

Intelligent Operations on SPECT and PET Imaging

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Abstract: *The rapid advancement of medical imaging technology has significantly enhanced diagnostic capabilities in healthcare, particularly through modalities such as Single Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET). This project aims to leverage deep learning techniques to perform intelligent operations on SPECT and PET images, enhancing diagnostic accuracy and efficiency. We develop a comprehensive framework that includes data acquisition and preprocessing, image enhancement.*

Our approach consists of two primary modules: data collection and image enhancement. In the data collection module, we compile and preprocess datasets from diverse clinical sources, ensuring consistency and robustness. The image enhancement module employs state-of-the-art deep learning models, including convolutional neural networks (CNNs) to denoise and improve the resolution of SPECT and PET scans. These enhancements aim to provide clearer and more detailed images, facilitating better visualization of anomalies such as tumors and metabolic activity.

This project lays the foundation for future developments in automated lesion detection and disease classification, contributing to more accurate diagnostics and improved patient outcomes in clinical practice..

Keywords: Convolutional Neural Network, SPECT & PET Medical Imaging, Brain Tumour, Deep Learning

I. INTRODUCTION

Medical imaging techniques like SPECT and PET play a crucial role in diagnosing and monitoring diseases. However, interpreting these images can be challenging due to noise, low resolution, and complexity. To address this, a project aims to develop an intelligent framework using deep learning techniques to enhance SPECT and PET image analysis, improving diagnostic accuracy and clinical decision-making.[1]

Positron Emission Tomography (PET) and Single-Photon Emission Computed Tomography (SPECT) are medical imaging techniques that help diagnose and treat diseases. Over the last decade, these techniques have shifted from just detecting and diagnosing diseases to also predicting treatment outcomes and characterizing tissues. PET is a more sensitive and quantitative imaging tool that provides better image resolution than SPECT. However, PET is more expensive and requires specialized equipment. On the other hand, SPECT is cheaper and easier to distribute, with radiopharmaceuticals that have longer half-lives, allowing for more accurate descriptions of biological processes. Researchers are continually developing new radiopharmaceuticals and improving imaging technologies. This article reviews the current state of PET and SPECT radiopharmaceuticals and their applications in medical imaging, highlighting the advantages and limitations of each technique.[2]

The human brain is vulnerable to various diseases, including neurodegenerative disorders and psychiatric conditions. Molecular neuroimaging techniques, such as PET and SPECT, enable non-invasive investigation of brain diseases. These techniques provide insights into biological processes at the cellular and molecular levels, allowing for early diagnosis and therapeutic trials. This review focuses on PET/SPECT techniques and their applications in clinical neurosciences, particularly in neurodegenerative disorders like Alzheimer's and Parkinson's diseases.[3]

In modern days, checking the huge number of MRI (magnetic resonance imaging) images and finding a brain tumour manually by a human is a very tedious and inaccurate task. It can affect the proper medical treatment of the patient.

Again, it can be a hugely time-consuming task as it involves a huge number of image datasets. There is a good similarity between normal tissue and brain tumour cells in appearance, so segmentation of tumour regions become a difficult task to do. So, there is an essentiality for a highly accurate automatic tumour.[4]

Brain tumours are deadly illnesses that require early diagnosis. Traditional diagnosis methods using Magnetic Resonance Imaging (MRI) are time-consuming and require expertise. This study proposes two deep learning models that use Convolutional Neural Networks (CNNs) to detect brain tumours from MRI images. The models achieved up to 97.8% and 100% classification accuracy, outperforming other state-of-the-art models.[5]

Cancer is the leading cause of death worldwide, according to the World Health Organization. Early detection can help, but it's not a guarantee. Clinical imaging plays a crucial role in diagnosing and treating diseases, including cancer. It involves non-invasive methods like MRI, CT scans, and others to visualize the body's internal structures. Image processing techniques, such as image segmentation, can enhance image quality and aid in diagnosis.[6]

Brain tumours are abnormal masses that form in the brain, affecting human life. They can be benign or malignant, causing various disorders and symptoms. Treatment options include surgery, medication, and radiation. In the US, approximately 700,000 people live with brain tumors, with a 35% survival rate for malignant cases. Recently, deep learning models have been applied to biomedical applications, including brain tumor classification. This study proposes a new model, Brain MR Net, which uses attention modules, hypercolumn technique, and residual blocks to classify brain MR images and focus on diseased areas.[7]

