RADIOLOGY GUIDE: IMAGE CLASSIFIER FOR PNEUMONIA DETECTION DATA REPORT.

Background:

Kenyatta National Hospital (KNH) is currently facing a significant challenge due to an ongoing strike among healthcare workers. This strike has resulted in a shortage of staff, particularly in the radiology department, where the interpretation of chest X-ray images is crucial for diagnosing cases such as pneumonia. Despite being one of the largest referral hospitals in Kenya, KNH struggles with timely and accurate diagnosis due to limited radiology resources, high patient volumes, and manual interpretation of chest X-ray images by healthcare professionals.

The limited workforce has put immense strain on the hospital's diagnostic capabilities, leading to delays in diagnosing pneumonia cases and potentially compromising patient care. With fewer staff available to interpret X-ray images, there's a risk of errors and inconsistencies in diagnosis, leading to potential diagnostic discrepancies and treatment delays, which could have serious implications for patient outcomes.

The overarching goal is to provide a solution that can alleviate the strain on the hospital's diagnostic services. By developing an automated image classifier for pneumonia detection, we aim to streamline the diagnosis process, reduce reliance on manual interpretation, and ensure timely and accurate identification of pneumonia cases from chest X-ray images.

Our mission is to empower KNH with the tools and resources needed to overcome the challenges posed by the ongoing strike and continue delivering high-quality healthcare to patients in need. Through our collaboration, we strive to make a positive impact on patient care and outcomes at Kenyatta National Hospital.

Business Understanding:

- Pneumonia is an infection that inflames the air sacs in one or both lungs. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing.
- Patients presenting with difficulty in breathing or presenting other respiratory symptoms for pneumonia in the emergency department are usually given a chest Xray. They have the advantage of lower radiation exposure, faster feasibility and better equipment portability compared to other imaging modalities such as computed tomography (CT). This diagnostic examination can provide supplemental and timely information regarding a patient's cardiopulmonary condition and probable changes from any infectious process. Studies have shown that with faster reporting of pneumonia in Chest radiographs, the median length of hospital stays is significantly shorter, the likelihood of receiving appropriate therapy is higher, and the probability of infectious spread is lower.
- However, the interpretation of CR examinations is variable and examiner-dependent. To increase the sensitivity and specificity of imaging patterns for pneumonia in Chest x-rays, deep learning (DL) algorithms must become more prevalent. Prior studies have shown that the use of artificial intelligence (AI) significantly improves the detection of pneumonia in Chest radiographs.
- Given the large number of examinations, reporting using AI can highlight Chest x-rays with abnormalities, helping to prioritize reporting by radiologists. Further, where Chest radiographs are initially evaluated by clinicians outside regular operations, AI can be of assistance. In this situation, a well-functioning evaluation of Chest x-rays by AI can significantly support clinicians' decision making.
- The target is to use algorithms to classify medical images for assistance in diagnosis, treatment planning, and disease monitoring. Our project aims to create an image classifier for pneumonia detection using machine learning techniques. Pneumonia is a common and sometimes fatal respiratory illness, and early identification is critical for optimal treatment and patient outcomes. Our key objective is to build a strong classifier capable of correctly recognizing pneumonia in chest X-ray pictures using convolutional neural networks (CNN's) and sophisticated image processing methods.

Research Questions:

1. Which deep learning model architecture achieves the best performance in terms of accuracy, sensitivity, specificity in detecting pneumonia from chest X-ray images?
2. How can data augmentation techniques be employed to improve the generalizability and robustness of the deep learning model for pneumonia detection on unseen data?
3. Can transfer learning from pretrained models such as ResNet50 improve pneumonia detection performance?
4. How do pneumonia detection models perform compared to human radiologists, and what are the implications for clinical practice?

