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Multi-disease detection system with X-ray images using deep learning techniques

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Abstract

In the realm of medical diagnostics, advanced deep learning algorithms have become powerful tools for detecting and diagnosing diseases. This study introduces a groundbreaking Multi-Disease Detection System designed specifically for analyzing X-ray images. It focuses on detecting Alzheimer's disease, brain tumors, COVID-19 infection, and pneumonia, marking a significant advancement in medical imaging analysis and clinical decision-making. The system utilizes CNN and RNN to attain unparalleled accuracy and reliability in disease detection. By processing MRI and CT scans for Alzheimer's and brain tumor detection, and chest X-ray or CT images for COVID-19 and pneumonia detection, the framework identifies key features indicative of disease pathology. Through careful image preprocessing, noise is minimized, and features are enhanced to optimize CNN performance. Subsequently, RNNs analyze the temporal sequences of features, particularly crucial for diseases like COVID-19 with rapidly evolving symptoms. The system is trained and evaluated on a diverse dataset encompassing various disease stages and manifestations, demonstrating superior accuracy, sensitivity, specificity, and AUC-ROC metrics. This Multi-Disease Detection System represents a significant breakthrough in medical imaging, to take out healthcare specialists with a robust device for timely and accurate disease detection. By leveraging deep learning techniques, it not only improves patient outcomes but also transforms healthcare delivery, ushering in an era where early disease detection is commonplace.

Subject Classification: *68xx.*

Keywords: *Multi-disease detection, Deep learning techniques, CNN, Healthcare, Diagnosis.*

1. Introduction

Deep learning methodologies are revolutionizing medical diagnostics, particularly in the realm of analyzing X-ray images. This introduction delves into a pioneering Multi-Disease Detection System [1], which harnesses "deep learning" techniques to identify a variety of diseases. Deep learning, inspired by the difficult workings of the human brain, has significantly enhanced the analysis of medical images [2], leading to more precise disease detection and diagnosis. The fusion of deep learning with

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medical imaging has opened avenues for novel ailment detection approaches [3][4].

The primary goal of the Multi-Disease Detection System is to facilitate earlier and extra accurate diagnosis of "Alzheimer's disease" with help of novel methodologies [5]. "Alzheimer's disease", a debilitating brain disorder impacting memory and cognitive abilities [6-8], necessitates timely intervention for optimal management. By scrutinizing X-ray images [9], this system aims to pinpoint subtle brain alterations indicative of Alzheimer's, enabling prompt diagnosis and tailored treatment plans. Early detection of brain polyps is paramount for effective intervention. Leveraging advanced Convolutional Neural Networks (CNNs) [10-12], the Multi-Disease Detection System scrutinizes X-ray images to uncover signs of brain tumors [8] [10]. Given the diverse nature of these tumors, early identification is critical for guiding appropriate treatment strategies.

2. Literature Survey

Wang, Shuo, et al. [1] propose a novel approach for diagnosing Alzheimer's disease by utilizing various brain scans. Their deep-learning model, which integrates MRI, PET, and cerebrospinal fluid data, outperforms models using individual scan types alone, enhancing early detection of Alzheimer's. Islam, Muhammad M., et al. [2] present a specialized computer program for detecting and categorizing brain tumors in MRI images. This program employs a multi-scale CNN [9] to accurately identify different tumor types [7] by analyzing features of various sizes in the images. Authors [11] discuss the use of deep learning for detecting corona from chest X-rays. They evaluate different novel models, such as CNNs and RNNs, highlighting their strengths & weaknesses, which aids doctors in more accurately identifying COVID-19 cases [13-15].

3. Proposed Methodology

The system proposes using transfer-learning and data expansion to handle with inadequate labeled data. Data augmentation creates more training data by making small changes to images, refining the model's adaptability. It also emphasizes the need for interpretability in decision-making for medical professionals, achieved through techniques like attention mechanisms and explainable AI.

