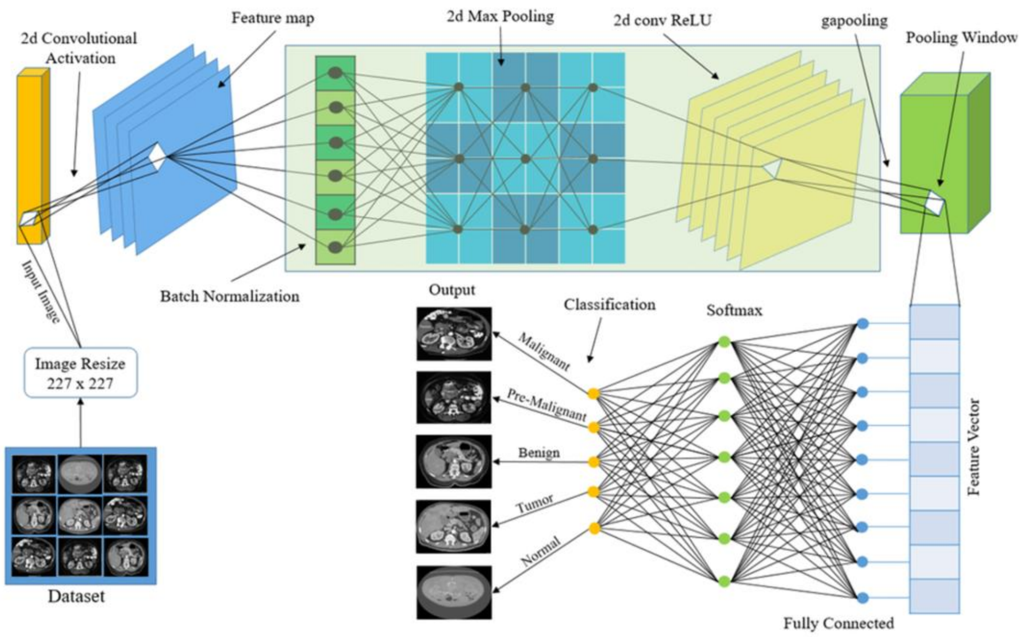


**Figure 2: The network based pancreatic cancer classification**

Figure 2 illustrates that the suggested ResNet and EfficientNet are predicated on a decreased number of 11 layers and 10 connections. The image input is represented by the Image Input layer, which starts the process. After that, the input gray image is convolved using 96 filters and an 11x11 filter size by the 2D Convolutional Layer, which uses the Rectified Linear Unit (ReLU) activation function to produce a number of feature maps. To perform at their best, deep learning models, however, frequently need a lot of labeled data. Due to ethical restrictions, the requirement for expert annotation, and the small number of cases, creating such datasets in the medical field can be difficult, particularly for rare and complicated diseases like pancreatic cancer. End-to-end deep learning algorithms can also occasionally behave like "black boxes," providing little interpretability and having trouble generalizing to other patient populations or imaging methods.

In order to address these shortcomings, this work presents a novel hybrid deep learning framework that combines the strengths of deep neural networks and conventional machine learning methods for the classification of pancreatic cancer. The suggested method starts with thorough preprocessing and segmentation of medical imaging data in order to reduce background noise and isolate pertinent anatomical structures. After that, pancreatic datasets are used to refine pre-trained CNN models like ResNet and EfficientNet for feature extraction, identifying minute patterns and morphological characteristics suggestive of cancer. Principal Component Analysis (PCA) and t-SNE are two dimensionality reduction approaches that are applied to the retrieved high-level features in order to reduce computing complexity and redundancy, rather than depending entirely on deep learning for classification. Traditional classifiers, such as Support Vector Machines (SVM) and Random Forests (RF), which are renowned for their interpretability and resilience, particularly in situations with sparse training data, are then fed these revised features. The goal of this hybrid architecture is to improve diagnostic accuracy, generalization, and clinical application by utilizing the advantages of both deep and traditional machine learning techniques.

