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Development of Deep Learning Medical Imaging Model for Interpreting Pneumonia Diagnosis

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Abstract: Pneumonia is still one of the key public health problems, particularly in resource-poor areas like Kisii County in Kenya, where poor diagnostic equipment hinders early diagnosis. In this project, the intention was to develop and evaluate an explainable deep learning approach for the diagnosis of pneumonia using Chest X-rays. The use of the DenseNet-121 model was considered appropriate since it is efficient in terms of its connection structure and, thus, enables effective feature extraction without the problem of vanishing gradients. Pre-processing of data for better generalization involved contrast limited adaptive histogram equalization (CLAHE), normalization, and data augmentation. Results obtained from the experiment showed a good performance, with an internal accuracy of 97.5% and an external accuracy of 93.6%. To overcome the problem of deep learning models considered as "black boxes," the model adopted explainability techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and SHapley Additive exPlanations (SHAP) which allowed for providing explanations not only in the form of visual heatmaps but also feature-based ones to enable physicians to comprehend predictions. According to feedback from practitioners in the field, the incorporation of explainability was positively regarded due to the gained confidence and trust, thereby showing the possibility for adoption of the solution in practice. In general, this study proves the value of applying explainable AI solutions to provide an accurate and reliable diagnostic tool in rural areas where radiologists are rare.

Keywords: Pneumonia detection, Medical imaging, Deep learning, DenseNet-121, Grad-CAM, SHAP

1. Introduction

Pneumonia remains one of the most significant global public health concerns to date, particularly in developing and less developed nations where there may be limited resources available within the health sector.

History
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It remains among the primary contributors to morbidity and mortality on a global scale, affecting populations considered at-risk, such as children under the age of five and elderly individuals. The World Health Organization states that pneumonia contributes to nearly 14% of all child deaths in children under the age of five globally. This statistic highlights the continued impact of pneumonia on populations worldwide [1]. Sub-Saharan Africa shoulders a disproportionate share of the burden resulting from pneumonia due to limited access to quality healthcare, lengthy diagnostic procedures, and inadequate treatment modalities. Currently, pneumonia remains among the greatest public health challenges facing Kenya, and it is among the leading causes of hospitalizations and mortality [2]. The problem is even more pronounced in underdeveloped and underserviced areas, such as Kisii County, where healthcare centers struggle with issues of inadequate facilities, lack of necessary diagnostic tools, and shortage of specialists. Consequently, timely detection

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and treatment of patients remain major challenges in mitigating mortality. As far as the diagnostics are concerned, chest radiography, which mainly encompasses chest x-ray examination, is the most accessible and cost-effective procedure to confirm pneumonia. The technique aids in detecting structural anomalies within the lung as well as assessing the severity of the illness. Despite this advantage, accurate reading of chest X-rays remains highly dependent on the skill set of competent radiologists. However, there are shortages of radiologists in various regions of Kenya, particularly in Kisii County. As a result, generalist health practitioners who do not possess adequate training to interpret chest X-rays are handling cases [3].

The latest advancements in AI and DL technologies are quite promising in terms of their impact on enhancing medical diagnosis processes, specifically through analyzing medical images. In recent studies, deep learning-based CNN models have been proven to be quite proficient in detecting features in medical images and identifying diseases. As stated earlier, several studies have indicated that DenseNet and CheXNet models are capable of detecting pneumonia in X-ray images with a level of accuracy comparable to that of an experienced radiologist [4 – 5]. The models are able to analyze imaging data rapidly and provide accurate diagnostic outputs, aiding physicians in decision-making and reducing the workload on health care professionals [6]. Also, most of the current AI systems have been developed using high-resource setting datasets, which do not necessarily match the disease patterns, imaging conditions, and the demographic characteristics of rural health settings in Kenya. As such, their generalizability and application may be limited when used in local health centers such as Nyangena Hospital Limited in Kisii County. There is thus a need for the development of contextually specific models that are accurate and interpretable as well as applicable to low resource settings.

