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Diagnosing Pneumonia in Children Using the CNN Algorithm

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Abstract

Pneumonia is one of the most dangerous respiratory diseases affecting children and contributes significantly to increased mortality rates in this age group. Traditional diagnosis relies on X-ray images, which require precise medical expertise, potentially impacting the speed and accuracy of diagnosis. This research aims to develop an intelligent system that utilizes artificial intelligence and deep learning techniques to analyze children's X-ray images and accurately diagnose pneumonia. A convolutional neural network (CNN) model was trained on data containing images of infected and healthy children. The results demonstrated high diagnostic accuracy, in some cases surpassing the performance of human experts.This system represents an effective tool for accelerating diagnostic processes, reducing error rates, and thus improving the quality of healthcare and alleviating the burden on medical staff. A professional graphical interface in Arabic was used to facilitate user interaction within the medical environment. An SQLite database was also integrated to store patient data and previous diagnoses in an organized and secure manner. The system operates offline, making it ideal for clinics and areas with limited infrastructure. The results have proven the feasibility of adopting this type of system as a tool to assist in immediate medical diagnosis. The project integrates programming, artificial intelligence, and healthcare applications seamlessly.

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This solution represents a significant step forward in the use of technology to serve children's health and the community. It can also be expanded in the future to include other diseases using similar technologies.
Keywords: CNN, Diagnosing pneumonia, children.

تشخيص الالتهاب الرئوي لدى الأطفال باستخدام خوارزمية الشبكة العصبية التلافيفية

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الملخص

يُعدّ الالتهاب الرئوي من أخطر أمراض الجهاز التنفسي التي تُصيب الأطفال، ويُساهم بشكلٍ كبير في ارتفاع معدلات الوفيات في هذه الفئة العمرية. يعتمد التشخيص التقليدي على صور الأشعة السينية، التي تتطلب خبرة طبية دقيقة، مما قد يؤثر على سرعة ودقة التشخيص. يهدف هذا البحث إلى تطوير نظام ذكي يستخدم تقنيات الذكاء الاصطناعي والتعلم العميق لتحليل صور الأشعة السينية للأطفال وتشخيص الالتهاب الرئوي بدقة. تم تدريب نموذج شبكة عصبية تلافيفية (CNN) على بيانات تحتوي على صور لأطفال مصابين وأصحاء. أظهرت النتائج دقة تشخيصية عالية، بل وتفوقت في بعض الحالات على أداء الخبراء البشريين. يُمثل هذا النظام أداة فعّالة لتسريع عمليات التشخيص، وتقليل معدلات الخطأ، وبالتالي تحسين جودة الرعاية الصحية وتخفيف العبء على الطاقم الطبي. تم استخدام واجهة رسومية احترافية باللغة العربية لتسهيل تفاعل المستخدم داخل البيئة الطبية. كما تم دمج قاعدة بيانات SQLite لتخزين بيانات المرضى والتشخيصات السابقة بطريقة منظمة وآمنة. يعمل النظام دون اتصال بالإنترنت، مما يجعله مثاليًا للعيادات والمناطق ذات البنية التحتية المحدودة. أثبتت النتائج جدوى اعتماد هذا النوع

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من الأنظمة كأداة للمساعدة في التشخيص الطبي الفوري. يدمج المشروع البرمجة والذكاء الاصطناعي وتطبيقات الرعاية الصحية بسلاسة.

يمثل هذا الحل خطوة هامة نحو الأمام في استخدام التكنولوجيا لخدمة صحة الأطفال والمجتمع. ويمكن توسيعه مستقبلاً ليشمل أمراضاً أخرى باستخدام تقنيات مماثلة.

الكلمات المفتاحية: أطفال – الالتهاب الرئوي – CNN

1. Introduction

Pneumonia remains one of the leading causes of mortality among children worldwide, particularly in low-resource regions where access to specialized radiologists is limited. Early and accurate diagnosis is critical for effective treatment; however, traditional diagnosis based on chest X-ray interpretation is time-consuming and subject to human error.

