**Deep Learning-Based Classification of Lung Cancer Using Chest X-Ray Images: Implementation and Performance Evaluation**

**Abstract**Lung cancer remains one of the leading causes of mortality worldwide, necessitating advancements in diagnostic tools to improve early detection and treatment outcomes. Deep learning techniques, particularly convolutional neural networks (CNNs), have demonstrated immense potential in image classification tasks, including medical diagnostics. This study details the implementation of a deep learning pipeline for lung cancer classification using chest X-ray images, leveraging the ResNet50 architecture pre-trained on ImageNet. Employing data augmentation, class rebalancing, and K-fold cross-validation, the model achieved promising results, demonstrating its utility in clinical settings. This article discusses the methodology, implementation, and evaluation metrics, with a focus on the practical challenges and solutions encountered.

**Introduction**The early detection of lung cancer significantly improves patient prognosis, but current diagnostic methods often rely on costly and invasive procedures. Recent advancements in artificial intelligence (AI) and machine learning (ML) have enabled the development of automated diagnostic tools using medical imaging data. CNNs, a subset of deep learning models, have shown state-of-the-art performance in medical image analysis, including applications in lung cancer detection from chest X-rays (Das et al., 2020; Hussain et al., 2022). This article presents a step-by-step implementation of a ResNet50-based CNN model for lung cancer classification, utilizing a publicly available dataset of chest X-ray images (Quynh Le CL, 2023).

**Methodology**

*Dataset Preparation*The dataset used in this study was sourced from Kaggle (Quynh Le CL, 2023) and contains chest X-ray images categorized into "Cancer" and "Normal" classes. The dataset was divided into training, validation, and test sets. Class imbalances were addressed using oversampling techniques and class weighting (Buda et al., 2018).

*Data Augmentation*To enhance generalization and avoid overfitting, data augmentation techniques such as rotation, zooming, and horizontal flipping were applied to the training set using the ImageDataGenerator module from TensorFlow (Shorten & Khoshgoftaar, 2019).

*Model Architecture*The ResNet50 architecture, pre-trained on ImageNet, was used as the feature extractor. A global average pooling layer, followed by dense layers with dropout regularization, was added to the base model to perform classification. The model was compiled with the Adam optimizer and sparse categorical cross-entropy loss function (He et al., 2016).

*Cross-Validation and Class Weights*Stratified K-fold cross-validation was employed to evaluate the model's robustness. Class weights were calculated to handle the imbalance in class distribution effectively (Buda et al., 2018).

*Training and Callbacks*The model was trained for three epochs per fold using a batch size of 32. Early stopping, model checkpointing, and learning rate reduction on plateau were implemented to optimize training (Goodfellow et al., 2016).

**Results and Discussion**

*Performance Metrics*The model's performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). On the test set, the model achieved an accuracy of 94.5% and an AUC-ROC score of 0.89, demonstrating high discriminatory power between cancerous and normal samples.

*Confusion Matrix and Classification Report*The confusion matrix revealed strong performance across both classes, with precision and recall scores exceeding 90% for each class. These results highlight the model's effectiveness in minimizing false positives and false negatives, which are critical in medical diagnostics.

*Visualizing Predictions*Predictions were visualized using a sample of test images to understand the model's decision-making process. Most predictions aligned with the ground truth, further validating the model's reliability.

**Challenges and Limitations**Despite the promising results, several challenges were encountered. The dataset size was limited, which may restrict the model's generalizability to diverse populations. Additionally, the binary classification framework oversimplifies the diagnosis of lung cancer, which often involves nuanced distinctions between subtypes and stages. Future studies should explore multi-class classification and incorporate larger, more diverse datasets.

**Conclusion**This study demonstrates the feasibility of using a ResNet50-based CNN model for lung cancer classification from chest X-ray images. The proposed pipeline, incorporating data augmentation, class balancing, and cross-validation, achieved competitive performance metrics, underscoring its potential for deployment in clinical workflows. Future research should aim to address dataset limitations and extend the framework to multi-class problems.

**References**

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