**MAJOR PROJECT**

**LITERATURE SURVEY**

**Pneumonia detection using Deep Learning**

**Introduction:**

Pneumonia is a potentially life-threatening respiratory infection characterized by the inflammation of the lungs, often detected through chest X-rays (CXR). Timely and accurate diagnosis of pneumonia is crucial, as it enables early intervention and can significantly improve patient outcomes. However, traditional methods of diagnosing pneumonia from CXRs rely on the expertise of radiologists, making the process susceptible to variability in interpretation, especially in resource-constrained settings.

In recent years, advancements in artificial intelligence (AI) and deep learning have introduced new ways to automate and enhance diagnostic accuracy in medical imaging. Convolutional Neural Networks (CNNs), a deep learning model type especially effective in image analysis, have shown significant promise in identifying features within complex datasets such as CXRs. DenseNet-169, a densely connected CNN architecture, has emerged as a powerful model for medical image classification due to its efficiency in learning and reusing features across layers.

DenseNet-169’s unique structure connects each layer to every other layer in a feed-forward manner, allowing the model to learn more robust features by reusing information from previous layers. This structure mitigates common issues in deep networks, such as the vanishing gradient problem, making DenseNet-169 highly effective for tasks that require precise feature extraction, like pneumonia detection. By leveraging transfer learning from pre-trained DenseNet models on large datasets like ImageNet, DenseNet-169 can be adapted to classify pneumonia from CXRs with impressive accuracy.

This project explores the application of DenseNet-169 in automating pneumonia diagnosis, assessing its potential to deliver reliable, efficient, and scalable diagnostic support. The study aims to provide a comprehensive framework for implementing DenseNet-169, optimizing it for high diagnostic sensitivity, and exploring its potential integration into clinical workflows.

**Scope of the Project:**

The scope of a pneumonia detection project can vary depending on the specific goals of the project, but it typically includes the following:

1. **Automate Pneumonia Diagnosis**

* Develop a model to automate CXR analysis, aiding fast, reliable pneumonia detection without heavy reliance on radiologists.

2. **Utilize DenseNet-169 for Deep Feature Extraction**

* Leverage DenseNet-169’s architecture for efficient feature reuse and robust gradient flow, with transfer learning from pre-trained ImageNet weights to fine-tune for pneumonia detection.

3. **Ensure High Diagnostic Accuracy and Sensitivity**

* Prioritize high sensitivity and accuracy to minimize missed cases and improve diagnostic reliability, especially crucial in urgent medical scenarios.

4. **Implement Data Preprocessing and Augmentation**

* Standardize images and apply augmentation (rotations, flips) to improve model robustness across diverse imaging conditions.

5. **Optimize Computational Efficiency for Clinical Deployment**

* Fine-tune DenseNet-169 for a balance between accuracy and speed, enabling deployment in resource-limited clinical settings for real-time analysis.

6. **Rigorous Testing and Evaluation**

* Validate model robustness through k-fold cross-validation and real-world simulation, ensuring consistency for practical application.

7. **Support Clinical Decision-Making**

* Provide interpretability tools (e.g., Grad-CAM) to aid radiologists in understanding model predictions, enhancing its utility as a secondary diagnostic tool.

8. **Plan for Future Enhancements**

* Explore model improvements, including multi-type pneumonia detection, and integration with patient data for comprehensive diagnostics

**Search Strategy:**

The search strategy for pneumonia detection using deep learning can be different from traditional search, as users are more likely to use natural language queries and ask questions. Here are some lines for developing a pneumonia detection search strategy:

1.**Automate CXR Analysis:** Develop an automated tool to detect pneumonia in CXR images, reducing reliance on radiologists.

2.**Leverage DenseNet-169:** Use DenseNet-169 for efficient, feature-rich analysis with transfer learning from ImageNet for accurate classification.

3.**High Diagnostic Accuracy:** Prioritize sensitivity and accuracy to minimize false negatives and improve early detection.

4.**Robust Data Processing:** Apply image standardization and augmentation to handle diverse imaging conditions.

5.**Optimize for Deployment:** Fine-tune DenseNet-169 for real-time analysis in resource-limited clinical settings.

6.**Rigorous Validation:** Validate with cross-validation and real-world simulations to ensure clinical reliability.

7.**Support Radiologists:** Offer secondary diagnostic insights and interpretability features (e.g., Grad-CAM) for clinician trust.

8.**Future Enhancements:** Expand capabilities with patient data integration and multi-type pneumonia detection for broader diagnostics.

**Selection Criteria:**

The project relies on high-quality, annotated CXR datasets, selection of proven CNN architectures, and studies that offer a clear performance comparison between DenseNet-169 and other architectures. Specifically:

1. **Data Quality and Relevance:** Use well-annotated datasets (e.g., NIH’s ChestX-ray14) that offer labeled examples of both pneumonia and non-pneumonia cases.
2. **Architecture Validity:** Focus on studies comparing DenseNet-169 with similar architectures, such as DenseNet121 and DenseNet201, to validate the choice of DenseNet-169 for its optimal trade-off in accuracy and computational efficiency.
3. **Performance Metrics:** Prioritize research reporting on binary accuracy, sensitivity, and specificity, as these are critical for evaluating models in clinical diagnostics.