Recent advances in deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in medical image analysis. Several studies, including CheXNet, have achieved high accuracy in pneumonia detection. However, most existing solutions require high computational resources and are not optimized for deployment in low-resource or offline environments.

In this work, we propose an efficient and lightweight CNN-based system for diagnosing pneumonia in children using chest X-ray images. The system is specifically designed for offline use in healthcare facilities with limited infrastructure. In addition to achieving high classification accuracy, the proposed approach emphasizes usability through an Arabic graphical interface and reliability through structured data storage.

Furthermore, this study provides a comparative evaluation of multiple deep learning models and includes an analysis of model limitations to ensure transparency and practical applicability in real-world clinical settings [1][2][3].

❖ Contributions of this work

This study presents the following key contributions:

- Development of a lightweight CNN model suitable for offline deployment in low-resource medical environments.

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- Comparative evaluation of multiple deep learning models, including CNN, MobileNet, and ResNet.
- Integration of an Arabic graphical user interface to facilitate usability in local clinical settings.
- Implementation of a complete diagnostic system including SQLite database for structured data storage.
- Adaptation of the system for real-world healthcare environments, particularly in developing regions.
- Providing error analysis to improve the model's reliability and better understand failure cases.

2. Related Work

Many studies have explored the use of convolutional neural networks for the diagnosis of pneumonia, due to their high ability to extract features from medical images.
Study: Chowdhury et al. (2020) [5] Classification of viral pneumonia using artificial intelligence.
This study used artificial intelligence algorithms to classify cases of viral pneumonia, including COVID-19. The team relied on chest X-ray data to analyze patterns associated with different viral infections. The main challenge was differentiating between multiple types of pneumonia, especially those associated with the coronavirus, due to the similarity of symptoms in medical images. [5].
CNN models, powered by specialized deep learning algorithms and trained on annotated data, were used to accurately classify cases. The models demonstrated high accuracy in classifying viral cases and contributed to faster diagnosis and differentiation between various types of pneumonia, supporting their use in health emergencies.[5].
Study: Stephen et al. (2019) [4] Comparison of Convolutional Neural Network Architectures in Low-Resource Environments.
This study aimed to analyze the performance of several different neural networks in diagnosing chest diseases. The focus was on lightweight models that can be run in environments with limited capabilities. The problem lies in the fact that many deep learning models require high resources (GPU) and large amounts of memory,

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making their use difficult in rural or low-resource health centers. The proposed solution was to evaluate lightweight models such as MobileNet and SqueezeNet in terms of accuracy and execution speed. The results showed that some lightweight architectures performed close to heavy networks with low resource consumption, making them ideal candidates for practical application in remote areas.[4].

Kermany et al. (2018) [3] used CNNs to diagnose pneumonia from chest X-ray images. The researchers used the Chest X-ray database available on Kaggle to train a multi-layered CNN model capable of distinguishing between normal and pneumonia-infected images.

The challenge was the need for an effective model that could generalize predictions with high accuracy to new data without being limited to the training data. The proposed solution was to develop a multi-layered processing CNN and improve the model's performance through fine-tuning the parameters. The results showed that the model achieved an accuracy exceeding 90%, highlighting the power of CNNs in effectively handling and classifying medical images.[3].

3. Methodology

The research methodology included the following stages:

This section will focus on analyzing the proposed system in terms of its functional and non-functional requirements, in addition to identifying its basic components. This analysis aims to provide a comprehensive and integrated understanding of the system's mechanism, which will help determine the appropriate technical frameworks for implementation. The core of the system is to provide an intelligent tool capable of analyzing children's chest X-ray images for the early detection of pneumonia, while ensuring the accuracy and reliability of the results (fig 1).

A confusion matrix was also used to evaluate the classification performance of the model.