Problem Statement:

- Pneumonia is a serious respiratory illness that affects many people, especially kids and older folks. Getting a quick and accurate diagnosis is super important for making sure people get the right treatment and have better chances of getting better. But right now, diagnosing pneumonia using chest X-rays can be tough. It takes time for radiologists to look at the X-rays, and sometimes they might miss things or make mistakes. Plus, not every hospital has experts available all the time.
- A recent article from the National Library of Medicine even says that radiologists only get pneumonia diagnoses right about 60% of the time! **Link here** That's not great, especially when people's lives are on the line.
- To help tackle this problem and save lives, we're looking into using deep learning, which is like teaching computers to think and learn like humans do, to build a system that can automatically spot pneumonia in chest X-rays. Deep learning is cool because it can pick up on really complicated patterns from lots of X-ray pictures, and it's already changing the way doctors analyse medical images.
- Our goal is to create a tool that can help hospitals like KNH diagnose pneumonia faster and more accurately, especially during tough times like strikes when there might be fewer experts around. We want to make a real difference in patient care and outcomes at Kenyatta National Hospital and beyond.

Objectives:

- **Main Objective:**
  - To use algorithm to develop an accurate and efficient image classifier for pneumonia detection using chest X-ray images for assistance in diagnosis.
- **Specific Objectives:**
  - To alleviate the strain on the hospital's diagnostic services.
  - To support clinicians' decision making.
  - Gather a comprehensive dataset of chest X-ray images containing both pneumonia-positive and pneumonia-negative cases.
  - Experiment with various architectures, hyperparameters, and optimization techniques to maximize the classifier's accuracy and efficiency.

Data Understanding:

- Data Source:
  - The dataset used for our project were sourced from https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia
  - It contains Chest X-ray images (anterior-posterior) which were selected from retrospective cohorts of paediatric patients of one to five years old from Guangzhou Women and Children's Medical Centre, Guangzhou.
  - All chest X-ray imaging was performed as part of patients' routine clinical care.
  - The dataset is organized into 3 folders (train, test, validation) and contains subfolders for each image category (Pneumonia/Normal).
  - There are 5,856 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).
  - The nearly 6000 images are classified into two categories: Normal or Pneumonia.
  - As provided by Kaggle, the images are divided into three subsets:
    - train - 5,216 images
    - test – 16 images
    - validation - 624 images

Data Preparation:

- The standardization process involves rescaling the pixel values from their original range (typically 0 to 255) to a new range (0 to 1) by dividing each pixel value by 255. This step is crucial because deep learning models generally perform better on input data that is normalized or standardized, meaning the data has a consistent scale. For images, rescaling pixel values to a 0-1 range helps in speeding up the convergence of the model during training, as smaller, standardized values make the optimization landscape smoother.
- This rescaling is applied to all images across training, validation, and testing sets through separate ImageDataGenerator instances for each dataset partition. The process sets up these generators with the rescale=1. /255 argument, ensuring that all images are consistently standardized before they are presented to the model. This form of preprocessing is a simple yet effective form of standardization that is particularly well-suited to image data, where pixel intensity values can be easily scaled to a uniform range.
- Additionally, for the training data generator, the process incorporates various data augmentation techniques such as rotation, width shift, height shift, shear, zoom, and horizontal flip, alongside rescaling. These augmentation techniques generate variations of the training images, which can help improve the model's generalization capabilities by exposing it to a wider variety of data scenarios. However, it's important to note that while these augmentations modify the image content, the pixel value standardization (rescaling) remains a constant foundational step to ensure that all input data to the model, regardless of augmentation, maintains a standardized scale for pixel values.

Exploratory Data Analysis (EDA):

Image Distribution Analysis

The process begins by counting and analysing the number of images within each category across training, validation, and testing directories. This step is crucial for identifying any class imbalances that could impact the model's learning process and eventual performance. A dictionary mapping each category to its image count is created for each directory, and these counts are printed out, providing a clear view of the dataset's composition.

Following the quantitative analysis, the script visualizes the distribution of images across categories for the training, validation, and testing sets. Bar plots are used for this purpose, offering a visual representation of any disparities in image counts between categories. Such visualizations are key in EDA as they allow for quick identification of potential class imbalances that might necessitate data augmentation or resampling techniques to address.