A brain tumor is an unnatural growth of brain cells that can affect human function and spread to other organs. According to the WHO, brain cancer accounts for less than 2% of human cancer, but causes severe morbidity. Brain tumors can be primary or secondary, benign or malignant. MRI is a common non-invasive technique for detecting and classifying brain tumors. Gliomas are the most prevalent type of brain tumor, classified into four grades. Other types of brain tumors include meningioma and pituitary tumors, which can be benign or malignant and cause various complications.[8]

Deep learning, a type of artificial intelligence, has gained significant attention for its potential to solve complex problems. Its application in medical imaging has shown promising results, with AI/DL algorithms effectively learning from large and complex data sets.[9]

Myocardial single-photon emission computed tomography (SPECT) is widely used to diagnose myocardial ischemia, but its accuracy is affected by photon absorption artefacts. To overcome this, researchers proposed a deep-learning model that translates SPECT images to positron emission tomography (PET) images, which are considered the gold standard. The study evaluated the performance of this model in correcting attenuation artefacts in SPECT images.[10]

II. LITERATURE REVIEW

The application of deep learning in medical imaging, particularly in SPECT and PET analysis, has gained considerable attention in recent years. This literature review highlights significant studies that explore the potential of deep learning techniques for enhancing diagnostic capabilities through SPECT and PET imaging.

Gupta, A., et al. "Deep Learning in SPECT Imaging: A Review." (2020)

This review paper discusses the various deep learning approaches employed in SPECT imaging, emphasizing the potential for improved image quality and diagnostic accuracy. The authors categorize the techniques based on their applications, such as noise reduction, segmentation, and classification of pathological conditions. The paper concludes that while significant progress has been made, further research is needed to standardize these methods and validate them against clinical outcomes.

Huang, Y., et al. "A Deep Learning Approach for Automatic Segmentation of Cardiac PET Images." (2019).

In this study, the authors propose a deep learning model based on U-Net architecture for the automatic segmentation of cardiac PET images. They demonstrate that their model outperforms traditional segmentation techniques in terms of accuracy and processing time. The findings indicate that deep learning can significantly enhance the delineation of cardiac structures and improve the assessment of cardiac function in clinical practice.

Li, H., et al. "3D Convolutional Neural Networks for PET Image Classification" (2021).

This research presents a novel approach using 3D Convolutional Neural Networks (CNNs) for classifying PET images related to Brain tumor disease. The authors emphasize the importance of utilizing volumetric data to capture spatial

features in PET scans. Their model achieved a higher classification accuracy compared to conventional methods, demonstrating the effectiveness of 3D CNNs in detecting early-stage Alzheimer's disease.

Zhang, L., et al. (2022). "Anomaly Detection in SPECT Images Using Deep Learning Techniques."(2022).

The authors of this paper explore deep learning techniques for anomaly detection in SPECT images. They develop a model combining autoencoders and CNNs to identify abnormal patterns in SPECT scans. The results indicate that the proposed method can effectively distinguish between normal and abnormal images, highlighting its potential for assisting radiologists in clinical decision-making.

Khan, A., et al. "Enhancing PET Image Quality with GANs: A Deep Learning Approach."(2023).

This study investigates the use of Generative Adversarial Networks (GANs) to improve the quality of PET images. The authors present a novel GAN architecture that enhances image resolution and reduces noise in PET scans. Their experimental results demonstrate substantial improvements in image quality, suggesting that GANs can be a valuable tool for enhancing diagnostic accuracy in PET imaging.