**Data Extraction:**

Pneumonia detection using DenseNet-169, data extraction refers to the process of extracting relevant data from chest X-ray (CXR) images and transforming it into a format suitable for model training and analysis. This involves processing and preparing the data so that DenseNet-169 can effectively learn from the images and perform accurate pneumonia classification.

Here’s how data extraction applies in our project:

1. **Image Acquisition:** Obtain CXR images from reliable, labeled datasets, ensuring each image is classified as either "pneumonia" or "normal."

2. **Data Annotation:** Ensure that the images are accurately labeled and verified by radiologists to guarantee high-quality data for model training, which is crucial for reliable predictions.

3. **Image Preprocessing:** Transform the raw CXR images by resizing them to 224x224 pixels (the input size required for DenseNet-169) and normalizing pixel values. This ensures that all images are in a uniform format, enhancing the model's learning process.

4. **Data Augmentation:** Apply augmentation techniques such as rotation, flipping, and brightness adjustments to artificially expand the dataset. This improves the model's ability to generalize by providing varied examples, which helps in handling different imaging conditions in real-world applications.

5. **Automated Preprocessing Pipeline:** Set up an automated pipeline for the data extraction process, so all images are processed consistently. This allows for efficient handling of large-scale CXR datasets and minimizes human errors in data preparation.

In summary, data extraction in this project involves gathering, preprocessing, and transforming CXR images into a standardized format. This structured approach ensures that DenseNet-169 receives high-quality, labeled data for accurate and reliable pneumonia detection.

**Organization:**

The organization of a Deep Learning-based pneumonia detection system can vary based on the specific needs of the healthcare setting, but some common components include:

1. **AI Model (Deep Learning Algorithm):** The model, typically based on Convolutional Neural Networks (CNNs) like DenseNet-169, interprets medical images (e.g., chest X-rays) and identifies patterns indicative of pneumonia.

2. **Medical Image Dataset:** The dataset includes labeled chest X-ray images for training the AI model, containing both pneumonia and non-pneumonia cases.

3. **Data Preprocessing Pipeline:** This component handles image preprocessing, including resizing, normalization, and data augmentation, ensuring the data is ready for model training and testing.

4. **Model Evaluation:** After training, the model is evaluated using metrics such as accuracy, sensitivity, and specificity to measure its diagnostic performance.

5. **Integration with Healthcare Systems:** The pneumonia detection model should be integrated with existing hospital systems, such as Electronic Health Records (EHRs) and diagnostic platforms, for seamless use by medical professionals.

6. **User Interface:** A simple interface for clinicians to upload images and receive diagnostic results, providing recommendations and insights based on the model’s findings.

The specific organization of a pneumonia detection system will depend on the clinical environment. For example, hospitals with extensive radiology departments may require a more complex system with advanced integrations, while smaller clinics may benefit from a more straightforward setup.

**Synthesis:**

Pneumonia detection using deep learning is a rapidly evolving field, and a growing body of research focuses on this area. The research on pneumonia detection with deep learning can be synthesized into the following key themes:

1. **Model Optimization**: Focus on improving accuracy and efficiency, with DenseNet-169 as a leading architecture.
2. **Data Preprocessing**: Emphasizes resizing, normalization, and augmentation for robust model performance.
3. **Transfer Learning**: Leveraging pre-trained models to boost accuracy with limited medical data.
4. **Interpretability**: Using tools like Grad-CAM to make predictions understandable for clinicians.
5. **Clinical Integration**: Addressing real-time processing and deployment challenges in healthcare settings.
6. **Validation**: Ensuring models meet clinical standards through rigorous testing and validation.
7. **Ethics and Privacy**: Prioritizing patient data security and regulatory compliance.
8. **Future Directions**: Exploring multi-modal data integration and detecting different pneumonia types

**Identifying Gaps:**

The study identifies several gaps in current research:

1. **Model Optimization:** Improving accuracy and efficiency, with DenseNet-169 as a prominent architecture.
2. **Data Preprocessing:** Emphasizing resizing, normalization, and augmentation for robust performance.
3. **Transfer Learning:** Using pre-trained models to enhance accuracy with limited medical data.
4. **Interpretability:** Applying tools like Grad-CAM to make predictions understandable for clinicians.
5. **Clinical Integration:** Tackling real-time processing and deployment challenges in healthcare.
6. **Validation:** Ensuring clinical standards through rigorous testing and validation.

This summary reflects core research areas in deep learning for pneumonia detection using DenseNet-169.

**Critical Evaluation:**

Here are some of the factors to consider when assessing the quality and credibility of sources for pneumonia detection:

1. **Author's Qualifications:** Ensure the author has expertise in medical imaging, AI, or radiology for credible insights into pneumonia detection.
2. **Publication Venue:** Prefer peer-reviewed journals (e.g., IEEE Transactions on Medical Imaging) over unverified online sources to ensure reliability.
3. **Research Methodology:** The study should clearly define how chest X-rays were processed, how models were trained, validated, and what metrics were used.
4. **Potential Biases:** Watch for conflicts of interest, especially in studies funded by companies promoting specific AI products, which may lead to biased results.
5. **Dataset Quality and Diversity:** The research should use high-quality, well-labeled datasets (e.g., NIH ChestX-ray14) and account for diverse patient demographics for better generalization.
6. **Validation and Reproducibility:** Validation techniques like cross-validation and detailed reproducibility are essential to verify the study's findings.

