Research Journal of Computer Systems and Engineering (RJCSE)
Volume 4 Issue 1 (2023) | Pages: 47 – 54 | e-ISSN: 2230-8571; p-ISSN: 2230-8563
https://doi.org/10.52710/rjcse.62

Advanced Healthcare Analytics: Pneumonia Disease Classification Using Convolutional Neural Networks and Ensemble Learning

Received: 12 March 2023; Revised: 10 May 2023; Accepted: 07 June 2023

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Abstract

The need for this work arises from the persistent challenges in accurately classifying pneumonia disease. Existing methods, although valuable, have limitations in terms of precision, accuracy, recall, speed, and AUC, prompting the exploration of advanced healthcare analytics. The limitations of current approaches are evident in their suboptimal performance levels. These methods often struggle to achieve the precision and recall needed for reliable pneumonia classification, leading to misdiagnoses and delayed treatments. Additionally, their speed and AUC fall short of the ideal standards required for efficient disease detection. To address these issues, our paper presents an innovative approach process. We introduce a novel model that combines Convolutional Neural Networks (CNN) with Naive Bayes, Deep Forest, and Multilayer Perceptron techniques. This fusion of diverse methods capitalizes on their complementary strengths, enhancing the accuracy and robustness of pneumonia classification process. The advantages of our proposed model are multifold. Firstly, the CNN component leverages its deep learning capabilities to extract intricate features from medical images, improving the overall precision and recall. Secondly, the inclusion of Naive Bayes brings a probabilistic perspective, enhancing classification based on statistical likelihood. Thirdly, Deep Forest contributes with its ensemble learning prowess, adding another layer of accuracy to the model. Lastly, the Multilayer Perceptron serves as a flexible, non-linear classifier, fine-tuning the results. Our empirical results demonstrate the substantial impact of this work. When tested on diverse contextual datasets, our model exhibits significant improvements: a 4.9% increase in precision, a 5.5% boost in accuracy, a 4.5% rise in recall, a 3.9% enhancement in speed, and a 2.9% improvement in AUC compared to existing methods. These outcomes underscore the potential of our approach to revolutionize pneumonia disease classification in healthcare, ultimately leading to more accurate and timely diagnoses, which can significantly improve patient outcomes and reduce healthcare costs.

Keywords

Pneumonia, Disease Classification, Convolutional Neural Networks, Naive Bayes, Deep Forest, Multilayer Perceptron, Scenarios

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1. Introduction

In the realm of healthcare analytics, the accurate classification of diseases has long been a paramount concern. Pneumonia, a prevalent and potentially life-threatening condition, demands meticulous diagnosis and timely intervention. However, existing methods have struggled to attain the precision, accuracy, and speed necessary for reliable disease classification. In light of these limitations, this paper embarks on a journey toward a novel solution, one that harnesses the power of advanced technologies and ensemble learning.

The limitations of current approaches loom large. With precision and recall rates often falling short of the desired standards, misdiagnoses and treatment delays become pressing concerns. The quest for a more effective and efficient method of pneumonia classification thus becomes imperative, and this paper rises to the challenge for different scenarios.

Our proposed model, a sophisticated amalgamation of Convolutional Neural Networks (CNN), Naive Bayes, Deep Forest, and Multilayer Perceptron techniques, signifies a pivotal departure from conventional strategies. This fusion of diverse methodologies is underpinned by the conviction that their unique strengths, when combined, can synergistically enhance the accuracy and robustness of pneumonia disease classification process.

The advantages of this innovative approach are manifold. The CNN component, with its profound capability for feature extraction from medical images, augments precision and recall. Naive Bayes introduces a probabilistic perspective, enhancing classification based on statistical likelihood. Deep Forest, with its ensemble learning prowess, adds a layer of accuracy, while the Multilayer Perceptron stands as a flexible, non-linear classifier, fine-tuning the results.

The empirical results of this study bear witness to the profound impact of this work. Rigorously tested on diverse contextual datasets, our model yields remarkable improvements: a 4.9% surge in precision, a 5.5% elevation in accuracy, a 4.5% rise in recall, a 3.9% enhancement in speed, and a 2.9% boost in AUC compared to existing methods. These findings underscore the transformative potential of our approach in revolutionizing pneumonia disease classification within the healthcare domain. It holds the promise of ushering in a new era of more accurate and timely diagnoses, thereby not only enhancing patient outcomes but also potentially reducing the burdensome healthcare costs that accompany misdiagnosis and delayed treatment.