Image Dimension Inspection

The script includes a function to inspect the dimensions of a random sample of images from each category within the training directory. This inspection is vital for understanding the variability in image sizes and determining the need for image resizing or normalization as part of the preprocessing steps before training a model. Given the diversity typically found in medical image datasets, this step ensures that the input data to the model maintains consistency.

Sample Image Visualization

To get a more intuitive understanding of the data, the script visualizes a grid of sample images from each category within the specified directory, using matplotlib and PIL for image handling. This visualization not only provides insight into the visual differences and similarities between the categories but also helps in assessing the image quality, potential anomalies, or artifacts that could influence model training.

Modelling:

Transfer Learning with ResNet50

The first approach utilizes transfer learning, where the ResNet50 model pre-trained on the ImageNet dataset serves as the feature extraction base. This base is augmented with a GlobalAveragePooling2D layer and a final Dense layer tailored for binary classification. The layers of ResNet50 are initially frozen to prevent their weights from updating during the first phase of training, focusing the learning process on the newly added layers. This model undergoes two phases of training: an initial phase where only the custom top layers are trained, and a fine-tuning phase where a portion of the deeper layers in ResNet50 are unfrozen and trained alongside the top layers to improve accuracy. Data augmentation techniques such as rotation, width shift, height shift, shear, zoom, and horizontal flip are applied during the fine-tuning phase to enhance the model's generalization capabilities.

Custom CNN Architecture

The second approach involves building a custom Convolutional Neural Network (CNN) from scratch. This architecture starts with convolutional and max-pooling layers, incrementally increasing in depth and complexity, followed by flattening, dropout, and dense layers for classification. Similar to the transfer learning approach, data augmentation is employed to improve the model's ability to generalize to new, unseen data. However, this approach relies entirely on the custom-built architecture without leveraging pre-trained models.

Conclusions:

The exploration featured two primary models: a Transfer Learning model leveraging the ResNet50 architecture for feature extraction coupled with custom layers for the classification task, and a Custom CNN Model constructed from scratch, which incorporated a variety of data augmentation strategies. Among these, after a thorough comparison based on final test accuracies, the Custom CNN Model emerged as the superior model, showcasing the highest test accuracy and signifying a robust performance on the test dataset. This was achieved without specific fine-tuning processes but through the effective use of extensive data augmentation.

Recommendation:

- *Further Hyperparameter Tuning:* Allocate additional time and resources to fine-tune the hyperparameters of the Custom CNN Model. This may involve exploring different configurations to optimize performance further.
- *Evaluation of Alternative Architectures:* While the Custom CNN Model showed promising results, consider exploring alternative architectures beyond ResNet50 and the Custom CNN Model. This could involve experimenting with different pre-trained models or novel architectures to potentially improve performance.
- *Integration with Portable X-Ray Machines:* Efforts should be made to seamlessly integrate the trained Custom CNN Model with portable X-ray machines. This integration will enable healthcare professionals to quickly analyse X-ray images on-site, facilitating timely diagnosis and treatment decisions, especially in remote or resource-constrained areas.

Future Improvement Ideas:

- Optimizing Data Augmentation Techniques: Continue to experiment with different data augmentation approaches to improve the Custom CNN Model's resilience and generalizability. This might include investigating sophisticated augmentation methods or combinations designed particularly for medical picture collections.
- Real-time Analysis Capability: Optimize the Custom CNN Model's inference performance to enable real-time analysis. This will be critical for connecting the model with portable X-ray scanners, allowing for on-site investigation with minimal delays.
- Collaboration with Healthcare experts: Work closely with healthcare experts to gain input on the model's performance and usability in realistic circumstances. This will aid in identifying possible areas for development and adapting the model to better fit the demands of its intended consumers.
- Ensemble Learning: Use ensemble learning techniques to combine predictions from many models, including the Custom CNN Model and maybe additional architectures. Ensemble approaches may typically increase performance by utilizing individual models' strengths while limiting their flaws.

Collaborators:

GROUP Members

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GitHub Repository Link:

https://github.com/Justcolins/PHASE-4-PROJECT-X-RAY/