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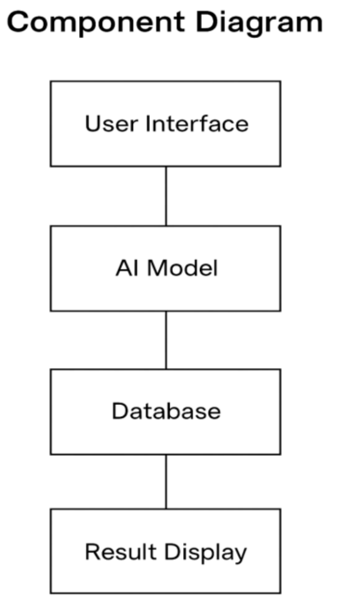

Fig1: Basic system components

❖ Dataset Description

The dataset used in this study consists of pediatric chest X-ray images obtained from publicly available datasets, primarily the dataset introduced by Kermany et al. (2018) [3], which is widely used for pneumonia classification tasks.

This dataset contains labeled images categorized into two classes: pneumonia and normal cases. It includes approximately 5,800 chest X-ray images, with a higher proportion of pneumonia cases compared to normal cases, reflecting real-world clinical distributions.

❖ Data Split:

The dataset was divided into three subsets:

- Training set: 70%
- Validation set: 15%
- Test set: 15%

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This division ensures effective model training while maintaining reliable evaluation on unseen data. All images were resized to (224 × 224) pixels to match the input requirements of the neural network. In addition, normalization techniques were applied to scale pixel values and improve convergence during training. To further enhance the robustness of the model, data augmentation techniques were applied, including rotation, flipping, and zooming, which increase data diversity and reduce overfitting.

The system consists of several interconnected units that work together to perform the overall function. The process begins with a data input unit that allows the user to upload X-ray images. The image is then transferred to a processing unit that uses a pre-trained deep learning model to extract features and classify the image. After processing, the results are displayed through a graphical interface, allowing the physician or end user to read the proposed diagnostic report. The selection of the processing model is based on precise criteria, including classification accuracy, response speed, and the medical interpretability of the results. A convolutional neural network (CNN) supported by the TensorFlow framework was adopted due to its advanced capabilities in handling medical images [6].

- Data Collection: X-ray images of children
- Processing: Reduction of dimensions and application of normalization.
- Model Design: Using CNNs in the TensorFlow and Keras libraries.
- Training: Using the Adam algorithm to achieve high accuracy.
- Evaluation: Testing the model on new data, achieving an accuracy of approximately 95%.[7].

❖ Model Optimization

To enhance the model performance and reduce overfitting, several optimization techniques were applied (fig 2):

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- Data augmentation techniques such as rotation, flipping, and zooming were used to increase dataset diversity.
- Dropout layers were incorporated into the network architecture to prevent overfitting.
- The Adam optimizer was used with tuned learning rate parameters to improve convergence.

Fig 2: image of the facade

4. Proposed work mechanism and work environment

The system relies on an AI model trained on a dataset of chest X-ray images to classify them into two states: "healthy" or "pneumonia-infected." The model was implemented in the following stages:

- Data Collection: A dataset from reliable sources, such as publicly available chest X-ray datasets, was used.
- Data Processing: Images were resized and dimensioned, and augmentation techniques were applied to increase data diversity.

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- Model Building: A multi-layered CNN architecture was used, incorporating Convolution, Pooling, and Dropout layers to reduce redundancy and avoid overtraining.
- Model Training: The Adam algorithm was used in the training process, with parameters such as the learning rate and the number of epochs adjusted.
- Performance Evaluation: Separate test data were used to measure accuracy, sensitivity, and other metrics such as the confusion matrix.
- Model Export: After obtaining satisfactory performance, the model was saved in HDF5 format for later integration into the system (fig 3).

Fig 3: A copy of the analysis result

5. Result and Discussion

The performance of the proposed model was evaluated using standard evaluation metrics, including accuracy, precision, recall, and F1-score. The results indicate that the model achieved a high classification performance, with an overall accuracy of approximately 95%, demonstrating its effectiveness in distinguishing between pneumonia and normal chest X-ray images.