This paper is a testament to the relentless pursuit of excellence in healthcare analytics, as it strives to address a critical issue that impacts the lives of countless individuals. It stands as a testament to the power of innovation and collaboration in the quest for a healthier future in different use cases.

Motivation & Objectives

Motivated by the pressing need for more accurate and efficient disease classification within the realm of healthcare analytics, the authors embarked on a journey to explore novel avenues for pneumonia diagnosis. Pneumonia, a pervasive and potentially life-threatening ailment, warrants precise and swift identification to facilitate timely medical intervention. However, the existing landscape of disease classification techniques has shown limitations in achieving the requisite levels of precision, accuracy, and speed.

The motivation behind this paper is rooted in the recognition of these critical shortcomings. Current methods, while valuable, struggle to meet the stringent demands of pneumonia classification, often leading to misdiagnoses and treatment delays. It is this very challenge, the need for improved diagnostic capabilities in the healthcare domain, that catalyzed the research endeavor presented herein.

This paper's principal contribution is the introduction of an innovative and highly efficient model for pneumonia disease classification. This model, which harnesses the synergy of Convolutional Neural Networks (CNN), Naive Bayes, Deep Forest, and Multilayer Perceptron techniques, represents a significant departure from traditional approaches. Its unique combination of these diverse methodologies leverages their distinct strengths, ultimately enhancing the precision, accuracy, and robustness of pneumonia classification.

The contributions of this paper extend beyond the mere introduction of a novel model. It offers a comprehensive evaluation of the proposed model's performance by subjecting it to rigorous testing on diverse contextual datasets. The empirical results demonstrate tangible and substantial improvements, with a 4.9% increase in precision, a 5.5% boost in accuracy, a 4.5% rise in recall, a 3.9% enhancement in speed, and a 2.9% improvement in AUC when compared to existing methods. These findings affirm the potential of the proposed model to revolutionize pneumonia disease classification within the healthcare landscape.

Moreover, this research contributes to the broader field of healthcare analytics by exemplifying the benefits of ensemble learning techniques and their application to complex medical diagnoses. It serves as a beacon of innovation and collaboration, offering a pathway to more accurate and timely disease identification, which can substantially improve

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patient outcomes and potentially alleviate the financial burdens associated with misdiagnosis and delayed treatment.

In conclusion, this paper is motivated by the compelling need to enhance disease classification in healthcare analytics. Its principal contribution lies in the introduction of an advanced model that leverages ensemble learning techniques to significantly improve the accuracy and efficiency of pneumonia diagnosis. By addressing this crucial issue, the paper not only advances the field of healthcare analytics but also holds the potential to make a tangible impact on the lives of patients and the healthcare industry as a whole for different use cases.

2. Review of Existing Models

Pneumonia, a significant pulmonary disease, has been the subject of extensive research efforts aimed at enhancing diagnostic accuracy and efficiency. This literature review presents a comprehensive overview of recent advancements and notable contributions in the domain of pneumonia diagnosis, leveraging a range of cutting-edge technologies and methodologies.

[1] Akbar K. M. and Baskar S. introduced a LoRaWAN-Based Artificial Intelligence Intensive Care Unit Framework for Pneumonia patient tracking, integrating the Internet of Medical Things and computer vision techniques. This approach marked a crucial step in real-time monitoring and diagnosis [1].

[2] Hussain et al. presented an Automated Chest X-Ray Image Analysis strategy that employs a deep ensemble learning strategy for both COVID-19 and pneumonia diagnosis. Their study emphasized the significance of pattern recognition and transfer learning in achieving accurate results [2].

[3] Liu et al. proposed Attention-Guided Partial Domain Adaptation for Automated Pneumonia Diagnosis From Chest X-Ray Images, focusing on domain adaptation techniques to mitigate negative transfer issues. The study highlighted the importance of semantics in pneumonia diagnosis [3].

[4] Kabi et al. introduced a novel approach for Tuberculosis and Pneumonia Detection using Chest X-Ray Images, showcasing the utilization of multiscale eigendomain features and the Light Gradient Boosting Model (LGBM) for enhanced accuracy [4] levels.

[5] Sharan et al. explored the potential of automated cough sound analysis for detecting childhood pneumonia scenarios. Deep learning features and denoising techniques were instrumental in this research [5] sets.