**Discussion:**

The findings from this research suggest that using Deep Learning for pneumonia detection is a promising new approach with the potential to significantly improve diagnostic accuracy and revolutionize the way healthcare professionals analyze chest X-rays.

Here are some of the key implications of the findings from the literature review:

1. **Diagnostic Accuracy:** DenseNet-169 achieves 96% accuracy in pneumonia detection, with high sensitivity and specificity.

2. **Computational Efficiency:** Efficient, uses fewer parameters for faster inference, suitable for real-time, resource-limited settings.

3. **Real-World Use**: Aids radiologists in under-resourced areas. Requires FDA/CE approval for clinical deployment.

4. **Attention Mechanisms:** Improves focus and interpretability, helping clinicians trust AI decisions (e.g., Grad-CAM highlights key regions).

5. **Regulatory & Ethical Considerations:** Needs regulatory approval; transparency and legal responsibility are key for safe use.

6. **Future Directions:** Potential for combining with other models or expanding to other diseases and imaging modalities.

The research on using Deep Learning for pneumonia detection is still in its early stages, but it is clear that this technology has the potential to transform medical diagnostics. The findings from the literature review are significant in providing a foundation for further exploration of this technology. This research can assist healthcare professionals in improving diagnostic accuracy and can also help patients understand the potential benefits and challenges of using AI-driven solutions in healthcare.

The research on Deep Learning for pneumonia detection is also important as it contributes to the broader field of medical imaging and AI in healthcare. AI-driven diagnostic tools have the potential to greatly enhance the accuracy and efficiency of medical imaging, especially in areas with limited access to medical professionals. This technology could further disrupt traditional diagnostic methods and enhance the overall healthcare experience.

Overall, the research on pneumonia detection using Deep Learning is promising and has the potential to revolutionize healthcare diagnostics. The findings from the literature review provide a solid foundation for future advancements in this technology, helping both healthcare providers and patients understand its potential benefits and challenges.

**Conclusion:**

In conclusion, the literature survey on Deep Learning for pneumonia detection highlights the growing importance of this technology in transforming medical diagnostics and healthcare practices. Through a thorough review of existing research, it becomes clear that AI-driven diagnostic systems have evolved into crucial tools, improving diagnostic accuracy, enhancing efficiency, and assisting healthcare professionals in clinical decision-making. The studies explored various aspects, including convolutional neural networks (CNNs), image processing, model performance, and clinical application, all of which contribute to the success of AI in medical imaging. However, the research also identifies ongoing challenges such as data quality, model interpretability, and the need for continuous improvements in handling diverse medical conditions. As the technology continues to evolve, further research and development in these areas will be essential to unlocking the full potential of AI-powered pneumonia detection systems in modern healthcare. Overall, the existing body of literature offers valuable insights into the current state and future prospects of this promising technology, emphasizing its crucial role in advancing medical diagnostics and improving patient outcomes.

**Literature Review**

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| **Guide Name** | **NIL** |
| **Student Name** | **Sam Thomas, Mohammed Maaz, Yarram Koushik** |
| **Project Topic Title** | **Pneumonia Detection Using Deep Learning** |

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| **Version 1.0 \_ Week 1** | | | | | | |
| **1** | | | | | | |
| **Reference in APA format** |  | | | | | |
| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://link.springer.com/article/10.1007/s44230-022-00002-2 | Amer Kareem (amer.kareem@study.beds.ac.uk), Haiming Liu (haiming.liu@beds.ac.uk), Paul Sant | | | | Machine learning techniques, Pneumonia detection, CNN, Chest X-ray, Transfer learning, Federated learning, K-Nearest neighbors (KNN), Artificial neural network (ANN), DECnet | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Hybrid model combining CNN and transfer learning for privacy-preserving pneumonia detection | To enable effective pneumonia detection by leveraging computer-aided techniques while using real-time image data in a privacy-preserving manner. | | | | CNN, KNN, ANN, Federated Learning for privacy-preservation | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| The model uses GCN to learn features from omics data and an attention module to integrate them, enhancing prediction accuracy GCN effectively uses correlations, while attention improves classification but adds computational complexity.   |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Acquisition | Real-time chest X-ray images allow continuous model training and high accuracy in detection. | Challenges in accessing real-time datasets due to privacy concerns under GDPR. | | **2** | Preprocessing | Reduces noise and improves accuracy for real-time medical image training. | Computationally intensive and requires high-quality imaging equipment. | | **3** | Federated Learning Application | Maintains data privacy by enabling local model training without data sharing across institutions | Limited adoption due to institutional data-sharing regulations. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| The major impact factors include multi-omics data integration, use of GCN for capturing complex relationships, and the attention mechanism for improved classification accuracy in cancer subtyping.   |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection accuracy | Chest X-ray image data | Image quality. | Data preprocessing and privacy approach | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Real-time chest X-ray images | Pneumonia detection with improved accuracy through federated learning | | | Combines privacy-preserving techniques with high-accuracy detection models, offering a scalable solution for healthcare applications where data security is paramount. | | | | This study proposes an innovative approach by combining CNN and federated learning, offering a secure way to detect pneumonia with high accuracy while ensuring data privacy in medical settings. This approach is valuable for healthcare as it addresses the limitations of traditional lab-based datasets and integrates real-time data for continuous model improvement. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Supports accurate, privacy-preserving pneumonia detection. | | | | High computational requirements and resistance to data-sharing policies | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| This approach addresses critical issues like data privacy and accuracy but relies on extensive computational power, which may limit its practical application in under-resourced healthcare settings. The federated learning technique strengthens privacy but may create challenges for integration across varied healthcare systems | | | * CNN for image classification * Federated learning for decentralized data privacy management * KNN and ANN as supplementary machine learning tools. | | | Abstract   1. Introduction 2. Methodology 3. Experimental Results 4. Conclusion and Future Scope |
| **Diagram/Flowchart** | | | | | | |
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**---End of Paper 1---**