Proposed Technologies

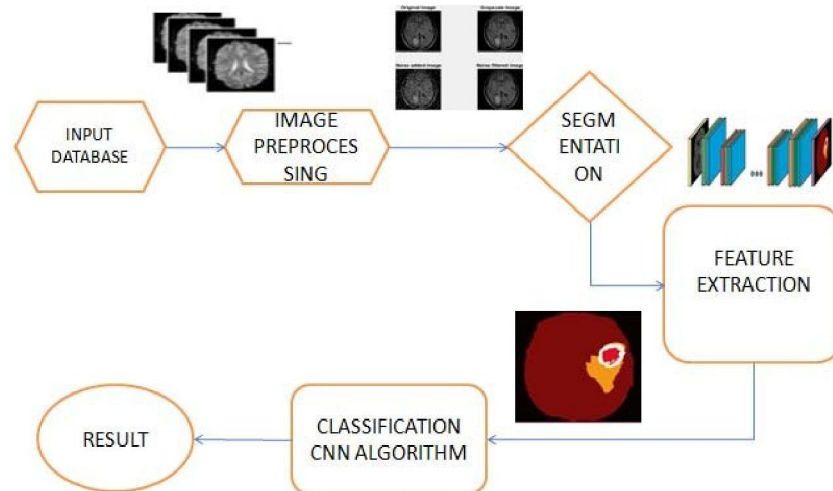


Fig.1 Convolutional Neural Network

Architecture:

Sequential model with distinct layers.

Conv2D Layers: Utilized 32 filters of 3x3 kernels with ReLU activation.

Max Pooling Layers: Applied 2x2 max pooling to reduce spatial dimensions.

Flattened Layer: Transformation of output into a 1D array.

ReLU Activation: Introduced non-linearity for better generalization on complex data.

Output Layer: Comprised of 4 neurons with softmax activation for multi-class classification.

Model Compilation:

Optimizer: Adam optimizer employed.

Loss Function: sparse categorical cross entropy chosen based on existing literature.

Modules Developed

Module 1: Data Preparation and Preprocessing Module

Dataset: The dataset consists of medical images from PET and SPECT scans stored in DICOM (.dcm) format. We converted them to PNG format for easier processing.

Collect and prepare SPECT and PET images for analysis

Image enhancement and preprocessing are crucial steps before training your model to ensure the DICOM (.dcm) images are in a suitable format for deep learning.

Below are the common preprocessing and enhancement steps typically performed when converting DICOM to PNG:

1. DICOM to PNG Conversion

DICOM File Loading: Use libraries like pydicom to load .dcm files.

Pixel Value Extraction: Extract the pixel array from the DICOM file, which contains grayscale intensity values.

Normalization: Normalize the pixel values to the range [0, 255] for image visualization or [0, 1] for model input. Resize to 224x224 pixels.

Python Libraries for Medical Imaging:

pydicom: To handle DICOM files.

NumPy: NumPy is used to extract features from medical images, such as texture features or shape features.

Cv2: OpenCV provides functions for image resizing, normalization, and data augmentation, which are essential steps in preparing data for deep learning models.

2. Enhancement Module:

To improve the quality and highlight important features in the medical images:

Histogram Equalization: Improves contrast by redistributing pixel intensities.

CLAHE (Contrast Limited Adaptive Histogram Equalization): A localized version of histogram equalization to enhance contrast in specific areas.

Noise Reduction: Use filters (e.g., Gaussian or median filters) to reduce noise while preserving edges.

Edge Enhancement: Use sharpening filters or edge-detection techniques to highlight boundaries and structures.

Output Processing:

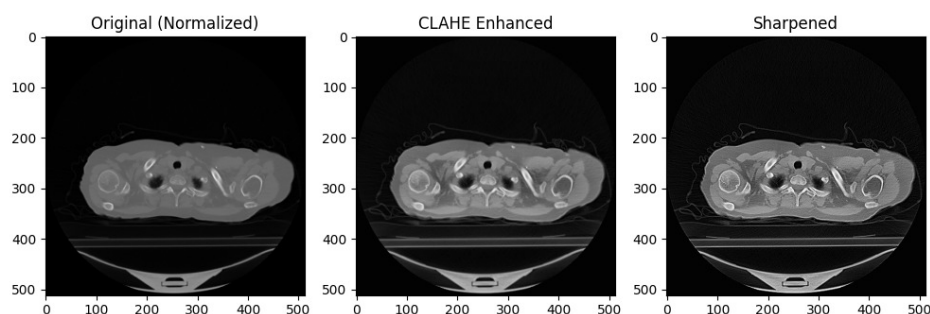


Fig 1. Result of Preprocessing and Enhancement Module

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