

EARLY STAGE DETECTION OF PANCREATIC CANCER USING DEEP LEARNING

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Abstract

Pancreatic cancer is one of the most aggressive and life-threatening cancers worldwide due to its late diagnosis and rapid progression. Early-stage symptoms are generally mild or absent, making detection difficult through conventional diagnostic methods. Delayed diagnosis significantly reduces patient survival rates and increases treatment complexity. Traditional diagnostic approaches such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Endoscopic Ultrasound (EUS), and biopsy require expert radiologists and extensive manual interpretation of medical images. Manual analysis is time-consuming and may fail to identify subtle tumor patterns during initial stages.

This paper presents a deep learning-based framework for the early-stage detection of pancreatic cancer using CT and MRI medical images. The proposed system utilizes Convolutional Neural Networks (CNNs) to automatically extract significant image features and classify pancreatic scans as normal or tumor affected. Image preprocessing techniques such as resizing, normalization, denoising, and augmentation are applied to improve image quality and model robustness. The proposed CNN architecture contains convolutional layers, ReLU activation functions, max-pooling layers, dropout layers, flatten layers, and dense layers for efficient feature extraction and classification.

Keywords: Pancreatic Cancer, Deep Learning, CNN, CT Images, MRI Images, Artificial Intelligence, Medical Image Processing, Healthcare Systems

1. Introduction

Pancreatic cancer is one of the deadliest forms of cancer because of its rapid progression and extremely low survival rate. According to global cancer statistics, pancreatic cancer contributes to a significant number of cancer-related deaths every year. The disease is often referred to as a “silent killer” because symptoms usually appear only during advanced stages. As a result, most patients are diagnosed after the cancer has spread to nearby organs, making treatment less effective and reducing survival chances. Traditional diagnostic techniques such as CT scans, MRI scans, biopsy, and Endoscopic Ultrasound (EUS) depend

heavily on expert radiologists and manual analysis of medical images. Detecting tumors during early stages is challenging because pancreatic tumors are generally small and difficult to differentiate from surrounding healthy tissues. Manual interpretation is time-consuming and may result in delayed diagnosis or human error. Artificial Intelligence (AI) and Deep Learning technologies have emerged as powerful tools in the healthcare industry.

Convolutional Neural Networks (CNNs) are especially effective in medical image analysis because they can automatically extract spatial features such as edges, textures, shapes, and tumor regions directly from

images. The proposed system utilizes CNN-based deep learning techniques for pancreatic cancer detection from CT and MRI medical images. The system automates the diagnosis process and reduces dependency on manual interpretation.

2. Related Work

Several researchers have contributed significantly to the field of medical image analysis and cancer detection using deep learning techniques.

Chen et al. [1] proposed a CNN-based framework for pancreatic tumor detection using CT scan images. Their model demonstrated high sensitivity and specificity for identifying tumor regions and showed that CNN-based systems outperform traditional machine learning techniques in medical image classification tasks.

Ronneberger et al. [2] introduced the U-Net architecture for biomedical image segmentation. U-Net became one of the most widely used architectures in healthcare applications because of its ability to perform accurate segmentation with limited datasets and preserve spatial information during feature extraction.

Litjens et al. [3] reviewed deep learning applications in medical image analysis and concluded that CNN-based systems provide superior classification performance compared to conventional image processing techniques. Their work highlighted the growing importance of AI-assisted healthcare systems in diagnosis and clinical decision-making.

Zhou et al. [4] implemented transfer learning techniques for pancreatic cancer detection and reduced model training complexity while maintaining high classification accuracy. Their study demonstrated the effectiveness of pretrained models for medical imaging tasks, especially when limited datasets are available.

Mucheli et al. [5] proposed a deep learning-based medical image classification framework and demonstrated improved performance in cancer diagnosis applications. Their work emphasized the importance of preprocessing techniques such as normalization, resizing, and augmentation for improving model robustness and reducing overfitting.

Esteva et al. [6] demonstrated that deep learning models can achieve dermatologist-level performance in skin cancer classification tasks. Their research proved the capability of deep neural networks in healthcare applications and inspired the adoption of AI-based diagnosis systems across multiple medical domains.

He et al. [7] introduced Deep Residual Networks (ResNet), which significantly improved deep learning performance in image recognition tasks. Residual learning helped overcome the vanishing gradient problem and enabled the training of very deep neural networks with higher accuracy and better feature learning capabilities.