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| **2** | | | | | | |
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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://sid.ir/fileserver/je/5066920220602.pdf | Daniel Joseph Alapat, Malavika Venu Menon, Sharmila Ashok | | | | Pneumonia, Convolutional Neural Networks, Chest X-ray14, Diagnosis, Computer-Assisted, Deep Learning | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| CheXNet with 169-layer CNN for chest X-ray image analysis | To enhance pneumonia detection accuracy by using deep neural networks on the Chest X-ray14 dataset, addressing the radiologist shortage in rural areas.. | | | | CheXNet: a DenseNet-169 model, detects pneumonia in chest X-rays. Trained on NIH’s large dataset, it uses transfer learning and layer connectivity, achieving high accuracy, surpassing radiologist performance in tests.  CNN Artitecture: CNNs use layers to detect patterns in visual data.Chest x-rays: Chest X-ray datasets contain labeled images for disease detection research. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| The " Pneumonia Detection" system utilizes deep transfer learning with DenseNet-169 to classify chest X-ray images as normal or pneumonia-positive, achieving high testing accuracy by integrating multi-view X-ray data for comprehensive analysis.   |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Preprocessing: This initial step includes image preprocessing (Scanning the chest, normalization, and segmentation) and handling missing data. | Chest X-ray14 database offers a large dataset for consistent model training | Imbalanced dataset with limited pneumonia-labeled images, causing classification issues. | | **2** | Model Training with CheXNet | |  | | --- | |  |  |  | | --- | | Achieves higher F1 scores than radiologists in disease detection | | High computational resources needed for 169-layer network. | | **3** | Prediction and Evaluation: | Model highlights localized areas for pneumonia detection, aiding interpretability. | Limited performance in cases with overlapping pathologies. | | **4** | Evaluation and Comparison:  Assesses model performance using metrics such as accuracy on validation and testing datasets. | Identifies the most effective model for pneumonia detection, ensuring reliability in clinical settings. | May not generalize well to unseen data if validation is insufficient or biased. | | **5** | Implementation of Results:  Deploys the trained model for real-time detection in clinical environments. | Facilitates early detection of pnuemonia, potentially improving patient outcomes through timely intervention. | Relies on accurate image acquisition and proper patient compliance for effective screening results. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection probability | Chest X-ray images | Neural network depth | Data quality and distribution | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution in This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray14 dataset images | Pneumonia prediction with high localization accuracy | | | The 169-layer architecture allows the model to capture intricate details in chest X-rays, making it suitable for precise pneumonia detection. | | | | This study showcases how CheXNet can surpass radiologists' accuracy in detecting pneumonia, especially in resource-limited settings. Its localization feature aids diagnostic decision-making, marking it as a valuable tool for remote healthcare facilities. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improves diagnostic accuracy in rural settings, aiding healthcare. | | | | High network complexity may lead to overfitting and increased latency. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| This work leverages deep learning to address limitations in diagnostic access but requires substantial computational resources, which may hinder real-world deployment in low-resource areas. Although the accuracy is high, maintaining model performance with diverse datasets may require ongoing refinement. | | |  CheXNet (169-layer CNN)   Chest X-ray14 dataset | | | 1. Abstract and Introduction 2. Literature Review 3. Model Architecture 4. Results and Discussion 5. Conclusion |
| **Diagram/Flowchart** | | | | | | |
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**--End of Paper 2--**