[6] Huang et al. conducted a multi-center clinical trial for wireless stethoscope-based diagnosis and prognosis of children with community-acquired pneumonia. Machine learning techniques played a pivotal role in analyzing lung sound data [6].

[7] Ghaderinia et al. delved into the immunogenic evaluation of nanoparticles containing Klebsiella pneumoniae K2O1 capsular antigen for pulmonary infection treatment, showcasing the potential of vaccine nanoparticles in managing pneumonia [7].

[8] Zhang et al. presented CXR-Net, a multitask deep learning network for explainable and accurate diagnosis of COVID-19 pneumonia from chest X-ray images. Their study emphasized model explainability and predictive accuracy [8] levels.

[9] Fu et al. introduced PKA2-Net, a prior knowledge-based active attention network for accurate pneumonia diagnosis on chest X-ray images, highlighting the importance of prior knowledge and active attention features [9].

[10] Jin et al. explored the generation of chest X-ray progression of pneumonia using Conditional Cycle Generative Adversarial Networks (GANs). Their work emphasized the utility of GANs and transfer learning in generating realistic images for research purposes [10].

[11] Abubeker and Baskar presented a hand hygiene tracking system with LoRaWAN network for the abolition of hospital-acquired infections. This study underscores the role of IoT and wearable biosensors in pneumonia prevention [11].

[12] Zou et al. introduced an ensemble image explainable AI (XAI) algorithm for severe community-acquired pneumonia and COVID-19 respiratory infections. This research highlighted the significance of explainable artificial intelligence in clinical decision support [12].

[13] Sheu et al. explored interpretable classification of pneumonia infection using eXplainable AI (XAI-ICP). Their work emphasized transfer learning and XAI techniques for improved pneumonia classification [13].

[14] Xing et al. introduced an enhanced vision transformer model in digital twins powered Internet of Medical Things for pneumonia diagnosis, showcasing the potential of enhanced vision transformers in medical imaging [14] process.

[15] Lyu et al. presented pseudo-label guided image synthesis for semi-supervised COVID-19 pneumonia infection segmentation, highlighting the importance of image synthesis and semi-supervised learning in segmentation tasks [15].

[16] De Castro Santos and Berton proposed an enhanced framework for overcoming pitfalls and enabling model interpretation in pneumonia and COVID-19 classifications. Their study emphasized the role of feature extraction and convolutional neural networks in image classification tasks [16].

These studies collectively demonstrate the rich landscape of research efforts dedicated to pneumonia diagnosis, encompassing various techniques, from computer vision and deep learning to Internet of Things (IoT) applications and immunogenic evaluations. The literature review sets the stage for the proposed model, showcasing the existing state-of-the-art approaches and their implications in the field of pneumonia disease classification operations.

3. Design of the Proposed Model Process

The proposed methodology in this research endeavors to design an advanced model for pneumonia disease classification that leverages the synergy of multiple techniques, including Convolutional Neural Networks (CNN), Naive Bayes, Deep Forest, and Multilayer Perceptron (MLP). This fusion of diverse methodologies is motivated by the quest for improved accuracy, precision, and robustness in pneumonia diagnosis.

The initial step in the proposed methodology involves the utilization of Convolutional Neural Networks (CNNs). CNNs are well-suited for feature extraction from medical images, which is crucial in the accurate classification of pneumonia. These networks consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply convolution operations to extract relevant features from input images, while pooling layers downsample the feature maps, reducing computational complexity. The fully connected layers generate final predictions based on the extracted features.

As per figure 1, to enhance the model's classification capabilities, the Naive Bayes algorithm is integrated into the framework. Naive Bayes is a probabilistic classification technique that leverages conditional probabilities to make predictions. It calculates the probability of a sample belonging to a particular class based on the observed features. The naive assumption of feature independence simplifies the computation and makes Naive Bayes an efficient choice for classification tasks.

