UNIVERSITY OF HOUSTON

Binary Classification using Machine Learning Models

Christopher Terry Emmanuel Chavez Samuel Todd
Dr. Nouhad Rizk PhD
Department of Computer Science, University of Houston

Abstract

This study explores the potential of machine learning models for early detection of pneumonia using pediatric chest X-ray images. We compare the effectiveness of traditional supervised learning models—Support Vector Classifiers (SVC) and Random Forest Classifiers (RFC)—with deep learning models, particularly Convolutional Neural Networks (CNN), in diagnosing pneumonia. Our dataset, sourced from Guangzhou Women and Children's Medical Center, includes anterior-posterior chest X-ray images of children aged one to five years.

Our analysis focuses on the accuracy, precision, recall, F1 scores, and the implications of false positives and negatives in disease detection. Techniques such as hyperparameter tuning, dropouts, and k-fold cross-validation are employed to enhance model robustness and reduce overfitting. We also delve into model interpretability, aiming to understand the features and patterns crucial for accurate classification.

The study's findings reveal significant insights into the strengths and weaknesses of each model, offering valuable guidance for their practical deployment in medical diagnostics. The overarching goal is to advance the integration of artificial intelligence in healthcare, potentially leading to more efficient, reliable, and scalable tools for pneumonia detection in pediatric patients.

Background

Pneumonia presents a major health risk, particularly in children, necessitating early and accurate detection. Traditional diagnosis methods, such as chest X-ray image analysis, are often limited by the complexity of image interpretation and disease variations.

Our study leverages machine learning to improve pneumonia detection in pediatric X-rays. We compare traditional supervised models like Support Vector and Random Forest Classifiers with advanced Convolutional Neural Networks, evaluating their accuracy, precision, recall, and F1 scores. This comparison aims to identify the most effective model for clinical application, considering the impact of false positives and negatives on patient care.

Additionally, we address the ethical implications of using artificial intelligence in healthcare, particularly in sensitive areas like pediatric diagnostics. Our research contributes to the development of innovative, more efficient diagnostic tools for pneumonia, aiming to improve patient outcomes in the healthcare sector.

Methods

Our study conducts a comparative analysis of three machine learning models for pneumonia detection in pediatric chest X-rays: Support Vector Classifiers (SVC), Random Forest Classifiers (RFC), and Convolutional Neural Networks (CNN). These models were chosen for their varied approaches and effectiveness in image classification.

Data Preprocessing: We used a dataset of 5,863 anterior-posterior chest X-ray images from children aged one to five, sourced from the Guangzhou Women and Children's Medical Center. Images were standardized in size and intensity for uniform model training and testing.

Model Implementation:
- *SVC*: Implemented in Python, focusing on linear kernels for computational efficiency.
- *RFC*: Optimized for image size (256 x 256 pixels), with default parameters providing the best results.
- *CNN*: Developed with dropout techniques to prevent overfitting, using 224 x 224 pixel images for feature mapping.

Performance Evaluation: Models were assessed based on accuracy, precision, recall, F1 score, and loss, with particular attention to correct classification of pneumonia-positive or pneumonia-negative images. The RFC showed the highest performance, followed by SVC and CNN.

Hyperparameter Tuning and Optimization: Attempts at tuning using tools like Optuna indicated that exposure to more data would be more beneficial than hyperparameter adjustments for the SVM and RF models.
Comparative Analysis: The study concluded with a comparison of the three models, evaluating their strengths and weaknesses in pneumonia detection and their potential for clinical application.

1. Input Layer
2. Convolutional Layer
3. Max Pooling Layer
4. Convolutional Layer
5. Max Pooling Layer
6. Convolutional Layer
7. Max Pooling Layer
8. Flatten
9. Dense
10. Dropout
11. Dense

Results

	Accuracy	Precision	Recall	F1 Score	Loss
RF	95.55%	95.88%	98.12%	96.99%	18.96%
SVM	94.45%	95.61%	96.84%	96.22%	15.77%
CNN	84.62%	81.41%	97.69%	88.81%	37.66%

Comparative Analysis:
- RFC emerged as the most reliable for pneumonia detection, with a strong balance of accuracy, precision, and recall.
- SVM was notable for high precision and lower false positive rates, suited for contexts requiring minimal false diagnoses.
- CNN, while less accurate, excelled in identifying positive cases, suggesting its use as a supplementary diagnostic tool.

Conclusion

RFC: Best overall performance, ideal for balancing accuracy with minimal false negatives.
SVM: High precision, valuable in reducing false diagnoses.
CNN: Strong in identifying true positives, useful as a supportive diagnostic tool.

These models, if integrated into clinical workflows, could significantly aid in early detection and treatment.

Future Direction

Data Diversity and Model Generalization: Expanding the dataset with X-rays from different angles and conditions.

Advanced Model Development: Investigating sophisticated deep learning architectures alongside ensemble techniques combining SVC, RFC, and CNN.

Ethical and Responsible AI Use: Emphasize transparent, interpretable models, mitigate biases, and adhere to privacy and regulatory standards.

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