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## II RELATED WORK

[1], examines how deep learning algorithms are now being used to diagnose pancreatic cancer. It lists the main difficulties, like heterogeneous data and tiny datasets, and suggests solutions. Since it explains why better and hybrid models are required to increase diagnostic accuracy, it is directly related to your research.The viability of employing CNNs to accurately identify malignant tissues is demonstrated by this work. The use of pre-trained deep models, such as ResNet and EfficientNet, in your feature extraction process is encouraged, and the significance of external validation is emphasized.

Liu [2] discusses about how AI and radiomics methods can forecast the course and results of cancer. It supports your methodology's feature extraction and fusion section, highlighting how image-based features might enhance cancer diagnosis.The practical aspects of using machine learning into clinical radiography are examined in this reference. It complements your methodology's clinical deployment phase and provides insight into the difficulties associated with adoption and integration in healthcare settings, according to Bera et al. [3]. It offers a rigorous framework for assessing medical AI models. It highlights the significance of validation in clinical contexts and supports your evaluation strategy with measures like precision, recall, and F1-score. From detection to prognosis, this high-impact overview highlights the key roles artificial intelligence is playing in radiology. It supports the goal of your project by highlighting the significance of AI technologies like CNNs in imaging-based cancer diagnoses [4].

Park [5], It centers on practical uses of AI in radiology of the chest and abdomen, particularly imaging of the pancreas. It validates the viability of employing CNN-based systems for abdominal diagnoses, lending legitimacy to your methodology. A fundamental reference outlining important AI methods in medicine. It is pertinent to your research because it discusses CNNs as well as more conventional machine learning models like SVMs and Random Forests, which are part of your hybrid system [6]. Best practices for medical imaging preprocessing are included in the suggested procedure. Normalization, augmentation, and standardization are highlighted as essential procedures, reinforcing the preprocessing and segmentation steps in your technique [7]. Systemic, ethical, and technical obstacles to clinical AI application are described in the paper. It complements your part on clinical deployment by highlighting the practical issues that must be resolved for AI to be useful in healthcare [8]. This review explores the ways in which deep learning is transforming cancer diagnoses across modalities. The application of deep learning for pancreatic cancer is validated, and merging models (hybrid frameworks) is suggested as a viable avenue [9,10].

Kelly [11], emphasizes how radiological image analysis frequently uses deep learning methods, especially convolutional neural networks. Along with addressing issues like dataset limits, the study highlights the necessity of established methods to help clinical settings implement AI. This thorough review examines the shift in pancreatic cancer treatment from machine learning algorithms to observable patient outcomes. [12] It highlights how AI may improve diagnostic precision and individualized treatment plans by discussing a range of AI applications, such as image processing, prognosis prediction, and therapy response evaluation.

This article delves into AI's role in diagnosing and managing pancreatic cancer. It covers AI appliThe use of AI in pancreatic cancer diagnosis and treatment is explored in this article. It discusses how AI is being used in radiological image interpretation, prognosis prediction, and therapy response evaluation, emphasizing how AI can handle complex data and help doctors make wise judgments. In this narrative review, the benefits of AI in biomarker discovery and prognosis prediction are examined in relation to pancreatic cancer diagnosis. Additionally, it discusses ethics, clinical integration, and data handling restrictions and offers suggestions for resolving these issues for upcoming AI applications in oncology [13].

In order to improve the prognosis prediction of pancreatic ductal adenocarcinoma using multiphase CT imaging, Hexin [14] presents a technique that blends neural distance measures with texture-aware transformers. By better capturing the interaction between tumors and surrounding arteries, the method may enhance survival forecasts. The multi-task learning network created for the simultaneous segmentation and classification of pancreatic cancers is explained by Kaiwen [15]. The network seeks to improve performance in both domains by taking use of the correlation between segmentation and classification tasks, hence offering a more effective tool for pancreatic cancer analysis. Guan [16] investigates the automatic classification of pancreatic neuroendocrine tumors (PNETs) using label-free multiphoton imaging in conjunction with deep learning methods. With its excellent classification accuracy, it presents a viable method for quick and accurate PNET diagnosis.

