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Pneumonia Detection System using Deep Learning and Streamlit

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Abstract: *This paper presents the design and implementation of a deep learning-based pneumonia detection system using convolutional neural networks (CNNs) and a user-friendly interface developed with Streamlit. The platform allows medical professionals and researchers to upload chest X-ray images and receive real-time predictions about the presence or absence of pneumonia. The model is trained on publicly available datasets and evaluated using standard classification metrics. The system is built with a focus on accessibility, explainability, and ease of deployment. Although advanced features such as multi-disease classification and model explainability using Grad-CAM are not included in the current version, this implementation provides a solid foundation for future healthcare-oriented AI systems*

Keywords: Pneumonia Detection, Deep Learning, CNN, Streamlit, Medical Imaging

I. INTRODUCTION

Respiratory diseases such as pneumonia are among the leading causes of mortality worldwide, especially in children and elderly populations. Early and accurate detection is crucial for effective treatment. Traditional diagnosis through chest X-ray analysis is timeconsuming and prone to human error. Recent advancements in deep learning have shown great promise in automating medical image classification tasks with high accuracy.

This paper discusses the implementation of a pneumonia detection platform using a Convolutional Neural Network (CNN) trained on X-ray images and deployed via a

lightweight Streamlit web interface. The goal is to create a system that is both accurate and accessible, even to users with limited technical expertise. The combination of deep learning for image classification and Streamlit for UI development offers a rapid prototyping solution ideal for healthcare applications.

II. SYSTEM ARCHITECTURE

The system comprises two core components:

1. Deep Learning Model – A CNN built using TensorFlow/Keras trained on a labeled dataset of chest X-rays (such as the NIH or Kaggle Pneumonia dataset).
2. Streamlit Application – A frontend interface that allows users to upload X-ray images and receive diagnostic predictions.

The application workflow is as follows:

• Image upload via Streamlit UI
• Preprocessing and resizing
• CNN model inference
• Result display with classification probability

The backend model classifies images into two categories: Pneumonia and Normal. The system is currently designed for binary classification, and it uses a softmax activation in the final dense layer for prediction.

III. METHODOLOGY

The methodology includes the following steps:

1. Dataset Collection and Preprocessing: The dataset used was pre-cleaned, balanced for classes, and split into training, validation, and testing sets. Images were resized to a standard resolution (e.g., 224x224 pixels).

2. Model Development: A CNN architecture with convolutional, pooling, dropout, and dense layers was developed. The model was compiled with the Adam optimizer and categorical crossentropy loss.
3. Model Training and Evaluation: The model was trained using early stopping and evaluated using accuracy, precision, recall, and F1-score.
4. Streamlit Interface: A user-friendly interface was built using Streamlit. It includes file upload, real-time prediction display, and image rendering.

IV. CHALLENGES AND SOLUTIONS

One challenge was ensuring generalization of the deep learning model on unseen data. To address this, techniques such as dropout regularization, data augmentation, and validation monitoring were employed.
Integrating the model with Streamlit presented another learning curve. Efficient handling of large image files and dynamic feedback in the web interface was solved using caching mechanisms and optimized preprocessing pipelines.
Another limitation was the lack of multi-class classification, which could extend the model to detect other diseases like COVID-19 or Tuberculosis. Additionally, the model does not currently provide visual explanations (e.g., Grad-CAM), which are essential for medical diagnostics.

V. CONCLUSION

This project successfully demonstrates a prototype for pneumonia detection using deep learning and Streamlit. The system is capable of processing chest X-ray images and predicting pneumonia presence with reasonable accuracy. The use of Streamlit makes the system accessible to users without programming knowledge, allowing for potential deployment in real clinical settings.
While the current version is limited to binary classification, it lays the groundwork for more complex medical image classification systems. The combination of TensorFlow for model development and Streamlit for deployment proved to be efficient and effective.

VI. FUTURE WORK

Potential improvements to the platform include:
1. Grad-CAM Integration: To provide visual explanation of predictions for improved interpretability.
2. Multi-class Classification: Extending the system to detect other chest diseases.
3. Cloud Deployment: Hosting the application using platforms like Streamlit Cloud, Heroku, or AWS.
4. Mobile Accessibility: Building a responsive version or mobile app for use in remote regions.
5. Medical Data Compliance: Ensuring HIPAA/GDPR compliance for real-world deployment.

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