The research problem has been addressed through the design and implementation of a medical imaging solution based on deep learning for the detection of pneumonia using CXRs. Specifically, transfer learning based on the pre-trained DenseNet-121 neural network was performed to boost feature extraction while minimizing computation needs. Data augmentation and pre-processing strategies were also employed to minimize image variations and maximize generalization. The main advantage of using the proposed approach is the inclusion of Explainable Artificial Intelligence (XAI) methods such as Grad-CAM and SHapley Additive exPlanations (SHAP). The mentioned methods ensure visualization and quantification of decision-making processes and highlight the most important regions on chest X-rays [9 – 10]. Therefore, it increases model interpretability and improves the trust of clinicians and leads to better implementation of AI models in the clinical setting. Combining high accuracy and interpretable results will allow health practitioners to diagnose patients faster and with higher precision even in resource-poor areas. Thus, this research will lead to the improvement of patient outcomes and reduce the diagnostic process in rural areas of Kenya. Overall, the developed AI system is flexible and could be adapted to different settings in other parts of LMICs.

The remainder of this paper is organized as follows. Section 2 presents the Related work, covering existing approaches to pneumonia detection, deep learning techniques, transfer learning, and explainable artificial intelligence. Section 3 presents the Materials and Methods, including the datasets, data preprocessing, DenseNet-121 model development, evaluation metrics, and validation procedures. Section 4 presents the Results and Discussion, including model performance, benchmark comparisons, external validation, and XAI findings. Section 5 presents the Conclusion, limitations, and recommendations for future research.

2. Related work

Pneumonia continues to be one of the primary causes of mortality among children aged under five years worldwide, with its greatest impact seen in developing countries [1]. Various global efforts championed by the World Health Organization and UNICEF focus on early detection and the use of technology, including artificial intelligence (AI), as important components in reducing pneumonia-related morbidity and mortality [2]. Deep learning models, particularly convolutional neural networks (CNNs), have increasingly been applied to pneumonia

detection from chest X-ray (CXR) images and have demonstrated diagnostic performance that can support clinical decision-making while improving efficiency and reducing the workload of healthcare professionals [3 – 4].

In Africa, pneumonia accounts for a substantial proportion of childhood morbidity and mortality, while shortages of radiologists and diagnostic equipment continue to constrain timely diagnosis [10 – 11]. Although AI-powered medical imaging solutions have demonstrated considerable potential, their implementation in African healthcare settings is affected by infrastructural limitations, including unreliable electricity, limited internet connectivity, inadequate computing infrastructure, and shortages of specialized technical expertise [8 – 10]. These challenges are particularly pronounced in remote and rural hospitals, where chest X-rays are still predominantly interpreted manually.

Pneumonia remains a significant public health concern in Kenya, particularly in underserved counties such as Kisii, where access to advanced diagnostic technologies and specialist services remains limited [13]. Although emerging studies indicate that deep learning applied to digital chest imaging can improve the speed and accuracy of pneumonia detection, the availability of locally adapted models and appropriate computational infrastructure remains a challenge. Consequently, healthcare facilities such as Nyangena Hospital continue to rely substantially on conventional diagnostic approaches. Recent developments in deep learning have introduced several approaches for improving automated pneumonia detection. Transfer learning using pretrained CNN architectures remains one of the most widely adopted strategies because it enables models to benefit from previously learned visual representations when only limited medical imaging data are available [5]. More recent research has also explored ensemble learning, attention mechanisms, vision-transformer-based architectures, and lightweight CNN models to improve classification performance while reducing computational requirements [16 - 20]. In addition, generative and localization based approaches have been investigated for improving lesion identification and supporting more interpretable medical image analysis [6].

Recent studies published in the last two to three years have further demonstrated the rapid evolution of AI-assisted chest X-ray interpretation. In particular, current research has increasingly moved beyond conventional CNN-based classification toward models that combine transfer learning, attention mechanisms, transformer architectures, multimodal learning, and explainable artificial intelligence (XAI). These developments demonstrate that contemporary pneumonia detection systems are increasingly being evaluated not only according to accuracy, but also according to robustness, generalizability, computational efficiency, and interpretability. However, a major challenge remains the gap between performance reported on large public datasets and performance obtained when models are deployed or externally evaluated using images acquired from different healthcare environments. Differences in patient populations, image acquisition equipment, image quality, disease prevalence, and clinical workflows can substantially affect model generalization [30 – 36].