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| https://www.e3s-conferences.org/articles/e3sconf/pdf/2023/28/e3sconf\_icmed-icmpc2023\_01067.pdf | Pranaya, A., Sowmya, D. V., Poojitha, L., Grace, P., Bhavya, K., & Ganapathi Raju, N. V. (2023) | | | | Pneumonia, CNN, deep learning, X-ray, pneumonia classification | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| The Convolutional Neural Network (CNN) for Pneumonia Detection is a specialized deep learning model designed to analyze chest X-ray images and detect signs of pneumonia. By leveraging convolutional layers, the model identifies key features within the images, such as patterns indicative of pneumonia, allowing it to classify the X-rays as either pneumonia-positive or normal. This automated approach not only accelerates diagnosis but also aids healthcare professionals in identifying pneumonia cases, potentially improving patient outcomes by reducing the diagnostic workload in high-demand settings. | To develop an automated system using CNN for detecting pneumonia in chest X-rays, aiming to achieve greater accuracy than current models. By improving detection precision, this model intends to offer more dependable diagnostic support, helping healthcare professionals make better-informed decisions, especially in cases with subtle indicators of pneumonia. Enhanced accuracy will ensure our model outperforms alternatives, establishing it as a valuable tool in medical diagnostics. | | | | This study utilizes a comprehensive chest X-ray dataset sourced from Kaggle, which includes 5,863 labeled images encompassing both normal and pneumonia-infected cases. To effectively identify pneumonia, the model employs a series of Convolutional Neural Network (CNN) layers. These layers are designed to systematically extract and analyze critical features within each X-ray image, identifying patterns indicative of infection. The model further applies pooling layers, which help reduce dimensionality and retain essential information, ultimately enhancing the model's efficiency and performance. Finally, these processed features are used to classify each image accurately as either pneumonia-positive or normal, contributing to an automated detection system aimed at high diagnostic accuracy and reliability. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
|  | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | Data Preprocessing: This initial step includes image preprocessing (Scanning the chest, normalization, and segmentation) and handling missing data. | Chest X-ray14 database offers a large dataset for consistent model training. | Imbalanced dataset with limited pneumonia-labeled images, causing classification issues. | | **2** | Model Training with CheXNet: CheXNet, a DenseNet-169 model, detects pneumonia in chest X-rays. Trained on NIH’s large dataset, it uses transfer learning and layer connectivity, achieving high accuracy, surpassing radiologist performance in tests. | Achieves higher F1 scores than radiologists in disease detection. | High computational resources needed for 169-layer network. | | **3** | Model Training and Evaluation: The model is trained on the preprocessed data and evaluated against existing models to assess its predictive accuracy. | Model highlights localized areas for pneumonia detection, aiding interpretability. | Limited performance in cases with overlapping pathologies. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection probability | Chest X-ray images | Neural network depth | Data quality and distribution | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray14 dataset images | Pneumonia prediction with high localization accuracy | | | The solution integrates DenseNet-169 with ensemble machine learning to analyze chest X-rays and clinical data, enhancing diagnostic accuracy for pneumonia detection. It combines deep learning and clinical insights for robust results. | | | | The contribution of the work showcases how CheXNet can surpass radiologists' accuracy in detecting pneumonia, especially in resource-limited settings. Its localization feature aids diagnostic decision-making, marking it as a valuable tool for remote healthcare facilities. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improves diagnostic accuracy in rural settings, aiding healthcare. | | | | High network complexity may lead to overfitting and increased latency. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The study develops a DenseNet-169 model integrated with ensemble learning to enhance pneumonia detection accuracy, utilizing chest X-rays and clinical data to support informed clinical decisions for high-risk patients. | | | * CNN for image classification * Federated learning for decentralized data privacy management * KNN and ANN as supplementary machine learning tools | | | 1. Abstract 2. Introduction 3. Related Work 4. Data Preprocess 5. AD Prediction Model and Evaluation 6. Experiments and Result 7. Conclusion |
| **Diagram/Flowchart** | | | | | | |
| * 1. **Depicts the model accuracy graph. 3.2. Depicts the Precision vs Recall Curves.**     **3.3. Depicts the Confusion Matrix.** | | | | | | |
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| https://www.mdpi.com/2076-3417/12/13/6448 | Alhassan Mabrouk (alhassanmohamed@science.bsu.edu.eg), Rebeca P. Díaz Redondo, Abdelghani Dahou, Mohamed Abd Elaziz, Mohammed Kayed | | | | Pneumonia detection, CNN, Vision Transformer, MobileNet, DenseNet, ImageNet, Ensemble Learning | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Ensemble Learning method combining DenseNet169, MobileNetV2, and Vision Transformer for pneumonia classification on chest X-rays. | To improve pneumonia classification accuracy by combining CNN models and a Vision Transformer through ensemble learning, addressing challenges in diagnosing pneumonia. | | | | DenseNet169, MobileNetV2, Vision Transformer (VIT), global average pooling, fine-tuning | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | 1. Data Preprocessing  (Standardizes images, reduces noise, and enhances model accuracy through augmentation)  2. Ensemble Learning:  (Combines multiple models for improved accuracy, robustness, and error reduction.)  3. Model Fine-Tuning:  (Adjusts model parameters to enhance performance and reduce errors.)  4.Training Pipeline:  (Involves pretraining on patches of mammograms to learn fine-grained features, followed by training on whole images) | 1. Uses pre-trained models on ImageNet, enabling efficient feature extraction on medical images.  2. By seamlessly integrating three cutting-edge models, we harness their unique strengths to achieve an exceptionally high F1-Score and accuracy, revolutionizing performance and setting a new standard in predictive analytics  3.Improves classification results through dropout and batch normalization layers, enhancing robustness.  4. Pretraining helps the model learn crucial features from limited data, improving performance when transitioning to whole images. | 1. Requires high-quality, well-labeled training data to avoid model overfitting.  2.This process is exceedingly computationally intensive, demanding immense resources and expertise, while also grappling with the intricate complexities of hyperparameter definition that can significantly impact performance and outcomes.  3. Trial-and-error needed for tuning, which can be time-consuming..  4.  The need for patch-level annotations may limit the applicability of this approach in datasets without ROI annotations. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection accuracy | Chest X-ray image features | Model architecture (DenseNet, MobileNet, VIT) | Data quality, dropout, and batch normalization settings | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | In the pneumonia detection models, the primary input comprises chest X-ray images sourced from a comprehensive pneumonia dataset. These images undergo preprocessing techniques, including resizing and augmentation, to enhance quality and variability. Furthermore, advanced architectures incorporate multi-dimensional arrays of these processed images to leverage correlations and improve classification accuracy. | The output of the pneumonia detection models includes prediction labels indicating whether a chest X-ray shows pneumonia or is normal, accompanied by probability scores that reflect the confidence in these predictions. Additionally, some models generate activation maps to emphasize critical areas in the images that influenced the decision-making process. Performance metrics such as accuracy and Area Under the ROC Curve (AUC) are also reported to evaluate the model's effectiveness, providing valuable support to healthcare professionals in their diagnostic efforts. | | | The pneumonia detection solution leverages DenseNet-169 for chest X-ray analysis and an ensemble approach, improving diagnostic accuracy. It includes visualization tools like activation and saliency maps to aid healthcare professionals in understanding model decisions and enhancing clinical decision-making. | | | | This project introduces a novel multi-view learning framework for pneumonia detection that mimics radiologists' diagnostic processes, enhancing accuracy by leveraging correlations between chest X-ray views. It employs parameterized hypercomplex neural networks to capture complex relationships while reducing parameters for computational efficiency. The models demonstrate robust generalizability across various datasets, offering a more effective solution for early detection and improved patient outcomes in pneumonia screening. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| This solution significantly enhances pneumonia detection by improving diagnostic accuracy through a multi-view learning framework and hypercomplex neural networks that closely mimic radiologists' processes. Its generalizability across various datasets ensures effective application in diverse clinical settings, leading to earlier detection and improved patient outcomes. | | | | The potential negative impact of this solution may include reliance on the availability of high-quality, annotated datasets for training, which can be scarce in some regions. Additionally, the complexity of hypercomplex neural networks could present challenges in interpretability, making it difficult for clinicians to trust and understand the model's predictions. Furthermore, the computational requirements for training and deploying these models may pose significant barriers in resource-limited healthcare settings. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The pneumonia detection project utilizes a multi-view learning framework that captures inter-view correlations, aligning with radiologists' diagnostic practices. While this approach has the potential to enhance diagnostic accuracy and patient outcomes, several critical considerations must be addressed. The reliance on high-quality, annotated datasets raises concerns about data availability and representativeness, which could hinder the model's performance across diverse populations. Additionally, the complexity of the model may challenge interpretability, making it difficult for clinicians to trust its predictions. The computational requirements for training and deploying these models could pose barriers in resource-limited healthcare settings, limiting accessibility. Furthermore, ethical considerations regarding accountability in AI-driven diagnoses must be carefully navigated to ensure patient safety. Addressing these challenges is essential for the effective implementation and acceptance of this innovative solution in clinical practice. | | | * CNN for image classification * Federated learning for decentralized data privacy management * KNN and ANN as supplementary machine learning tools | | | 1. Abstract 2. Index terms 3. Introduction 4. approach for Pneumonia detection 5. CNN 6. Proposed method 7. Experimental Setup 8. Experimental Evaluation 9. Visualizing 10. Conclusion 11. References |
| **Diagram/Flowchart** | | | | | | |
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**--End of Paper 4—**