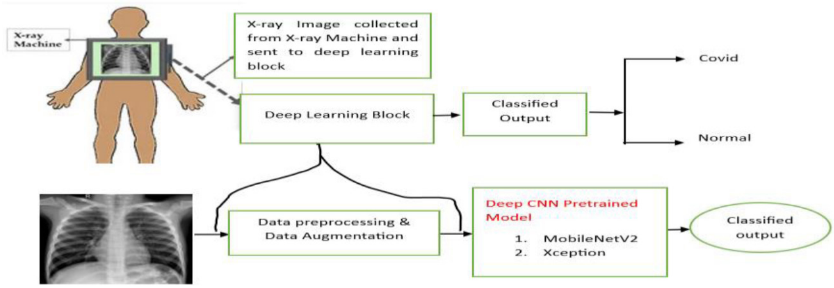

Figure 1

System Architecture

Strengthening the model against potential attacks and data variations is addressed using adversarial training and robust optimization. Overall, the system aims to enhance multi-disease detection while prioritizing patient safety and privacy, integrating AI innovations into medical practice to improve healthcare delivery and patient care quality. The proposed system architecture shown in Figure 1.

3.1 *Description of Datasets*

We gathered four health-related datasets containing X-ray images. The Alzheimer's disease dataset has four classes: Alzheimer's Mild Demented (896 images), Alzheimer's Non-Demented (3200 images), Moderate Demented (64 images), and Alzheimer's Very Mild Demented (2240 images). The Brain tumor dataset includes Brain glioma (1296 images), Brain meningioma (1316 images), Brain no tumor (1600 images), and Brain Pituitary (1405 images). The COVID-19 dataset contains Covid Positive (3812 images) and Covid Normal (3255 images) categories. The pneumonia dataset comprises Pneumonia Disease Detection Normal (1583 images) and Pneumonia Disease Detection Positive (4273 images).

3.2 *Data preprocessing*

Images in lieu of disease detection tasks were organized for training, validation, and testing. Initially, datasets for Alzheimer's disease, brain tumor detection, COVID-19 detection, and pneumonia detection were loaded using TensorFlow's Keras. The images were then standardized to 128x128 pixels and grouped into batches of 64. Augmentation techniques like adjusting brightness and flipping were applied to increase data diversity. For corona and pneumonia detection, similar steps were taken with a target image size of 224x224 pixels and set size of 32. These processes designed to enhance the efficacy and adaptability of learning techniques across different disease detection tasks.

4. CNN Models for Multi Disease Detection

4.1 *Disease Exposure using CNN*

The "convolutional neural network (CNN)" used for Alzheimer's disease detection is built to analyze X-ray images and sort them into different disease groups. The model has various layers, starting with rescaling to standardize pixel values. Ensuing layers include convolutional and max-pooling layers to identify important features and decrease picture size. Dropout layers help prevent overfitting by randomly turning off some neurons during training.

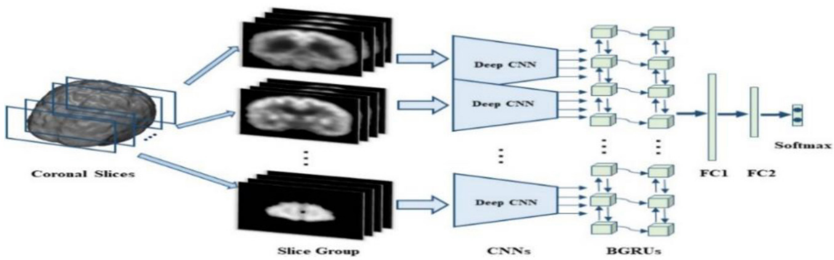

Figure 2

CNN Design

The final layers are fully connected dense layers, which classify the extracted features into specific disease categories. Through over 2 million trainable parameters, the CNN effectively detects Alzheimer's from X-ray images, improving early diagnosis for this neurological condition. The CNN design shown in Figure 2.