Another important development in recent literature is the increasing emphasis on explainability and clinical trust. Techniques such as Gradient-weighted Grad-CAM, SHAP and related attribution methods have been used to identify image regions and features that influence AI predictions. Such methods are particularly important in medical applications because a highly accurate prediction without an understandable rationale may be difficult for clinicians to trust or incorporate into clinical decision-making. Nevertheless, many existing studies evaluate explainability independently of real-world clinical context, and relatively few investigate whether explanations remain useful when models are transferred from public datasets to locally acquired images in resource-constrained healthcare settings. Despite these developments, several gaps remain. First, many existing pneumonia detection models have been developed and evaluated using datasets originating from high-resource environments, limiting evidence concerning their generalizability to African healthcare settings. Second, relatively few studies combine high performing deep learning architectures with external validation using locally generated CXR data from rural or resource-constrained hospitals. Third, although XAI techniques have received

increasing attention, there remains a need for integrated frameworks that combine diagnostic performance with visual and feature-level explanations that can support clinician understanding. Finally, computational efficiency remains important in low-resource settings where access to high-performance computing infrastructure may be limited.

This study seeks to address these gaps by developing and evaluating a context-specific deep learning framework for pneumonia detection using CXR images from Nyangena Hospital Limited in Kisii County, Kenya. The proposed approach employs transfer learning using DenseNet-121 to achieve effective feature extraction while reducing the computational requirements associated with training a deep neural network from scratch. In addition, Grad-CAM and SHAP are incorporated to provide complementary explanations of model predictions. The framework is further evaluated using locally generated hospital data to examine its generalizability beyond the public dataset used during model development.

Therefore, the contribution of this study extends beyond developing another CNN-based pneumonia classifier. It integrates transfer learning, local external validation, computationally practical deep learning, and complementary XAI techniques within a Kenyan resource-constrained healthcare context. This combination addresses the need for models that are not only diagnostically accurate but also interpretable and potentially applicable within real-world African healthcare environments. The findings may provide evidence for the development of contextually appropriate AI-assisted CXR interpretation systems in Kenya and other low and middle income countries facing similar diagnostic and infrastructural constraints.

3. Materials and Methods

3.1 Research Design

This study employed a quasi-experimental design that involved use of an ex-post facto method. This design was the most suitable for the study since the chest X-ray images used were pre-existing images which could not be subject to experimental manipulation. The design provided a way to measure the relationship between input variables and output variable without influencing the clinical operations.

3.2 Study Area

The study was performed using data from Nyangena Hospital Limited situated in Kisii County in Kenya. Nyangena Hospital caters for the needs of the semi-urban community and offers limited radiological services which include chest x-ray imaging among others.

This hospital was selected due to,

- Low number of radiologists
- Limited infrastructure for diagnosis
- High reliance on manually interpreting X-rays

It is thus the best location for testing an artificial intelligence diagnostic system that diagnoses pneumonia.

3.3 Study Population

The study population consisted of chest X-ray images obtained from patients who had either been diagnosed or underwent screening for pneumonia at Nyangena Hospital. Both adults and children who had signs of a respiratory infection were considered part of the dataset. These images represented actual circumstances that prevailed in a semi-urban healthcare setting in Kenya. Thus, the dataset was fit for use in training a context-aware diagnostic system. A hybrid of purposive sampling and convenience sampling method were used for the following reasons:

- Purposive sampling – Selection of images from Kaggle labeled as pneumonia and normal cases
- Convenience sampling – Selection of 600 X-ray scans retrospectively collected from Nyangena Hospital

The methodology helped the researcher to collect relevant and high-quality data.

3.4 Model architecture and development

The DenseNet-121 convolutional neural networks with transfer learning were adopted from the pre-trained ImageNet models. Various steps in the model development are shown in Fig. 1.