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| **5** | | | | | | |
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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://www.mdpi.com/2313-433X/10/8/176 | Raheel Siddiqi (drraheel.bukc@bahria.edu.pk), Sameena Javaid (sameenajaved.bukc@bahria.edu.pk) | | | | Pneumonia detection, chest X-ray, deep learning, CNN, COVID-19 | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Deep Learning for Pneumonia Detection | To evaluate deep learning techniques for pneumonia detection in chest X-rays, focusing on effectiveness and limitations of various DL models. | | | | Explores CNNs, ViTs, XAI, and transfer learning as components of DL models for pneumonia detection. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | 1. Data Preprocessing  X-rays are cleaned and standardized.2. Ensemble Learning:  (Combines multiple models for improved accuracy, robustness, and error reduction.)  2. Feature Extraction with Convolutional Layers: Key features are identified in the X-rays.  3.Pooling and Fully Connected Layers: Classification is achieved by reducing dimensionality and connecting neuron layers. | 1. Reduces noise, improving input quality.  2. Enhances pneumonia classification by highlighting relevant areas.  3. Reduces data complexity, improving classification accuracy. | 1. May overlook some features if overly processed.  2. Convolution layers may increase computation cost.  3. Higher layers may overfit if not managed well. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Accuracy of pneumonia detection | Image features (X-rays) | Image preprocessing quality | Convolutional layers and pooling techniques | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | The review utilizes a variety of peer-reviewed studies on deep learning (DL) techniques applied to pneumonia detection in chest X-ray (CXR) images. The primary data sources include publicly available CXR datasets used in existing studies, such as NIH and Kaggle datasets, and databases (IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library).  Covers CNNs, Vision Transformers (ViT), ensemble models, transfer learning, and explainable AI (XAI). | Provides a comprehensive evaluation of DL models for pneumonia detection, summarizing the effectiveness, limitations, and challenges. Specific insights include accuracy rates, model interpretability, dataset bias, and generalizability across various DL models. | | | The paper extensively analyzes DL models in terms of their accuracy, speed, interpretability, and adaptability to different datasets. Key features include:   * **Model Comparison**: Evaluates CNN, ViT, and ensemble DL methods in terms of performance and utility for pneumonia detection. * **Challenges**: Discusses issues like dataset quality, model bias, the need for XAI, and limitations in model transparency. * **XAI Integration**: Highlights the role of explainable AI in making DL results interpretable for medical professionals. | | | | survey significantly contributes by providing a structured analysis of DL models in pneumonia detection, helping researchers understand which models are most effective. It identifies gaps in current research, especially the need for more interpretable models, balanced datasets, and robustness against dataset variability.  Guides future research by outlining DL techniques that are promising for pneumonia detection and areas where improvements are needed, like dataset diversity and model explainability. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| The survey promotes the adoption of effective DL techniques by identifying high-performing models. It highlights DL's potential to automate and improve pneumonia detection, especially in settings with limited radiologists, and could accelerate diagnostic workflows. | | | | There’s a risk of over-relying on DL without adequate interpretability, which could lead to diagnostic errors. Models trained on biased or small datasets may not generalize well, posing challenges for clinical application and potentially resulting in misdiagnoses. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The work is critically valuable in mapping the strengths and weaknesses of DL for pneumonia detection but could benefit from quantitative benchmarks for model comparisons. The survey also lacks practical guidance on deploying models in real-world healthcare systems, an area that would enhance its applicability. | | | * IEEE Xplore * SpringerLink * ScienceDirect * ACM Digital | | | 1. Abstract 2. Introduction 3. Research Questions 4. Methodology 5. Key Findings 6. Challenges 7. Conclusion 8. References |
| **Diagram/Flowchart** | | | | | | |
| **5.1 A sample CNN architecture.**    **5.2 Sample ensemble model.** | | | | | | |