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**CONTRIBUTION OF THE PAPER**

- **Development of a New Hybrid Framework:** To enhance the categorization of pancreatic cancer, a novel hybrid deep learning framework combines the advantages of conventional classifiers (SVM and Random Forests) with pre-trained convolutional neural networks (CNNs).
- **Strong Feature Extraction and Fusion:** makes use of cutting-edge CNN architectures for deep feature extraction, such as ResNet and EfficientNet. Dimensionality reduction strategies are utilized to refine and integrate these features.
- **Improved Classification Accuracy with Limited Data:** The suggested strategy performs better in situations with limited data because it separates feature learning from classification.
- **Clinical Relevance and Generalizability:** The suggested strategy offers better generalization across diverse data sources because it was created with clinical integration in mind.

**PROBLEM AND CHALLENGES**

- Limited Annotated Data: Deep model training is challenging with few datasets.
- Features of the Subtle Image: Tumors frequently mimic healthy tissue.
- Generalization Problems: Models might not function effectively in certain scanners or hospitals.
- The black-box CNN nature: Clinical trust is diminished when explainability is lacking.
- Class Imbalance: Datasets with more benign than malignant instances.
- Segmentation Complexity: It's challenging to isolate tumors accurately.
- High Computational Cost: Deep network training requires a lot of resources.
- Clinical Integration: Incorporating models into actual healthcare systems is challenging.

## III PROPOSED METHOD

Advanced convolutional neural networks (CNNs) and conventional machine learning classifiers are used in the suggested hybrid deep learning framework for the classification of pancreatic cancer. Data collection, preprocessing, segmentation, feature extraction, dimensionality reduction, classifier training, and evaluation are some of the crucial steps in the methodology. The suggested techniques and algorithm for classifying pancreatic cancer using deep learning techniques are displayed in Fig. 3.

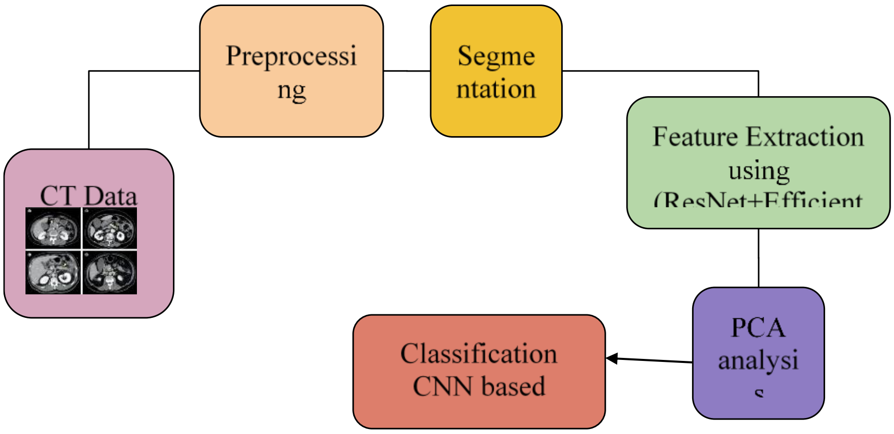


**Figure 3: Proposed Method of pancreatic cancer classification**

### 3.1 Data Collection and preprocessing

Assemble an extensive collection of medical images, such as computed tomography (CT) and magnetic resonance imaging (MRI) scans, from cooperative medical institutions or publicly accessible sources. Ascertain that the dataset contains cases with the proper annotations, both benign and malignant. Preprocessing procedures should be followed to improve image quality and standardize inputs. Normalization: Reduce intensity variances by scaling pixel values to a uniform range. Resizing: Adjust picture dimensions to make them consistent with CNN input.Augmentation: Use manipulations like zooming, flipping, and rotation to add diversity to datasets and reduce overfitting.