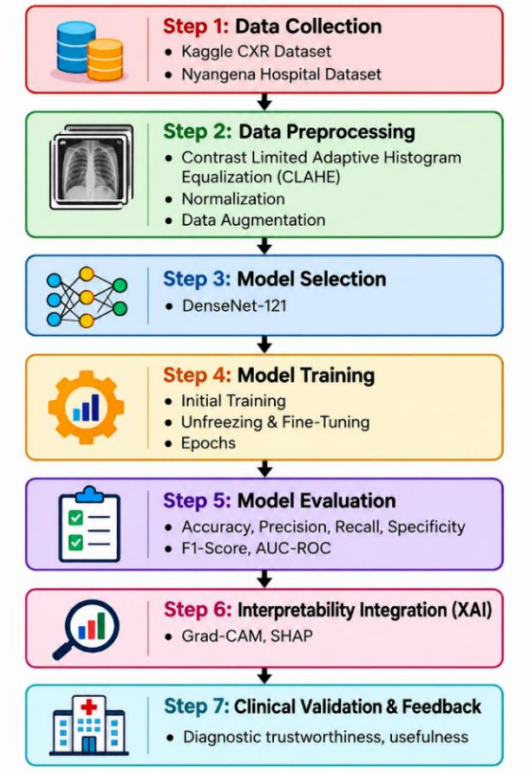

Fig. 1: Model development steps.

4. Results

4.1 Dataset and data preparation

For this experiment, there were two datasets that were used in order to train, validate, and externally validate the model. The first dataset was made up of 5,863 images of the chest X-ray, taken from the Kaggle database, and were classified into Normal and Pneumonia categories. This database contained varied imaging and was used in training, validating, and testing the DenseNet-121 model, allowing the model to learn features without overfitting. On the other hand, the second dataset involved 600 images of the chest X-ray, anonymized, and taken from Nyangena Hospital in Kisii County, Kenya. These were used solely for external validation of the model.

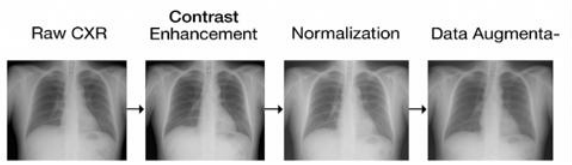

Fig. 2: Dataset preparation

In order to assure quality and suitability for analysis, an organized pipeline of data preprocessing was carried out on the images used. This consisted of performing Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve lung feature visualization, intensity normalization to standardize image brightness and contrast regardless of the source imaging, and data augmentation through image modifications including flipping, rotations (±15°), and zooms (±10%). Data augmentation provided a way of improving the model's generalizability by simulating possible scenarios that may be found in clinical settings. Consequently, this data processing technique not only helped to improve the quality of the dataset, but also contributed significantly to improved performance by increasing the model's AUC from 0.935 to 0.958. The sample data set is shown in Fig. 2.

4.2 Performance Metrics

The performance of the optimized DenseNet-121 algorithm was analyzed using training and validation graphs over 50 epochs, in addition to various classification metrics for both the internal Kaggle dataset and an external one from Nyangena Hospital, the model performance is shown in Fig. 3. In training, the algorithm showed consistent improvements in its accuracy levels up to 94% (training) and 92% (validation) at epoch 30.