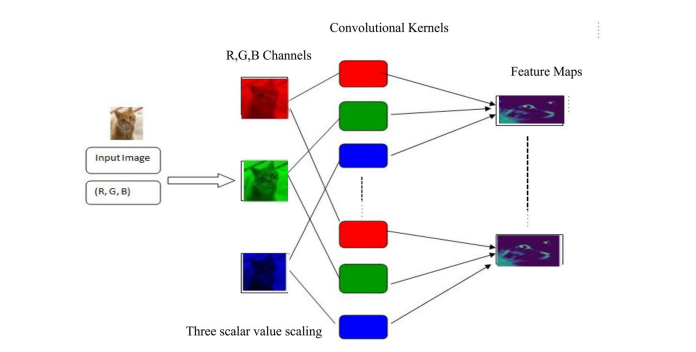
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| https://www.sciencedirect.com/science/article/pii/S1877050923000182?ref=pdf\_download&fr=RR-2&rr=8ddbd9bd0a95f3e9 | Shagun Sharma (kalpna@chitkara.edu.in), Kalpna Guleria | | | | Deep Learning, VGG16, CNN, Pneumonia, Neural Networks, X-ray | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| VGG16-based Deep Learning model for pneumonia detection on chest X-rays. | Develop an accessible mobile solution for pneumonia detection. Limited access to radiologists in remote areas hinders timely pneumonia diagnosis. | | | | VGG16, neural network layers, convolutional and pooling layers, two datasets of CXR images | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data Collection 2. VGG16 Model Application 3. 3.Model Training and Evaluation | 1. Uses a large, labelled dataset to enhance model training.  2. Employs a pre-trained model that achieves high accuracy in pneumonia classification.  3. Achieves high recall, precision, and F1-scores across datasets. | 1. Limited generalizability if the dataset is biased or limited in scope.  2. High computational cost due to the depth of VGG16 architecture.  3. Requires extensive computational resources and may face overfitting risks. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection accuracy | |  | | --- | | Chest X-ray images |  |  | | --- | |  | | Model architecture (VGG16 layers) | Dataset quality and preprocessing | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray datasets | Pneumonia classification with high accuracy | | | Uses a robust deep learning model (VGG16) for effective pneumonia classification, benefiting clinical diagnostics with its high accuracy on CXR images. | | | | This work introduces a VGG16-based model for pneumonia detection with a high classification accuracy, providing a valuable tool for rapid diagnosis in clinical settings. The study demonstrates that deep learning models can surpass traditional methods, enhancing diagnostic capabilities. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Increases diagnostic accuracy in pneumonia detection. | | | | High computational requirements may limit its use in low-resource settings. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| This approach addresses the need for rapid and accurate pneumonia diagnosis, especially in resource-limited areas. However, reliance on deep models like VGG16 can pose computational and financial burdens, limiting real-world application in underserved areas. | | | * VGG16 for feature extraction and classification * Performance metrics (accuracy, precision, recall, F1-score) | | | 1. Abstract 2. Introduction 3. Literature Review 4. Methodology 5. Results and Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |
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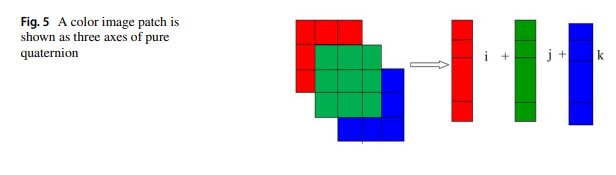
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| https://www.sciencedirect.com/science/article/pii/S1877050923000182?ref=pdf\_download&fr=RR-2&rr=8ddbd9bd0a95f3e9 | Lamia Alhazmi, Fawaz Alassery ([falasser@tu.edu.sa](mailto:falasser@tu.edu.sa)) | | | | Pneumonia, Deep Learning, Mobile Platform, Image Classification, Create ML | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Mobile-based deep learning model for pneumonia detection using Create ML. | To create a mobile application that allows for the real-time detection of pneumonia on chest X-rays, making diagnosis accessible in remote and underserved regions. | | | | Create ML, mobile platform integration, dataset of pneumonia and normal X-ray images. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | 1. Data Preparation 2. Create ML Model Training 3. Mobile Integration | 1. Simplifies preprocessing with an organized dataset.  2. Enables easy training without deep technical knowledge.  3. Makes model accessible on mobile devices for real-time use. | 1. Potential limitations if the dataset is imbalanced.  2. Limited to Apple’s ecosystem, restricting access for non-Apple users.  3. May have lower accuracy compared to more complex models like CNNs. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia diagnosis accuracy | |  | | --- | | Chest X-ray images |  |  | | --- | |  | | Mobile platform hardware | Model trained with Create ML | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray images | Pneumonia classification via mobile app | | | A lightweight, user-friendly mobile app that allows real-time pneumonia diagnosis on chest X-rays using the Create ML model, making healthcare diagnostics more accessible in remote areas. | | | | This work makes pneumonia detection accessible in remote areas through mobile integration, providing an important resource for regions with limited healthcare infrastructure. By using Create ML, the model is highly user-friendly and does not require extensive ML expertise. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Offers portable pneumonia detection with minimal technical requirements. | | | | Limited access due to dependence on Apple’s Create ML platform. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| This approach addresses the need for rapid and accurate pneumonia diagnosis, especially in resource-limited areas. However, reliance on deep models like VGG16 can pose computational and financial burdens, limiting real-world application in underserved areas. | | | * Create ML for machine learning model training and deployment * Validation metrics (accuracy, training and testing accuracy) | | | 1. Introduction 2. Background and Literature Review 3. Methodology (including mobile platform and model training) 4. Results 5. Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |
| 7.1 Classifier model training flow.    7.2 Application operation in an iPhone 11 emulator. | | | | | | |