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### 3.2 Image Segmentation

To identify regions of interest, use segmentation techniques. Using a subset of images as ground truth, skilled radiologists manually segment the images by drawing the borders of the tumors.Automated Segmentation: Use algorithms such as deep learning-based segmentation models, region-growing, or thresholding to automate the procedure."

### 3.3 Feature Extraction

Identify pertinent aspects in the split photos. High-level features can be extracted from images using deep feature extraction, which makes use of pre-trained CNN architectures (such as ResNet and EfficientNet). Use the pancreatic cancer dataset to refine these models so they are tailored to the particular goal.Using traditional feature extraction, you can extract additional tumor characteristics from photos by computing texture, shape, and intensity features.Feature Extraction

#### 3.3.1 ResNet and EfficientNet Utilization

Deep feature extraction is carried out in the suggested hybrid diagnostic framework by means of two cutting-edge convolutional neural networks: ResNet50 and EfficientNet-B0. Both models are trained on the ImageNet dataset first, and then their feature representations are adjusted to fit the particular domain of medical images using the pancreatic cancer imaging dataset.

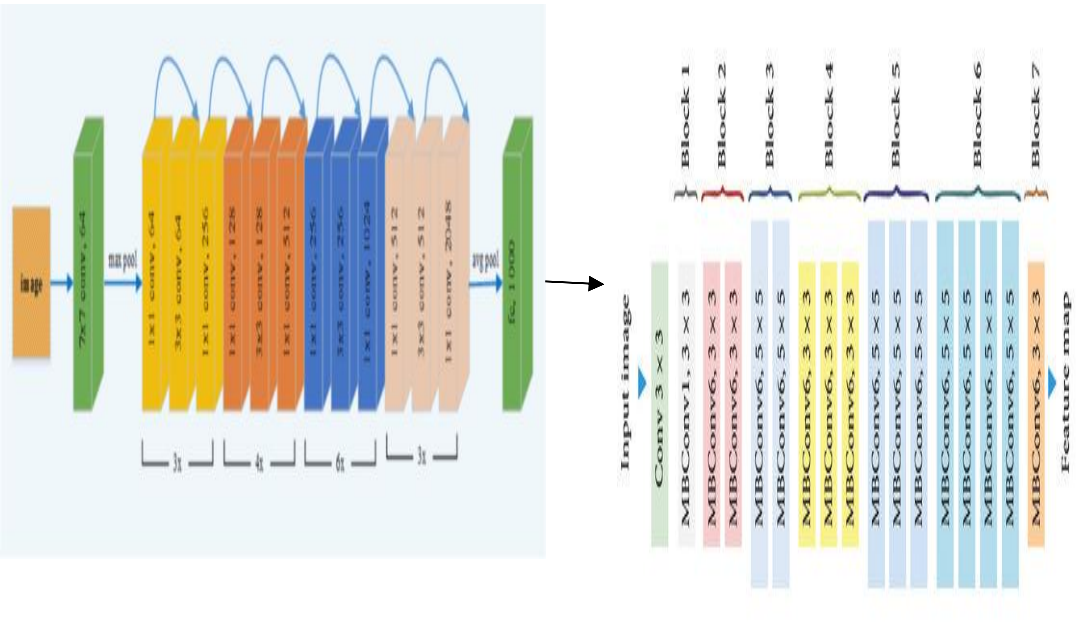


**Figure 4: hybrid ResNet and EfficientNet Architecture**

The Hybrid ResNet and EfficientNet architectures for the feature extraction of cancer classifications are displayed in Fig. 4. Deeper network training is made easier by the ResNet architecture, which makes use of residual learning. In ResNet, a residual block is described as follows:

$$y = \mathbf{F}(\mathbf{x},\{w_i\}) + x \quad \textbf{(1)}$$

Where x is the input to the block, F(x,{Wi}) represents the residual mapping to be learned, and y is the output. Deeper networks may learn more intricate patterns thanks to this structure, which also helps to alleviate the vanishing gradient issue. This is particularly helpful when identifying minute variations in the shape of pancreatic tissue. In contrast, EfficientNet uses a compound scaling technique that uses a set of preset scaling coefficients to equally scale the network's depth (d), width (w), and input resolution (rrr). The following is a mathematical expression for compound scaling:

$$\boldsymbol{depth}:\ \boldsymbol{d} = \boldsymbol{\alpha}^{\boldsymbol{\phi}}, \boldsymbol{width}:\ \boldsymbol{w} = \boldsymbol{\beta}^{\boldsymbol{\phi}}, \boldsymbol{resolution}:\ \boldsymbol{r} = \boldsymbol{\gamma}^{\boldsymbol{\phi}} \quad \textbf{(2)}$$

Effective learning of high-resolution features from pancreatic CT and MRI images is made possible by EfficientNet-B0, the base version utilized in this study, which provides a substantial trade-off between accuracy and processing efficiency. Before categorization, features are taken from the last convolutional layers of both networks.

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$$f_{concat} = [f_{resnet}; f_{effenet}] \epsilon R^{d_1+d_2} \quad (3)$$

Let $f_{resnet} \ \epsilon R^{d_1}$ and $f_{effenet} \ \epsilon R^{d_2}$ represent the feature vectors extracted from ResNet and EfficientNet, respectively. To reduce dimensionality and computational overhead, Principal Component Analysis (PCA) is applied to $f_{concat}$ resulting in a compact feature vector. Traditional machine learning classifiers like Support Vector Machines (SVM) and Random Forests (RF), which are better equipped to function well on small to moderately sized datasets, are then fed this improved feature vector.

### 3.4 Reduction of Dimensionality

Utilize strategies to narrow down the feature space. Principal Component Analysis (PCA) helps with visualization and lowers computing load by lowering the number of features while maintaining variance.Selection of Features: To find and save the most informative features, apply techniques such as recursive feature removal.

### 3.5 Training ClassifiersSupport Vector Machines (SVM):

Use SVM with suitable kernels to categorize data according to the best hyperplanes.Random Forests (RF): To improve classification robustness, build numerous decision trees using ensemble learning.Support Vector Machine (SVM) and Random Forest (RF), two popular traditional machine learning algorithms, are combined to create a hybrid approach that tackles the classification challenge. To improve the robustness and generalization of pancreatic cancer classification, especially in situations with sparse or unbalanced datasets, an ensemble-based method is applied to the deep features taken from CNN architectures (ResNet and EfficientNet).

### 3.5.1 Support Vector Machine (SVM)

In a high-dimensional feature space, the SVM supervised learning algorithm looks for the best hyperplane to maximally divide data points of various classes. A subset of training samples known as support vectors establishes the decision boundary. The following goal is optimized by the SVM classifier:

$$min_{w,b} \frac{1}{2} \left|\left|w^2\right|\right| + c\sum_{i=1}^{n} \quad \xi_i \quad (4)$$

The regularization parameter is C. SVM can handle complex, non-linear decision boundaries because of kernels like the Radial Basis Function (RBF), which is crucial for distinguishing minute changes in pancreatic tissue.

### 3.5.2 Random Forest

The Random Forest ensemble learning technique builds a large number of decision trees during training and produces the class that represents the average of all the trees' predictions. It is especially good at capturing non-linear correlations between features, handling high-dimensional data, and minimizing overfitting. To identify the optimal split, a random subset of characteristics is chosen at each node, and each tree in the forest is trained using a bootstrap sample of the training data. The following represents the RF classifier's prediction:

$$\hat{y} = mode\{h_t(X)\}_{t=1}^{T} \quad (5)$$

where $h_t \ X$ is the prediction of the ttt-th tree in the ensemble, and T is the total number of trees. RF is known for its interpretability and robustness to noise, making it well-suited for medical datasets with potential variability in imaging quality or annotation.