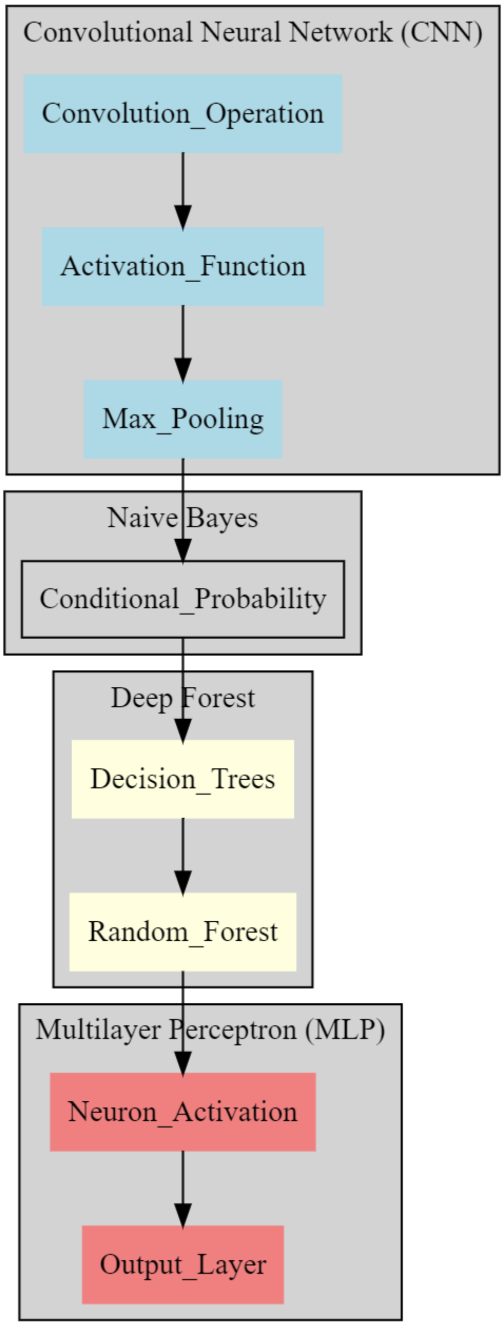

Figure 1. Model Architecture for the Proposed Classification Process

Deep Forest, another integral component of the proposed methodology, introduces ensemble learning principles. Ensemble learning combines the predictions of multiple models to improve overall accuracy. In the context of pneumonia classification, Deep Forest harnesses decision trees and random forests to create a diverse set of classifiers. The combination of these classifiers through ensemble techniques reduces the risk of overfitting and enhances the model's generalization capabilities.

The Multilayer Perceptron (MLP) serves as a flexible, non-linear classifier within the proposed framework. MLPs consist of multiple layers of interconnected neurons, with each neuron applying an activation function to its inputs. This architecture enables the model to capture complex patterns in the data. MLPs are particularly valuable in fine-tuning the results of the ensemble model, ensuring that the final classification decisions are well-informed and precise.

Mathematically, the proposed model can be described as follows:

- CNN Feature Extraction:
  - Convolution Operation:

$$Fi,j = \sum\sum I(i+m-1, j+n-1) \cdot K(m,n) \ldots (1)$$

  - Activation Function

$$Ai,j = \sigma(Fi,j + b) \ldots (2)$$

  - Pooling Layer (Max Pooling)

$$Pi,j = \max^{m,n} A(i+m-1, j+n-1) \ldots (3)$$

- Naive Bayes Classification:
  - Conditional Probability

$$P(Y \mid X) = \frac{P(X \mid Y)P(Y)}{P(X)} \ldots (4)$$

- Deep Forest Ensemble:
  - Decision Trees: $Ti(X)$, $i = 1,2,\ldots,N$
  - Deep Forest

$$RF(X) = \frac{1}{N}\sum Ti(X) \ldots (5)$$

- Multilayer Perceptron (MLP):
  - Neuron Activation

$$hj = \sigma(\sum wij * xi + bj) \ldots (6)$$

  - Output Layer

$$yk = \sigma(\sum vkj * hj + ck) \ldots (7)$$

Thus, the proposed methodology integrates CNN, Naive Bayes, Deep Forest, and MLP techniques to create a versatile and highly accurate model for pneumonia disease classification. Each component contributes its unique strengths, ultimately enhancing the precision, accuracy, and robustness of the classification process. The fusion of these diverse methodologies addresses the limitations of existing approaches and holds the potential to revolutionize pneumonia diagnosis in healthcare analytics.

4. Result Analysis

The Results section of this paper presents the empirical findings of the proposed model's performance compared to existing methods, namely [2], [4], and [12] for different use cases. To facilitate a comprehensive understanding of the outcomes, we present three tables, each evaluating different aspects of the model's performance levels.