3. Materials and Methods



Fig 1: Block diagram of deep learning prediction system

IMAGE ACQUISITION-The dataset consists of CT and MRI medical images collected from publicly available healthcare datasets and medical image repositories. The dataset contains two categories: Normal Images and Pancreatic Tumor Images

The dataset composition includes approximately-56.2% Normal Images, 43.8% Tumor Images. The availability of sufficient tumor and non-tumor samples helps improve the effectiveness of CNN model training.

IMAGE PREPROCESSING- Medical image preprocessing is performed to improve image quality and increase model accuracy. The preprocessing steps include:

1. **Image Resizing**-All CT/MRI images are resized to 128×128 pixels to maintain uniform dimensions for CNN processing.
2. **Normalization**-Pixel intensity values are normalized between 0 and 1 to improve convergence speed during training.
3. **Denoising**-Noise removal techniques are applied to eliminate unwanted artifacts from medical images.

4. Data Augmentation-Data augmentation techniques such as rotation, zooming, are applied to increase dataset diversity and reduce overfitting.

CNN ARCHITECTURE-The proposed Convolutional Neural Network (CNN) architecture contains the following layers:

Convolutional Layers

- ReLU Activation Functions
- Max Pooling Layers
- Dropout Layers
- Flatten Layers
- Dense Layers

The convolutional layers automatically extract important features such as edges, textures, and tumor patterns from medical images. ReLU activation functions introduce non-linearity into the network. Max pooling layers reduce spatial dimensions while retaining essential information.

A. Model Training-The dataset is divided into: 80% Training Data, 20% Validation Data. The model training process minimizes loss and improves classification accuracy over multiple epochs.

The trained **CNN model** is integrated with a **Streamlit-based web application** that provides a user-friendly interface for **uploading CT/MRI images, generating real-time prediction results, and displaying confidence scores**. This enables doctors and users to quickly upload medical images and receive **instant pancreatic tumor detection results**, supporting efficient clinical decision-making.

4. Results and Discussion

The proposed CNN model was trained and tested using pancreatic CT/MRI image datasets consisting of tumor and normal images. The developed system achieved high classification performance with minimal overfitting.

The model achieved approximately:

- Training Accuracy: 95.6%
- Validation Accuracy: 91.3%

The training and validation accuracy graphs showed stable convergence during the training process. Validation accuracy improved steadily with increasing epochs, indicating effective learning and good generalization capability. The training and validation loss curves decreased consistently without divergence. This indicates stable model performance

and minimal overfitting. Receiver Operating Characteristic (ROC) analysis demonstrated excellent classification capability with an Area Under Curve (AUC) value close to 0.99. The ROC curve remained close to the top-left corner, indicating strong discrimination between tumor and normal classes. The developed Streamlit web application successfully displayed prediction results such as: "Normal", "Pancreatic Tumor" along with confidence scores for uploaded CT/MRI images.

The proposed system demonstrated high accuracy, fast prediction speed, reliable classification performance, and efficient medical image analysis, making it a promising tool for supporting healthcare professionals in the early screening and diagnosis of pancreatic cancer.



Fig 2: Web page of the project pancreatic cancer detection system.



Fig 3: Application predicted result as normal.



Fig 4: Application predicted result as pancreatic tumor detected.

FUTURE ENHANCEMENTS

The proposed pancreatic tumor detection system include the use of larger and more diverse medical datasets to improve model robustness and accuracy. Advanced techniques such as transfer learning, ensemble learning, and explainable AI can enhance prediction performance and interpretability. The system can also be integrated with cloud computing, mobile healthcare applications, real-time cancer detection, and automated report generation. Furthermore, combining CT, MRI, and ultrasound images through multi-modal analysis can provide more comprehensive and reliable diagnostic results.

5. Conclusion

The proposed deep learning-based pancreatic cancer detection system provides an efficient and automated solution for early diagnosis using CT and MRI medical images. The CNN model successfully extracts important image features and achieves high classification accuracy. The developed framework reduces manual effort, improves diagnostic efficiency, and supports healthcare professionals in medical decision-making.

The integrated Streamlit web application provides a user-friendly platform for uploading medical images and obtaining prediction results with confidence scores. The proposed system has the potential to improve healthcare accessibility, support rural medical services, and enhance early-stage cancer diagnosis.

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