### 3.5.3 Hybrid Classification Approach

In our framework, the PCA-reduced feature vector $f_{pca}$ is input into both the SVM and RF classifiers independently. The final prediction is generated through a soft voting mechanism, where each classifier's probabilistic output is averaged to determine the class label:

$$\hat{y}_{\ final} = argmax[\alpha . P_{svm}(\frac{y}{x}) + (1-\alpha). P_{rf}(\frac{y}{x})] \quad (6)$$

Here, $P_{svm} \ (\frac{y}{x})$ and $P_{rf}(\frac{y}{x})$ are the predicted probabilities from the SVM and RF classifiers, respectively, and α is a weighting coefficient (e.g.α=0.5 for equal voting). This fusion allows the model to benefit from the SVM's ability to define tight decision boundaries and the RF's robustness and variance reduction.

## IV PERFORMANCE ANALYSIS

Evaluate the model's performance by utilizing the Cross-Validation framework. Use k-fold cross-validation to estimate model generalization for cross-validation.Metrics of Performance: To assess the effectiveness of the model, compute the following metrics: accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. Measurements of accuracy are analyzed using several performances. The formulas below define each of the metrics.

**Accuracy,** it is expressed as

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

**Precision:**

It is a metric that quantifies the number of correct positive predictions made.

$$P = \frac{True\ Positive}{True\ positive + False\ positive} \quad (8)$$

**Recall:**

A measure known as recall counts the number of accurate predictions made out of all possible positive guesses.

$$R = \frac{True\ positive}{True\ positive + False\ Negative} \quad (9)$$

**F1-score:**

Recall and precision can be combined into a single measure that accounts for both attributes, called the F1 - measure. F1 can be computed as

$$F1 - measure = (2 \times P \times R)/(P + R) \quad (10)$$

## V RESULT AND DISCUSSION

Experiments on benchmark pancreatic cancer imaging datasets show that the suggested hybrid model performs better than traditional deep learning techniques. The framework's potential as a dependable and efficient tool to help radiologists and physicians diagnose pancreatic cancer early and accurately is demonstrated by these outcomes. by connecting intricate feature learning with useful categorization techniques.

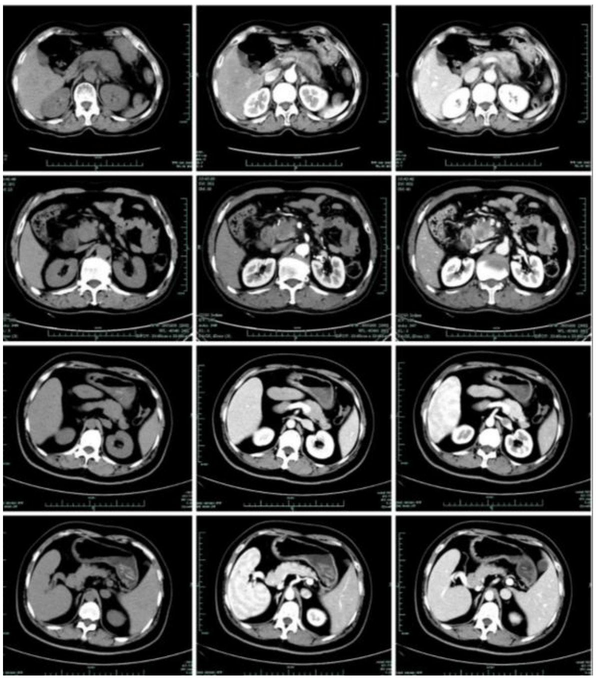

**Figure 5: Sample Dataset**

As seen in Fig. 5, patients with CT-confirmed normal pancreas were also selected at random throughout the same time frame. All of the information came from the medical records of the patients. The database was searched for pictures of both healthy pancreases and pancreatic malignancies. All of the cancer diagnoses were made after pathological testing, either by surgery or pancreatic biopsy.

