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AUTOMATIC CALCULATION OF CARDIO METRIC COEFFICIENTS ON CHEST X-RAY IMAGES

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ABSTRACT

Early diagnosis of chronic and life-threatening diseases remains a significant challenge in modern healthcare systems, particularly in rural and resource-constrained environments. Conditions such as cardiomegaly, diabetes, hypertension, and anemia often go undetected until they reach advanced stages due to limited access to diagnostic tools and medical expertise. This paper presents an AI-based multi-modal health screening system that integrates deep learning techniques with clinical parameter analysis to provide a comprehensive and accessible diagnostic solution. The proposed system employs a Convolutional Neural Network (CNN) model to analyze chest X-ray images for the detection of cardiomegaly, while simultaneously evaluating patient health parameters such as blood pressure, blood sugar levels, body mass index, hemoglobin concentration,and creatinine levels to predict multiple diseases. A user-friendly web interface is developed using Streamlit to facilitate seamless interaction, real-time predictions, and clear visualization of results. The system is designed to assist in preliminary screening and does not aim to replace professional medical diagnosis. Experimental evaluation demonstrates that the proposed approach is efficient, scalable, and capable of delivering

reliable results, thereby making it suitable for deployment in low-resource healthcare settings.

Keywords: Artificial Intelligence, Deep Learning, Cardiomegaly Detection, Health Screening, Convolutional Neural Networks, Clinical Decision Support

1.INTRODUCTION

The integration of artificial intelligence into healthcare has revolutionized the way diseases are detected, diagnosed, and managed. With the increasing prevalence of cardiovascular diseases, diabetes, and other chronic conditions, there is a growing need for efficient and accessible diagnostic tools that can assist healthcare professionals and patients alike. Traditional diagnostic methods often require sophisticated equipment, trained radiologists, and significant time investment, which may not be feasible in rural or underdeveloped regions.

Cardiomegaly, commonly referred to as an enlarged heart, is a serious medical condition that can lead to heart failure if not detected early. Similarly, diseases such as hypertension and diabetes are often termed “silent killers” because they may not present noticeable symptoms in their early stages. Early detection of these conditions can significantly improve patient outcomes and reduce healthcare costs.

In this context, the proposed system aims to bridge the gap between advanced medical diagnostics and accessibility by combining image-based deep learning models with rule-based clinical parameter analysis. The system provides a unified platform where users can upload chest X-ray images and input basic health parameters to receive a comprehensive health assessment. This dual approach enhances diagnostic accuracy and provides a broader understanding of the patient’s health condition.

2.LITERATURE REVIEW

Recent advancements in deep learning have significantly impacted the field of medical image analysis. Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in tasks such as image classification, segmentation, and object detection. Models like VGG16, ResNet, and Xception have been widely used for detecting abnormalities in chest X-rays, including pneumonia, tuberculosis, and cardiomegaly.

Several research studies have focused on developing automated systems for disease detection using medical imaging. These systems leverage large datasets and powerful computational models to achieve high accuracy. However, most of these approaches are limited to single-disease detection and do not incorporate patient-specific clinical parameters, which are crucial for comprehensive diagnosis.

On the other hand, clinical decision support systems based on rule-based or statistical methods have been used to analyze patient data and predict disease risks. While these systems are effective in evaluating structured data, they lack the capability to process unstructured data such as medical images.