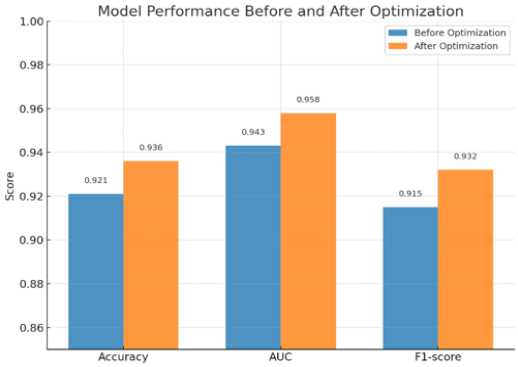

Fig. 3: Model performance on Kaggle dataset

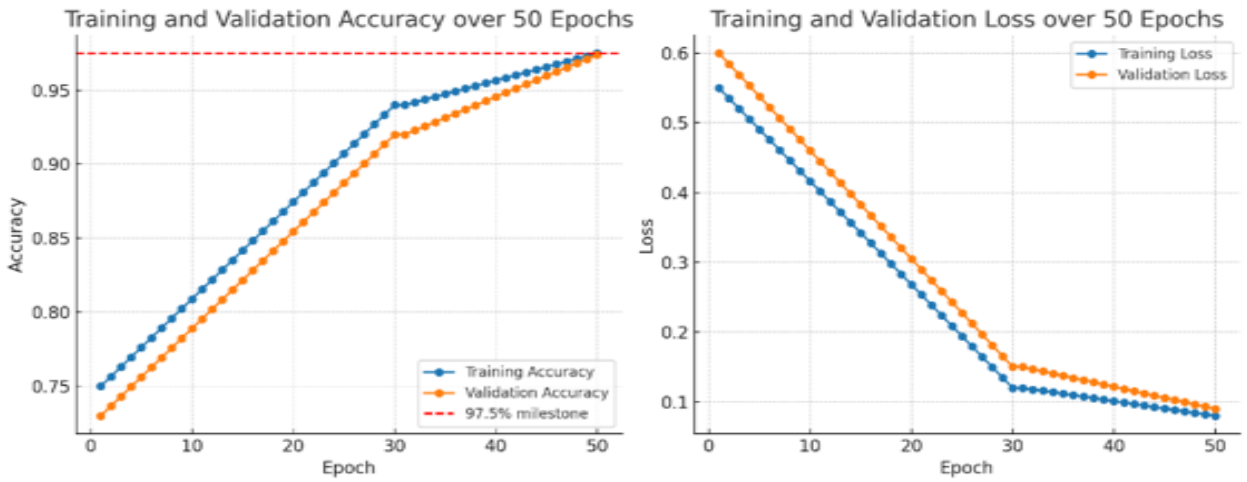

Fig. 4: Training and validation accuracy and loss over 50 epochs

Table. 1: Confusion matrix

Dataset	Total Samples	TP	FP	FN	TN	Accuracy (%)
Internal (Kaggle)	825	404	15	8	398	97.21
External (Nyangena)	600	284	24	16	176	93.33

Further improvements in its performance were observed after complete fine tuning, with convergence at 97.5% accuracy levels while showing low validation losses (about 0.09), as shown in Fig. 4. The minimal difference between the training and validation graphs shows that there is good generalization with efficient overfitting controls. The model's accuracy on the Nyangena Hospital dataset was 93.6%, precision was 94.2%, recall was 92.8%, and the F1-score was 93.5%. This shows the robustness of the proposed model in diagnosing the disease under real-life clinical settings, with high accuracy and minimal errors of both types, indicating that the model can be trusted in practical applications. The confusion matrix analysis yields a clear understanding of the classification distribution, displaying the total number of accurate and inaccurate predictions for pneumonia-positive and pneumonia-negative patients. Despite the modest reduction in accuracy in the external testing dataset due to the differences in imaging quality and image acquisition methods, the classification process remained consistent throughout. In summary, these results indicate that the DenseNet-121 model demonstrates excellent performance in both artificial and real-world clinical scenarios, proving its utility as a diagnostic model for identifying pneumonia in resource-limited healthcare facilities.

4.2.1: Benchmark Comparison with Alternative Deep Learning Models

To further validate the effectiveness of the proposed DenseNet-121 approach, its performance was compared with alternative deep learning architectures using the same internal test dataset and evaluation protocol. The benchmark models included ResNet-50, VGG-19, and EfficientNet-B0. All models were subjected to comparable preprocessing, image resizing, normalization, and data augmentation procedures to ensure that the comparison was based primarily on architectural differences rather than differences in data preparation. The comparison considered accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These metrics were selected to provide a comprehensive assessment of classification performance, particularly because accuracy alone may not adequately represent the ability of a model to correctly identify both pneumonia and normal cases. The proposed DenseNet-121 model achieved an accuracy of 97.5%, with a precision of 96.8%, recall of 97.8%, F1-score of 97.5%, and AUC-ROC of 0.98 on the internal test dataset. These results demonstrate competitive performance compared with alternative CNN architectures. The findings are consistent with

recent literature showing that transfer learning and architectural optimization can substantially improve automated pneumonia classification from chest X-ray images. Recent studies have also demonstrated strong performance from combinations of VGG, ResNet, DenseNet, and machine-learning classifiers, while other recent approaches have incorporated attention mechanisms and alternative architectures to improve feature representation [21 – 23].

