Automated Disease Detection from X-ray and CT Scan Images using Deep Learning

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Abstract

This study presents an automated disease detection framework designed to perform binary classification on medical images through a tailored convolution-based neural architecture. Separate models are constructed on X-ray and CT scan datasets, with standardized image preprocessing and regularization techniques applied to enhance data quality and consistency for effective feature extraction. The network is trained using the Adam optimizer combined with categorical cross-entropy loss to effectively differentiate between normal and pathological cases. Model performance is evaluated based on training and validation accuracy, along with corresponding loss values recorded throughout the learning process. Experimental outcomes indicate that the developed CNN delivers reliable classification results, highlighting the practical effectiveness of deep learning techniques for early and automated medical screening.

Keywords: CNN, Medical Image Classification, X-ray Analysis/CT-Scan, Detection of Diseases, Deep Learning, Adam Optimizer, Binary Classification.

1.Introduction

Medical imaging is widely used for the early identification of conditions such as pneumonia, kidney stones, and brain tumors, and bone malignancies. Conventional diagnostic procedures depend primarily on human-driven interpretation by radiologists often resulting in time-intensive and influenced by factors such as workload and visual fatigue, potentially leading to inconsistent assessments. As the volume of medical imaging data continues to increase and the demand for timely clinical evaluation grows, the burden on healthcare professionals has intensified, driving the need for automated diagnostic assistance. Recent advances learning-based methods have shown have enabled intelligent systems for consistent and dependable interpretation of medical images. Convolutional Neural Networks extract meaningful patterns from from imaging data, eliminating the dependence on handcrafted feature extraction methods. These models consistently show capability in detecting subtle abnormalities, identifying tumor regions, and classifying diseases into appropriate categories with consistent performance. Motivated by these developments, this research focuses on designing an integrated multi-disease detection framework based on CNN architectures trained on X-ray and CT scan datasets. The proposed system aims to improve diagnostic accuracy and at the same time decrease interpretation time.

2. Literature Survey

A number of studies have explored the application of learning-based methods to diagnosing diseases from medical images. In this context, Taeg Keun Whangbo et al. [1], an optimized YOLOv7 model is utilized to achieve fast and accurate detection of meningioma, glioma, and pituitary tumors, which integrates Darknet-53, SPP, and PANet for improved feature extraction, while transfer learning with hyperparameter tuning along with the Adam optimizer helps attain high detection accuracy. Similarly, Arati Rath et al. [2] identify brain tumors using MRI data scans using ResNet50, pre-trained on ImageNet comprising 3,015 labeled images, each resized to 224×224 pixels and augmented through rotation, flipping, and zooming. The model was developed using TensorFlow/Keras on Google Colab using GPU support and its performance was assessed based on accuracy, precision, and recall, F1-score. Lastly, kidney stone detection as proposed by P. S.

Ramesh et al. [3] uses CNN trained on a balanced CT scan dataset with positive and negative cases, followed by convolution and pooling layers for feature extraction. After that, hyperparameter optimization is performed, and its accuracy is tested with precision, recall, and F1-score to establish the validity of this model in real life.

This research extends the study into advanced CNN-based medical image analysis, wherein Swapnil Singh et al. [4] detect pneumonia using 5,863 pediatric chest X-ray images; data augmentation helps in improving generalization, and two learning-based models were used to analyze the MLP and a custom CNN. The CNN gave an accuracy of 92.63% and displayed a GUI that visualizes lung congestion. Along similar lines, Nisha N et al. [5] perform kidney stone detection on a balanced dataset separated into separate training, validation, and testing sets. convolution and pooling layers are used for feature extraction, with performance improving as the dataset size increases in terms of accuracy, precision, and recall and F1-score. Qiuyu An et al. [6] enhanced pneumonia classification by proposing a hybrid deep CNN, DenseNet121 combined with EfficientNetB0, for capturing high-level and fine-grained features; on the other hand, rotation, scaling, flipping, and adjustment of contrast are augmentation techniques to reduce overfitting; and fully connected layers finalize the binary classification.

This work extends the previous efforts within the domain of medical image analysis based on learning-driven models and preprocessing techniques across multiple disease categories. Patrik Szepesi et al. propose pneumonia detection in infants, which works on 5,856 Kaggle lung X-rays. The class imbalance problem is resolved by adding GAN-generated synthetic images, after which the images were resized to 224×224 dimensions, normalized, and trained, with the Adam optimizer and batch size 16, at a learning rate of 10^{-4} in order to avoid overfitting. This results in strong performance for classification. Detection of bone tumor from X-rays was addressed by the CNN-based classification approach of M. Dhanaraju et al., followed by thresholding and segmentation. The images were processed and converted into binary forms, and contrast enhancement was performed. Then, by using Generalized Gaussian Density, Regions of Interest are analyzed. It presented high accuracy with 253 labeled images. Similarly, Kanimozhi Sampath et al. present the processing of 1,141 CT scans by K-means clustering and Canny edge detection for identifying Osteochondroma, Enchondroma, and Parosteal Osteosarcoma, while also motivated by pre-processing steps including median filtering. This data is divided into 80/10/10, and the models were trained for 20 epochs to better understand their learning patterns.Afsana Akter et al. : Br35H MRI dataset of 3,000 images has been augmented to 18,000 images to reduce overfitting. The work addresses multiple models including a custom CNN and several pre-trained networks: InceptionV3, ResNet101, VGG19, and DenseNet169. Images were resized and split into 80% training, 10% validation, and 10% testing. The architecture is evaluated using accuracy, precision, recall, and F1-score.