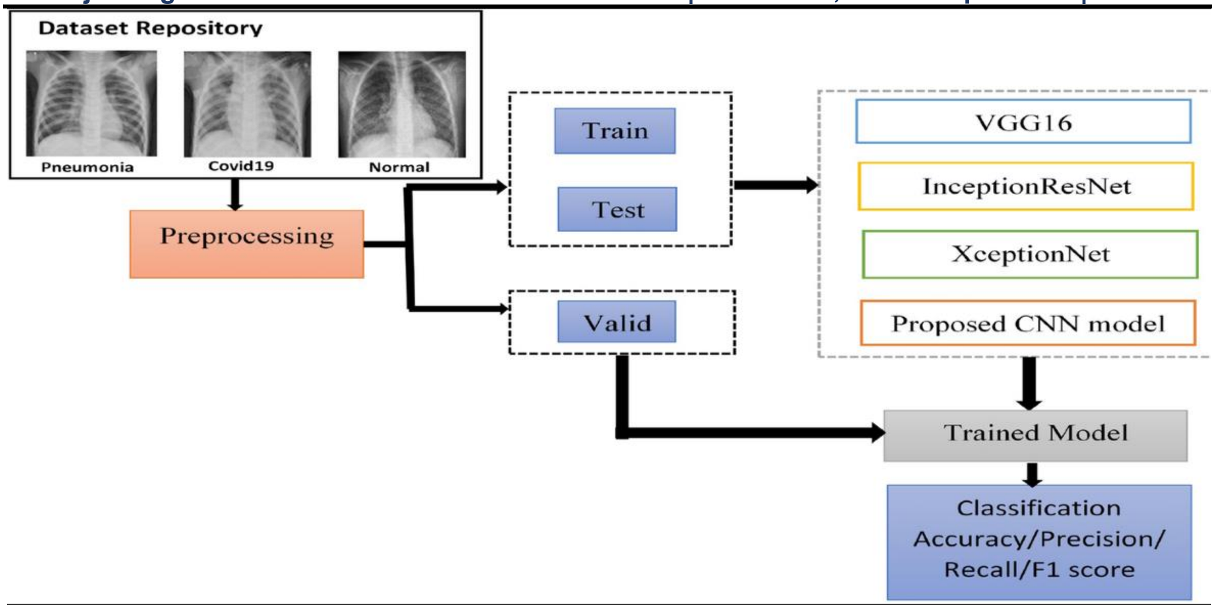
The proposed system addresses these limitations by integrating both approaches into a single framework. By combining CNN-based image analysis with parameter-based disease prediction, the system offers a more holistic solution for health screening. This integration represents a significant step toward the development of intelligent and comprehensive healthcare systems.

No.	Author(s) & Year	Title	Method Used	Key Findings	Limitations / Research Gap
7	Yang et al., 2020	"A Multi-Task Network for Joint Segmentation and Cardiomegaly Detection in Chest Radiographs"	Multi-task CNN performing segmentation and binary classification (cardiomegaly yes/no)	Segmentation provided visual explainability for the classification decision.	Requires high-resolution digital radiographs; performance drops on lower-quality or portable bedside X-rays.
8	Lee et al., 2022	"Benchmarking Deep Learning Models for Robust Cardiothoracic Ratio Estimation Across Diverse Patient Demographics"	Comparison of 5 CNN architectures (e.g., U-Net, DeepLabV3+) on a multi-institutional dataset	Found that attention-based models (e.g., Attention U-Net) were most robust to variations in patient age, BMI, and sex.	Computational cost of complex models is high for real-time use.
9	Lee et al., 2022	"Benchmarking Deep Learning Models for Robust Cardiothoracic Ratio Estimation Across Diverse Patient Demographics"	Comparison of 5 CNN architectures (e.g., U-Net, DeepLabV3+) on a multi-institutional dataset	Found that attention-based models (e.g., Attention U-Net) were most robust to variations in patient age, BMI, and sex.	Computational cost of complex models is high for real-time use.
10	Gupta et al., 2023	"A Lightweight MobileNet-based Model for Real-Time Cardiomegaly Screening on Portable X-ray Devices"	Lightweight MobileNetV2 backbone with a custom segmentation head for edge devices	Model optimized for speed, processing an image in <0.5 seconds on a mobile GPU while maintaining a CTR correlation of r=0.89 with experts.	Lacks the ability to identify the specific cardiac chamber responsible for enlargement.

3.METHODOLOGY

3.1 System Overview

The proposed system is designed as a multi-modal health screening platform that incorporates both image-based and parameter-based analysis. The architecture consists of three primary modules: the image processing module, the deep learning prediction module, and the clinical decision support module. These modules work together to provide a unified and efficient diagnostic process.