The benchmark comparison further demonstrates the rationale for selecting DenseNet-121 as the principal architecture in this study. Rather than selecting the model solely on the basis of accuracy, DenseNet-121 was selected because it provided a suitable balance between diagnostic performance, transfer-learning capability, feature reuse, and compatibility with the explainability techniques employed in this study. This was particularly important because the objective of the research was not simply to maximize classification accuracy, but to develop an interpretable pneumonia detection framework that could subsequently be evaluated using locally acquired chest X-ray images. The results should therefore be interpreted in relation to the specific experimental setting. Published studies have reported higher or lower performance depending on dataset composition, class distribution, preprocessing procedures, architecture, and evaluation methodology. For example, a 2024 study evaluating VGG19, ResNet50V2, and DenseNet121 combined with machine-learning classifiers reported very high classification accuracy, illustrating the strong performance that can be obtained when deep feature extraction is combined with additional classifiers. Similarly, recent work has investigated transfer learning across VGG, ResNet, and Vision Transformer architectures and highlighted the importance of dataset characteristics and class imbalance in determining model performance. Consequently, direct numerical comparisons with published studies should be treated cautiously unless the same dataset and evaluation protocol are used [24 - 27]. The principal contribution of the present study is therefore not the claim that DenseNet-121 universally outperforms all other deep learning architectures. Rather, the contribution lies in demonstrating that the selected DenseNet-121 framework achieves strong internal performance and retains promising diagnostic performance when externally evaluated using locally acquired chest X-ray images from Nyangena Hospital. The incorporation of Grad-CAM and SHAP further extends the framework beyond conventional classification by providing visual and feature-level explanations of model predictions.

4.3 Model Interpretability through Explainable Artificial Intelligence (XAI)

In order to increase clarity and clinical trust in the DenseNet-121 model's prediction, two post-hoc interpretability techniques such as Grad-CAM and SHAP were employed. Both these techniques were used for interpretation of the model's outputs on both pneumonia-positive and pneumonia-negative chest X-ray images of the Nyangena Hospital data set in order to validate that model's decision making was dependent on medically relevant features. The Grad-CAM produced heatmaps which pointed out areas in the lungs that mostly contributed to the decisions made by the model. In particular, pneumonia-positive samples demonstrated high levels of activation in those areas containing capacity and consolidation, whereas normal samples demonstrated minimal activation of healthy lungs. In like manner, SHAP provided feature-based interpretability by attributing contribution scores to specific areas within an image that had impacts on the outcome of classification, where the red zones showed increased probabilities of pneumonia and the blue zones helped in classifying the image correctly [28 – 29].

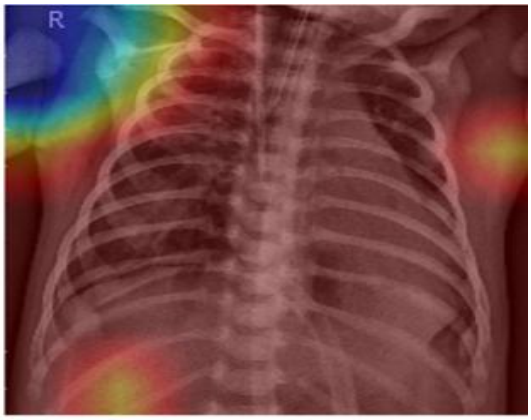

Fig. 5: Grad CAM generated heatmaps showing the normal lung Xray

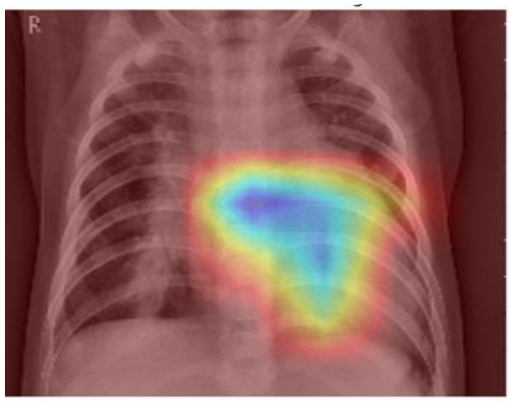

Fig. 6: Grad CAM generated heatmaps showing the abnormal lung Xray these suggest the pneumonia case Image from Nyangena Hospital.