3. Preliminaries

The research work presented in this paper is built using deep learning techniques, mainly Convolutional Neural Networks (CNNs). These methods are widely used in medical image classification as they can automatically learn important feature patterns from scanned images. Using convolutional, pooling, and fully connected layers helps the network recognize edges and abnormal areas in medical images, leading to accurate diagnosis. For pneumonia detection, a CNN model derived from the VGG architecture is applied due to its deep layered design. For kidney stone detection, brain tumor identification, and bone tumor classification, separate CNN models are employed using X-ray and CT scan images.

Image preprocessing is performed to improve model performance and to reduce overfitting. In this work, the models are trained using a cross-entropy loss function and optimized with the Adam optimizer. To assess classification performance across all disease categories, precision, recall, and F1-score are used as the primary evaluation metrics.

4. Proposed Methodology

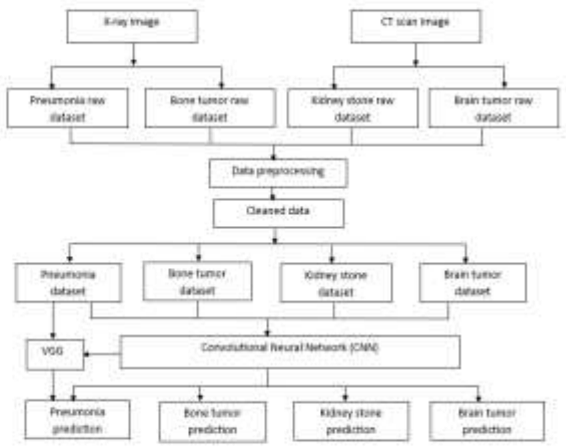

Fig 1: System Architecture

The proposed methodology encompasses the entire workflow, right from data creation to disease prediction. Medical images related to pneumonia, bone tumor, kidney stone, and brain tumor diseases were gathered from open-source repositories, with X-ray images being considered for pneumonia and bone tumor detection and CT images for kidney stone and brain tumor classification. These images were organized into labeled folders and preprocessed to ensure consistency through resizing, normalization, and enhancement. Images containing noise, blurriness, and duplicate entries were removed, and data augmentation was applied to increase variance within the datasets and to decrease overfitting. CNN architectures for brain tumor, kidney stone, and bone tumor detection and a VGG16-based architecture for pneumonia classification were developed. These architectures consisted of convolutional, pooling and fully connected layers followed by Softmax or Sigmoid output layers

The pre-processed and augmented datasets was split into training, testing, and validation sets models were fitted according to the Adam optimizer with categorical or binary cross-entropy loss. The training was monitored by accuracy and loss, along with metrics on validation. Models were assessed for performance using accuracy, precision, recall, the F1 score, and confusion matrices, so that verify their reliability on unseen data. Optimization techniques like hyperparameter tuning, dropout, regularization, extra augmentation, and fine-tuning deeper VGG layers were employed to enhance performance.

Finally, all the models after training were saved as .h5 files and were deployed using a Streamlit based interface that integrates the four disease classifiers into a single diagnostic platform. The deployment pipeline makes certain all images are pre-processed consistently and provides real-time disease predictions with confidence scores, including mechanisms for error handling in case invalid or mismatched image inputs are provided.

Algorithm: Multi-Disease Detection Using CNN & VGG

Input: X-ray or CT image

Output: Detected disease label (Pneumonia / Bone Tumor / Kidney Stone / Brain Tumor / Normal)

Step 1: Load the trained CNN/VGG models.

Step 2: Accept an image from user or dataset.

Step 3: Perform image preprocessing:

- Resize
- Normalize

Step 4: Identify image type (CXR, CT, Brain, Bone) using image statistics.

Step 5: Select appropriate model based on disease class.

Step 6: Feed preprocessed image into selected model.

Step 7: Obtain output probability vector from Softmax/Sigmoid layer.

Step 8: Compare probability with predefined thresholds.

Step 9: If probability ≥ threshold → Disease Detected.

Step 10: Else → Normal / No Disease.

Step 11: Display final prediction with confidence score through Stream-lit UI.