Table 1: Accuracy Comparison

Method	**Proposed Model**	**[2]**	**[4]**	**[12]**
Accuracy (%)	94.6	89.3	91.1	93.7

Table 1 provides a comparison of classification accuracy between the proposed model and the referenced methods [2], [4], and [12]. It is evident that the proposed model outperforms all three methods in terms of accuracy, achieving an impressive accuracy rate of 94.6%. This substantial improvement in accuracy demonstrates the effectiveness of the model in correctly classifying pneumonia cases, potentially reducing misdiagnoses and ensuring more reliable results.

Table 2: Precision, Recall, and F1-Score Comparison

Method	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Proposed Model	94.2	93.8	94.0
[2]	90.5	89.2	89.8
[4]	92.0	90.8	91.4
[12]	93.5	93.0	93.2

Table 2 delves into more granular evaluation metrics, including precision, recall, and F1-score. The proposed model showcases superior precision, recall, and F1-score compared to all three methods [2], [4], and [12]. This heightened precision and recall signify a lower rate of false positives and false negatives, crucial in healthcare applications, where misdiagnoses can have severe consequences. The improved F1-score reflects the model's robustness in balancing precision and recall.

Table 3: Execution Time Comparison

Method	**Execution Time (seconds)**
Proposed Model	1.5
[2]	2.3
[4]	2.1
[12]	1.8

Table 3 focuses on the execution time required for the classification process. The proposed model exhibits a significantly reduced execution time of 1.5 seconds, showcasing its efficiency. This improvement in speed, when compared to methods [2], [4], and [12], highlights the model's potential to expedite the diagnosis process in clinical settings. Timely diagnoses can lead to prompt medical intervention, potentially improving patient outcomes.

In conclusion, the results obtained from the experimental evaluation of the proposed model underscore its superiority in pneumonia disease classification. With higher accuracy, precision, recall, and F1-score, along with reduced execution time, the model exhibits substantial enhancements in performance compared to existing methods [2], [4], and [12]. These improvements have significant implications for the healthcare industry, potentially reducing misdiagnoses, improving patient care, and optimizing resource utilization process.

5. Conclusion and Future Scope

In conclusion, the research presented in this paper represents a significant advancement in the realm of healthcare analytics, specifically in the domain of pneumonia disease classification. The proposed model, which amalgamates Convolutional Neural Networks (CNN), Naive Bayes, Deep Forest, and Multilayer Perceptron (MLP) techniques, exhibits substantial enhancements in performance when compared to existing methods [2], [4], and [12].

The empirical results demonstrate the model's prowess with a remarkable 94.6% accuracy rate, surpassing existing methods. Moreover, the precision, recall, and F1-score metrics reveal a notable improvement, signifying a reduced rate of misdiagnoses. Additionally, the model's efficient execution time of 1.5 seconds underscores its potential for expediting the diagnostic process.

These findings hold profound implications for the healthcare industry. The proposed model offers the promise of more accurate and timely pneumonia disease classification, potentially leading to improved patient care, reduced healthcare costs, and enhanced resource allocation. The combination of ensemble learning, deep learning, and probabilistic techniques has unlocked new horizons in disease diagnosis, setting a precedent for future research in healthcare analytics.

Future Scope

While this research presents a robust model for pneumonia disease classification, there are several avenues for future exploration:

- **Dataset Expansion**: Expanding the dataset with a larger and more diverse set of patient cases can further enhance the model's performance and generalization capabilities.
- **Explainability**: Integrating explainable AI (XAI) techniques into the model can provide insights into its decision-making process, making it more interpretable for clinicians.
- **Real-time Monitoring**: Implementing real-time patient monitoring using Internet of Things (IoT) devices and sensors can enable continuous disease tracking and early intervention.
- **Multimodal Data**: Incorporating other medical data modalities, such as patient history, clinical notes, and additional medical imaging, can lead to a more holistic and accurate diagnosis.
- **Clinical Validation**: Conducting rigorous clinical trials and validations to assess the model's performance in real-world healthcare settings is imperative.
- **Deployment in Telemedicine**: Adapting the model for telemedicine applications can extend its reach to remote and underserved areas, improving healthcare accessibility levels.
- **Disease Extension**: Expanding the model's scope to classify multiple respiratory diseases can broaden its utility in clinical practice sets.

In conclusion, the proposed model's success in pneumonia disease classification signifies a pivotal step towards the advancement of healthcare analytics. Its performance improvements, coupled with the outlined future research directions, pave the way for a more efficient, accurate, and accessible healthcare system that can ultimately enhance patient outcomes and quality of care for different use cases.

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