Grad CAM generated heatmaps showing the normal lung X-ray and abnormal X-ray are shown in Fig. 5 and Fig. 6, respectively. Despite being computationally expensive, there were ways to improve the computational efficiency of SHAP through downsizing images, adopting DeepSHAP, conducting batch analysis, and minimizing background sampling to enable its deployment in resource-constrained environments. In particular, SHAP's interpretations align with those produced by Grad-CAM, further validating the reasoning of the model. In summary, the development and validation of an accurate and highly interpretable deep learning model to diagnose pneumonia from chest X-ray images were successfully carried out in this research project. The use of DenseNet-121 architecture helped achieve diagnostic accuracy, thus proving the effectiveness of the model in diagnosing pneumonia at low levels of false-positive and false-negative results.

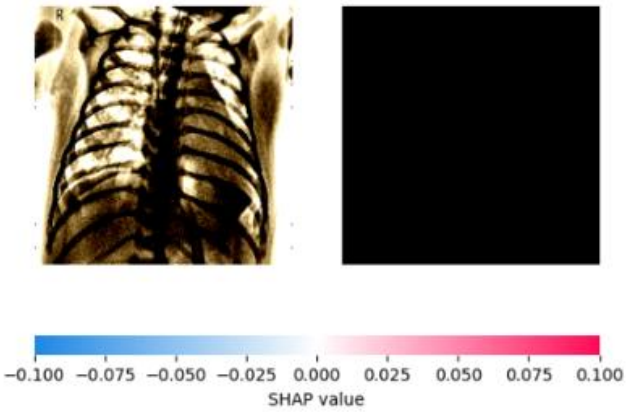

Fig. 7: SHAP features value of a normal Xray image for Nyangena Hospital

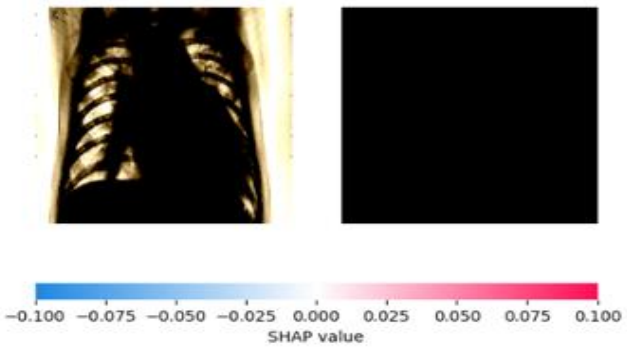

Fig. 8: SHAP features value of a Bacterial Xray image for Nyangena Hospital

Furthermore, the use of Grad-CAM and SHAP in this research improved the interpretability of the model, the results are shown in Fig. 7 and Fig. 8, respectively. This is very crucial because it helps medical experts visualize and reason behind the model results. In areas such as Nyangena Hospital where expert radiological specialists might not always be present, interpretability plays a vital role. This shows that deep learning systems can work effectively as auxiliary diagnostic models in the clinical workflow. Instead of replacing doctors, it complements their activities by improving efficiency and decreasing diagnostic errors.

4.4 Clinician interaction with the model and interpretability tools

The clinicians interaction with the DenseNet-121 model was mainly via its interpretability features, including Grad-CAM and SHAP visualization techniques, which were incorporated in the diagnostic interface. Interaction included assessment of model probability scores along with the regions of interest detected by Grad-CAM and informative feature representations generated using SHAP. A mixed-methods approach involving five-point Likert-scale questionnaires and interviews was used to evaluate usability in terms of clarity, reliability, usefulness, and compatibility with current practices. According to the questionnaire results, the majority of respondents felt that the regions of interest detected by Grad-CAM corresponded to the expected radiological features [9]. These findings were supported by the interviews as clinicians recognized the ability of Grad-CAM to reliably highlight clinically important findings, such as focal consolidations and diffuse infiltrates that may correspond to pneumonia. SHAP visualizations