4.2 *CNN Model for Brain Tumor Disease Detection*

The brain tumor detection model uses the "Xception architecture", initially proficient on the ImageNet dataset, to analyze images of size (299, 299, 3). The Xception base extracts essential features from these images. Dropout layers are auxiliary and the flattened structures are passed over dense covers with 128 neurons stimulated by ReLU. Another dropout layer is included before the final dense layer, which uses another activation

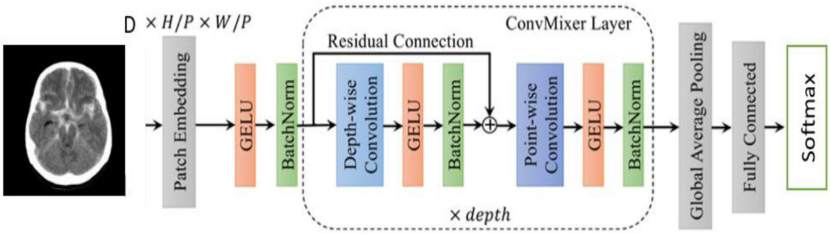

Figure 3

CNN Design for Brain Tumor

to predict brain tumor presence. This model also used the "Adamax optimizer" and categorical-cross-entropy loss function, monitoring correctness, precision, and recall. With over 21 million parameters, the CNN effectively detects brain tumors from input images, showing promise for medical submissions in brain tumor diagnosis and treatment. The xception architecture shown in Figure 3.

4.3 *MobileNetV2-Based Model for COVID-19 Disease Exposure*

This design for virus detection is created on the MobileNetV2 architecture, known for its efficiency and lightweight design, initially competent on the ImageNet dataset. It analyzes input images of size (224, 224, 3) to capture patterns related to COVID-19 infection. The pre-trained MobileNetV2 layers are kept frozen to retain their learned features and prevent overfitting.

"Tradition top layers are auxiliary for classification, as well as a flattening layer, a dense layer with 256 neurons initiated by ReLU". With around 18 million parameters, the MobileNetV2-based CNN effectively

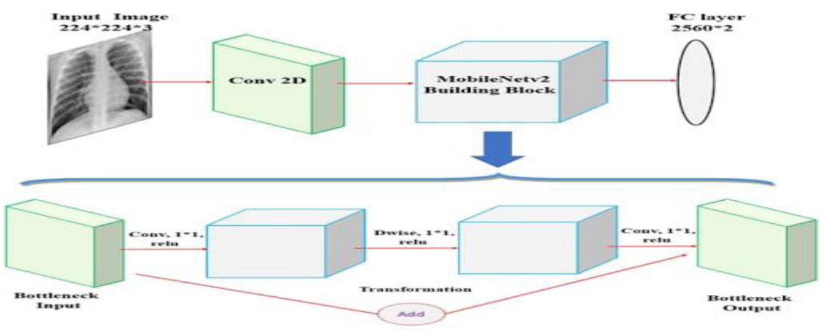

Figure 4

CNN Design for Corona

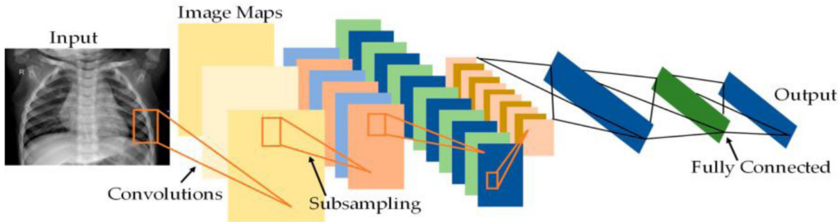

Figure 5

CNN Architecture for pneumonia

detects COVID-19 from input images, showing promise for use in healthcare settings for triage and diagnosis. Figure 4 shows the MobileNetV2 architecture.