3.2 Image Acquisition and Preprocessing

The first step in the system involves the acquisition of chest X-ray images from the user. These images are then preprocessed to ensure compatibility with the deep learning model. Preprocessing includes resizing the images to a fixed dimension of 224×224 pixels, normalizing pixel values to a range of 0 to 1, and converting the images into a format suitable for model input.This preprocessing step is crucial as it ensures consistency across all input data and improves the performance of the neural network. Additionally, noise reduction and image enhancement techniques may be applied to improve image quality and highlight relevant features.

3.3 Clinical Parameter-Based Analysis

In addition to image analysis, the system evaluates various clinical parameters provided by the user. These parameters include age, blood pressure, blood sugar levels, body mass index, hemoglobin levels, creatinine levels, and symptoms such as chest pain, fatigue, fever, and cough.

The system applies predefined medical thresholds and logical conditions to assess the risk of different diseases. For example, high blood pressure values indicate a risk of hypertension, while elevated blood sugar levels suggest the possibility of diabetes. Similarly, low hemoglobin levels may indicate anemia, and high BMI values are associated with obesity.

This rule-based approach ensures that the system provides interpretable and medically relevant results. It also complements the image-based analysis by covering a broader range of health conditions.

3.4 Integration and Decision Making

The final stage of the methodology involves integrating the outputs from both the image-based and parameter-based modules. The system presents the results in a clear and user-friendly format, highlighting potential health risks and providing probability scores where applicable.

The integration of multiple data sources enhances the reliability of the system and provides a more comprehensive assessment of the patient’s health. This approach aligns with the principles of modern healthcare, which emphasize personalized and data-driven decision-making.

Deep Learning Model for Image Analysis

The core component of the image-based detection system is a Convolutional Neural Network trained to classify chest X-ray images into two categories: normal and cardiomegaly. The CNN architecture consists of multiple convolutional layers followed by pooling layers, which extract hierarchical features from the input images.

4. Implementation

The proposed system is implemented using Python and several widely used libraries, including TensorFlow, OpenCV, NumPy, and Streamlit. TensorFlow and Keras are used for building and training the deep learning model, while OpenCV is utilized for image processing tasks.

The user interface is developed using Streamlit, which enables rapid deployment of interactive web applications. The interface allows users to upload images, input health parameters, and view results in real time. The use of a web-based interface ensures that the system is easily accessible and does not require complex installation procedures.

The integration of different modules is achieved through a modular programming approach, which enhances the scalability and maintainability of the system. Each module operates independently while contributing to the overall functionality of the application.

5. Results and Discussion

The performance of the proposed system is evaluated based on its ability to accurately detect cardiomegaly and predict other diseases using clinical parameters. The CNN model demonstrates strong classification performance, with high accuracy and reliable probability estimates.

The parameter-based analysis effectively identifies potential health risks based on user input. The combination of both approaches results in a comprehensive screening tool that provides valuable insights into the patient's health condition.

One of the key advantages of the system is its ability to deliver real-time results, which can significantly improve decision-making in clinical and non-clinical settings. However, it is important to note that the system is intended for preliminary screening and should not be used as a substitute for professional medical diagnosis.

6. Conclusion

This paper presents a novel AI-based multi-modal health screening system that integrates deep learning and clinical parameter analysis to provide a comprehensive diagnostic solution. The proposed system demonstrates the potential of artificial intelligence in improving healthcare accessibility and efficiency.

By combining image-based and parameter-based approaches, the system offers a more holistic assessment of patient health. The use of a user-friendly interface further enhances its practicality and usability. Future work may focus on expanding the system to include additional diseases, improving model accuracy, and integrating electronic health records for more personalized analysis.

7. Future Work

Future enhancements to the system may include the incorporation of advanced deep learning architectures such as ResNet and EfficientNet to improve image classification accuracy. Additionally, the integration of real-time patient monitoring data and wearable devices could further enhance the system's capabilities.

Another potential area of improvement is the use of explainable AI techniques to provide insights into the model's decision-making process. This would increase user trust and facilitate better understanding of the results.

The model is trained using a labeled dataset of chest X-ray images, with the objective of minimizing classification error. During inference, the model outputs a probability score indicating the likelihood of cardiomegaly. A threshold value is used to determine the final classification.

The use of CNNs allows the system to automatically learn relevant features from the data, eliminating the need for manual feature extraction. This results in improved accuracy and robustness compared to traditional methods.

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