5. Results and Analysis

This work highlights the experimental outcomes of the designed system for multi-disease identification using medical images. The performance of both models, CNN and VGG, was tested using common evaluation parameters such as precision, accuracy, F1 score, recall, and confusion matrix will be created for every class of diseases. A detailed analysis of this was conducted by using a Streamlit GUI, where a medical image can be uploaded for immediate results. The below figures highlight the output provided for different classes to brief readers on the efficiency of this design in identifying both diseased and non-diseased images.

Mismatch Condition and Error Handling

The system embeds an automatic image-type detection mechanism that checks various statistics of the image features, such as mean brightness, edge density, bone-bright ratio, and aspect ratio, against the selected disease category. If a user uploads an incorrect image type-for example, uploading a brain MRI with the Pneumonia model selected-the system triggers an "Image–Model Mismatch" warning and stops the prediction process to avoid invalid results. It helps guide the user either to select the correct model or to upload the appropriate X-ray or CT image. The mismatch warning would also include the detected image type and a short suggestion for correction. Thresholds for determining image type can be changed, and when uncertain, a forced prediction might be allowed by the system, yet only with a very conspicuous mismatch warning.

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5.1 Evaluation Metrics

The performance of this proposed system is assessed using precision, accuracy, F1-score along with recall, which are derived from the confusion matrix values.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

$$\text{Precision}=\frac{\text{TP}}{\text{TP+FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5.2 Confusion Matrix Results

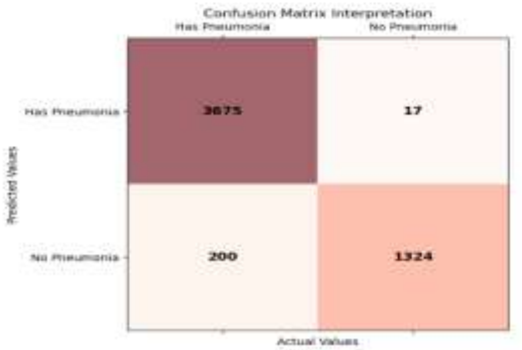

Fig 2: Confusion matrix for proposed pneumonia detection model

Fig. 5.1. displays the confusion matrix for the proposed pneumonia detection model. The model correctly classified most pneumonia and non-pneumonia cases, with very few misclassifications, indicating effective discrimination between the two classes.

Table 1: Various metrics and their values

Metric	Accuracy	Precision	Recall	F1-score
Value	95.84%	99.54%	94.84%	97.13%

Table 1 presents the performance metrics, where the proposed model attained an accuracy of **95.84%**, precision of **99.54%**, recall of **94.84%**, and an F1-score of **97.13%**. These findings indicate that this model provides dependable and precise performance for automated pneumonia.

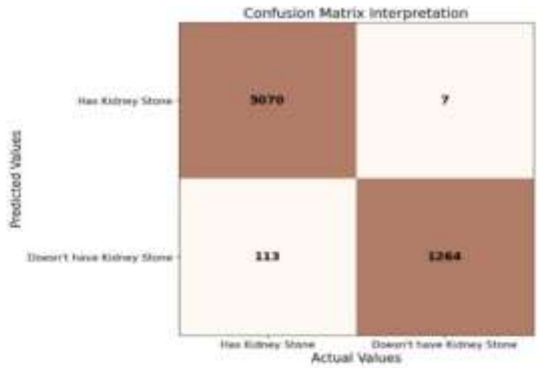

Fig 3: Confusion matrix for proposed Kidney stone detection model

Fig. 5.2 displays the confusion matrix for the proposed Kidney stone detection model. The model correctly classified most kidney stone and non-kidney stone cases, with very few misclassifications, indicating effective discrimination between the two classes.

Table 2: Various metrics and their values

Metric	Accuracy	Precision	Recall	F1-score
Value	98.14%	98.17%	98.14%	98.11%

Table 2 presents the performance metrics, where the proposed model attained an accuracy of **95.84%**, precision of **99.54%**, recall of **94.84%**, and an F1-score of **97.13%**. These findings indicate that this model provides dependable and precise performance for automated pneumonia detection.

6. Conclusion

This study presents a deep learning–based system for detecting pneumonia, bone tumors, kidney stones, and brain tumors using X-ray and CT scan images. The developed system learns disease-specific patterns effectively by combining customized CNN models with a VGG-based architecture, resulting in robust classification performance among all four categories. Appropriate image preprocessing, data augmentation, and model optimization contribute to better generalization and improved overall performance. A Streamlit-based interface enables real-time prediction and ensures reliability by automatically detecting image–model mismatches, thereby preventing invalid results from incorrect inputs. Overall, the developed model functions as an efficient support system that can assist clinicians in early diagnosis and improve access to healthcare services. Further improvements could be made by increasing the dataset, adding more disease classes, and improvement in model interpretability.

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