4.4 *CNN Model for Pneumonia Disease Detection*

The CNN model for pneumonia detection analyzes "chest X-ray" pictures and categorizes them as either pneumonia-positive or pneumonia-negative. It consists of multiple layers, "starting with convolutional layers followed by max-pooling layers to extract and down sample relevant features from the images". The model comprises four sets of layers, each with increasing filter sizes to capture more intricate features. After flattening the features, they pass through a dense layer with 256 neurons and ReLU initiation, followed by a dropout layer to curb overfitting.

Finally, a dense layer with sigmoid activation produces binary classification predictions for pneumonia. The model is trained using the Adam optimizer and binary cross-entropy loss, with accuracy as the monitored metric. With close to 5 million parameters, the CNN effectively identifies pneumonia from chest X-ray images, as depicted in Figure 5, demonstrating its potential as a valuable diagnostic tool for respiratory infections in medical settings.

5. Investigation Analysis and Outcome Discussions

After the training phase, the performance of the various testing datasets was assessed and compared using four key metrics: accuracy, recall, precision, and F1 score, as illustrated in Table 1.

In Figures 6 through 9, we can observe the training & validation loss (T&V Loss) as well as the training & validation accuracy (T&V accuracy) results for Brain tumor, Alzheimer's disease, Covid-19, and Pneumonia, displayed in sequence.

Table 1

Performance Evaluation of Multi-Diseases

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Alzheimer	99.37	99.45	99.62	99.5
Brain Tumor	99.65	99.34	96.04	99.54
COVID-19	95.90	98.89	93.45	96.09
Pneumonia	94.54	92.61	86.79	89.61

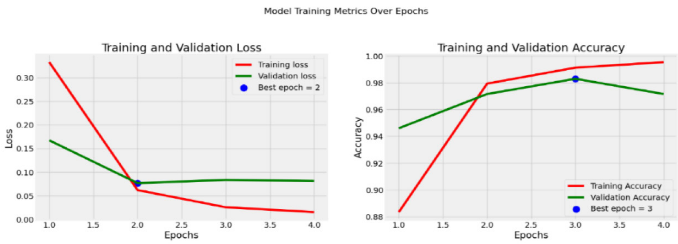

Figure 6

Brain Tumor a) T&V Loss b) T&V Accuracy

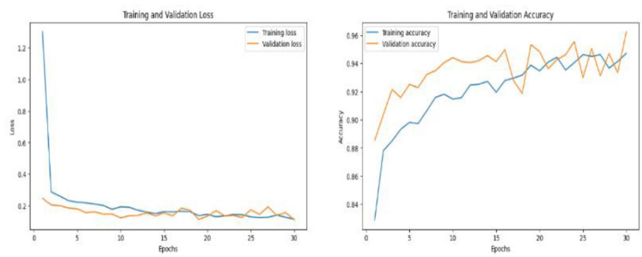

Figure 7

Alzheimer a) T&V Loss b) T&V Accuracy

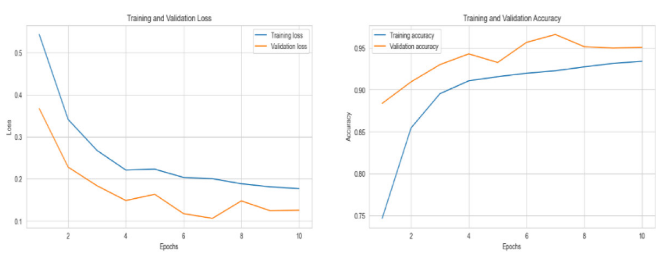

Figure 8

Covid19 a) T&V Loss b) T&V Accuracy

Figure 9

Pneumonia a) T&V Accuracy b) T&V Loss

6. Conclusion

Deep learning is improving medical diagnosis for diseases like brain tumors, COVID-19, and pneumonia. These algorithms offer accurate and efficient early detection and personalized treatment. Alzheimer's detection has 99.37% accuracy, brain tumors 98%, COVID-19 95.90%, and pneumonia 94.54%. Collaboration among researchers, healthcare providers, and policymakers is essential to address challenges and ensure responsible AI use, leading to better patient outcomes globally.

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