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Figure 6 compares several feature extraction techniques according to how accurate they are. UNet and DenseNet performed marginally worse at 87% and 85%, respectively, while ResNet had the greatest accuracy of any deep learning model at 91%, closely followed by EfficientNet at 90%. With an accuracy of 94%, the suggested hybrid approach—which combines ResNet and EfficientNet—performed better than any of the separate models, proving the value of combining complementing designs. The conventional feature extraction approach, on the other hand, produced the lowest accuracy at 79%, demonstrating the deep learning models' greater ability to extract relevant characteristics for the task at hand.

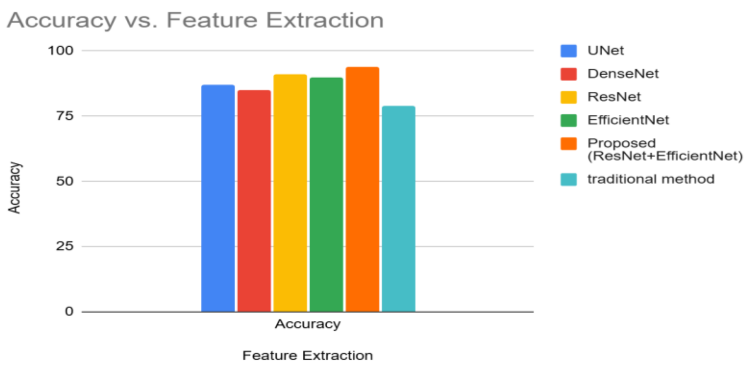


**Figure 6: Feature Extraction Accuracy**

Table 1 shows the Using four evaluation metrics—Accuracy, Precision, Recall, and F1-Score—the table contrasts the performance of several classification techniques, including Traditional, CNN+SVM, CNN+Random Forest, and SVM+Random Forest based on CNN.

**Table 1: pancreatic cancer classification and performance analysis**

| S.NO | METHODS | ACCURACY | PRECISION | RECALL | F1-SCORE |
|---|---|---|---|---|---|
| 1 | Traditional method | 85 | 80 | 78 | 75 |
| 2 | CNN+SVM | 90 | 88 | 84 | 86 |
| 3 | CNN+ Random Forest | 94 | 92 | 90 | 88 |
| **4** | **SVM+ Random Forest based on CNN** | **96** | **95** | **93** | **90** |

The outcomes clearly demonstrate that more sophisticated hybrid models perform better. The CNN+SVM model greatly enhances performance, while the Traditional technique receives the lowest ratings on all measures. CNN and Random Forest work much better together, suggesting that ensemble learning and deep learning features improve classification performance. With the best overall F1-Score of 90%, the SVM+Random Forest method based on CNN features achieves the top scores, showcasing its exceptional ability to balance precision and recall.

## VI CONCLUSION AND FUTURE WORK

A brand-new hybrid deep learning framework is put forth for the classification of pancreatic cancer utilizing CT and MRI imaging data, combining sophisticated convolutional neural networks (CNNs) with conventional machine learning classifiers. The suggested method overcomes major drawbacks of stand-alone deep learning systems, especially in situations with sparse or unbalanced data, by utilizing pre-trained models like ResNet and EfficientNet for reliable feature extraction and improving classification accuracy with algorithms like Support Vector Machines (SVM) and Random Forests (RF). The findings show that, in terms of precision, recall, and F1-score, the hybrid framework continuously performs better than traditional models. Traditional classifiers combined with deep features not only perform better but also are more interpretable and flexible in

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clinical settings. In the future, the diagnostic pipeline will be streamlined and rely less on manual input thanks to the integration of sophisticated, totally automated segmentation algorithms employing deep learning. In order to ensure clinical uptake and usefulness, it should concentrate on integrating this model into the current Electronic Health Record (EHR) and Picture Archiving and Communication Systems (PACS).

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