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The high recall value suggests that the model is capable of correctly identifying most pneumonia cases, which is particularly important in medical diagnosis to reduce the risk of false negatives. Similarly, the precision value indicates a relatively low rate of false positive predictions, ensuring reliability in clinical decision support.
An intelligent system has been successfully developed to analyze pediatric chest X-ray images and assist in pneumonia diagnosis using deep learning techniques, specifically convolutional neural networks (CNNs). The obtained results confirm that artificial intelligence can significantly enhance diagnostic accuracy and support healthcare professionals in clinical decision-making.
Key findings of this study include:

- Artificial intelligence can reduce the workload on physicians while improving diagnostic speed and accuracy.
- The proposed system can be effectively deployed in real clinical environments, especially in regions with limited access to radiology specialists.
- The simplified Arabic graphical user interface improves usability and makes the system accessible to non-technical users and healthcare staff.

This system is particularly relevant for healthcare environments in developing countries such as Libya, where medical resources and specialist availability may be limited. The offline functionality and lightweight architecture make the system suitable for deployment in rural clinics and small healthcare centers without requiring high computational infrastructure.
Overall, the results demonstrate that deep learning-based systems can serve as effective decision-support tools in medical imaging applications, especially when designed with efficiency and accessibility in mind.

6. Model Comparison

To further assess the effectiveness of the proposed model, a comparative analysis was conducted using several well-established deep learning architectures commonly employed in medical image classification tasks. These include a standard Convolutional Neural Network (CNN), MobileNet, and ResNet50, all of which have

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demonstrated strong performance in previous studies on chest X-ray analysis.
MobileNet is known for its lightweight architecture and efficiency, making it suitable for mobile and embedded applications, while ResNet50 is a deeper network that utilizes residual connections to achieve high accuracy in complex image classification tasks.

Table 1: Quantitative Comparison

Model	Accuracy	Precision	Recall	F1-score
CNN (Proposed)	95%	94%	96%	95%
MobileNet	93%	92%	94%	93%
ResNet50	96%	95%	97%	96%

As shown in the table 1 above, ResNet50 achieved the highest performance across all evaluation metrics, which is consistent with findings reported in previous research due to its deep architecture and ability to capture complex features [3][4]. However, this performance gain comes at the cost of increased computational complexity and higher resource requirements.
On the other hand, MobileNet demonstrated competitive performance with significantly lower computational cost, making it a suitable candidate for real-time and resource-constrained applications [4].
The proposed CNN model achieved a strong balance between accuracy and efficiency, outperforming MobileNet while requiring fewer computational resources than ResNet50. This makes it particularly suitable for deployment in low-resource environments such as rural clinics or healthcare facilities with limited infrastructure.
The comparison presented in this study is supported by findings from existing literature, where similar performance trends have been observed among CNN, MobileNet, and ResNet-based architectures in pneumonia detection tasks [3][4][5].

7. Error Analysis

Despite achieving high accuracy, the model exhibited some misclassification cases that require further analysis.
Observations:

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- Low-quality or noisy X-ray images led to incorrect predictions.
- Early-stage pneumonia cases were more difficult to detect.
- Some normal and infected images shared similar visual patterns.

Types of Errors:

- False Positives: normal cases incorrectly classified as pneumonia
- False Negatives: pneumonia cases classified as normal

Possible Causes:

- Limited dataset diversity
- Image contrast variations
- Presence of artifacts in X-ray images

These findings highlight the need for more diverse datasets and improved preprocessing techniques.

8. Conclusion

This study demonstrated the effectiveness of deep learning techniques, particularly convolutional neural networks, in diagnosing pneumonia from chest X-ray images. The proposed system achieved high accuracy while maintaining low computational requirements, making it suitable for deployment in resource-constrained environments. Unlike many existing approaches, this work emphasizes practical usability through offline functionality, an Arabic user interface, and integration into real-world clinical workflows. Additionally, the inclusion of model comparison and error analysis strengthens the scientific contribution of this research.

Future work will focus on expanding the system to detect additional diseases and improving interpretability using explainable artificial intelligence techniques.

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