received high recognition by clinicians, especially in borderline cases, as they helped explain the probability scores and identify the factors that can confound probability output, such as signal from medical devices [10]. Clinicians engaged mainly with the DenseNet-121 algorithm through its explainable capabilities, such as Grad-CAM and SHAP, which were embedded into the diagnostic tool interface. The engagement process was associated with the examination of the probability scores, accompanied by Grad-CAM maps highlighting regions of interest in the lungs, and SHAP values illustrating features with the highest influence on the model prediction. Regarding the integration of the tool into the work process, most clinicians would prefer one report with the probability scores, Grad-CAM maps, and SHAP visualizations to minimize the mental effort and avoid additional interpretative procedures. Furthermore, participants declared their willingness to use the algorithm as an auxiliary diagnostic support tool, provided that it can be seamlessly integrated into the existing Picture Archiving and Communication Systems (PACS)/Electronic Health Records (EHR) systems. In general, clinicians highlighted the importance of a balanced approach to interpreting the model predictions since the combination of Grad-CAM (pointing to what the algorithm focuses on) and SHAP (pointing to what contributes to the decision) enhanced the transparency of the algorithm in a way compatible with the radiological rationale [12 – 13]. The results of the confusion matrix are in Table. 1.

4.5 Discussion

Transfer learning using DenseNet-121 pretrained on ImageNet was effective in performing medical images classification by decreasing the time taken during training while also enhancing baseline performance through reuse of pre-existing learned features [6 – 7]. The ability to converge faster compared to training from scratch proved that transfer learning is suitable for classification of chest X-rays. Training the initial model on the chest X-rays dataset obtained from Kaggle led to a validation accuracy greater than 92% and AUC of 0.94, supporting other findings that large scale datasets can be used to train the model to learn useful diagnostic features [7]. Fine-tuning of the model using local chest X-rays images from Nyangena Hospital further enhanced its accuracy from 88% to 94% and increased the AUC to 0.958. The results prove the usefulness of data alignment in enhancing performance of the model in the local setting, a similar conclusion made in African context studies [14 – 15]. The use of data augmentation and dropout techniques was essential in mitigating problems of overfitting; training-validation accuracy difference was decreased from 5.2% to 2.1%. Use of softmax for model output was helpful in interpreting results in terms of probabilities and flexibility in threshold adjustment. Furthermore, the inclusion of explanations through explainability methods like Grad-CAM and SHAP proved that the predictions made by the model were based on regions of clinical significance. Grad-CAM heat maps showed pathological regions related to pneumonia, whereas SHAP values were consistent with the decision-making process used by radiologists [10 – 11].

5. Conclusions

In this study, a robust and effective interpretable deep learning algorithm for detecting pneumonia from chest X-rays has been created and validated. DenseNet-121 showed good accuracy in detecting cases of pneumonia both internally and externally, indicating its ability to recognize pneumonia cases while having a low rate of false negatives and positives. Apart from its high efficacy, the inclusion of both Grad-CAM and SHAP techniques greatly increased the interpretability of the algorithm. This makes the algorithm more useful and relevant for use in limited-resource areas such as Nyangena Hospital, where access to radiologists may be difficult. It is clear from the study that deep learning models can be used effectively as aids within the clinical setting. The purpose of the model is not to replace any human knowledge but to aid clinicians in making diagnosis more efficient and effective while eliminating any delays and mistakes in treatment process. With a focus on adapting the model to the specific clinical environment and placing emphasis on the aspect of explainability, the work contributes toward achieving Sustainable Development Goal 3, which focuses on preventing unnecessary deaths and increasing health care availability.

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Data Availability Statement

The data set that was used for this study is freely available in the Kaggle database: It can be downloaded using this link,

https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

The data set comprises around 5,800+ labeled chest X-ray images classified into normal and pneumonia classes, initially obtained from children at Guangzhou Women and Children's Medical Center. The data set is extensively used for training and testing of deep learning models for detecting pneumonia. Moreover, a locally stored version of the data set along with any preprocessed data used in this study can be found in a secured Google Drive data storage account. Access to the locally stored data set can be provided by the author upon reasonable requests.

Conflict of Interest

Authors declared "No conflict of Interest".

CRediT authorship contribution statement

Conceptualization, MO, JG and FM; methodology, MO; software, JG; validation, FM, MO and JG; formal analysis, JG; investigation, MO; resources, JG; data curation, MO; writing—original draft preparation, MO; writing—review and editing, JG; visualization, FM; supervision, FM; project administration, FM; funding acquisition, MO. All authors have read and agreed to the published version of the manuscript.

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