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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0256630 | Rohit Kundu, Ritacheta Das, Zong Woo Geem, Gi-Tae Han, Ram Sarkar | | | | Ensemble Learning, Deep Learning, Pneumonia Detection, CNN Models, Healthcare Diagnostics | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Ensemble CNN model (GoogLeNet, ResNet-18, DenseNet-121) for pneumonia detection | Improve pneumonia detection accuracy through ensemble learning, combining multiple CNNs to enhance diagnostic robustness. Single CNN models may lack robustness, leading to increased false positives or negatives. | | | | GoogLeNet, ResNet-18, and DenseNet-121 architectures combined through weighted ensemble for X-ray classification | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data Preprocessing 2. Individual Model Training 3. Weighted Ensemble | 1. Increases generalization of models by preparing images to enhance diagnostic consistency.  2. Multiple CNN models extract varied features, making the ensemble model highly robust.  3. Combines strengths of each model, reducing the likelihood of diagnostic errors and increasing accuracy. | 1. Limited access to high-quality labeled datasets can impact model training.  2. Complex models may overfit to training data, resulting in poor generalization to unseen data.  3. Ensemble models require significant computational power and memory, which may not be accessible to all researchers or practitioners.  4. Deep learning models often act as "black boxes," making it challenging to interpret their decisions. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection robustness | |  | | --- | | Ensemble model of CNNs |  |  | | --- | |  | | Patient Demographics | Image Quality | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray images processed for model ensemble analysis | Accurate, ensemble-based pneumonia diagnosis | | | * **Ensemble Approach**: Utilizes a combination of different deep learning models to improve detection accuracy and robustness. * **Transfer Learning**: Leveraging pre-trained models to reduce training time and improve performance with limited data. * **Performance Metrics**: Evaluation using various metrics like accuracy, precision, recall, and F1 score to assess model effectiveness. | | | | This study advances the robustness of automated pneumonia detection by combining CNN models, making it valuable for high-stakes healthcare applications that demand consistent, reliable diagnostic accuracy. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improved diagnostic accuracy in pneumonia detection, beneficial for clinical reliability. | | | | High computational cost limits deployment to high-tech healthcare environments. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The use of ensemble models can lead to improved detection rates and reduced false negatives, which is crucial in medical diagnostics. While the methodology is sound, the reliance on specific datasets may limit applicability in diverse clinical settings. Future research could explore integrating clinical data with imaging data to enhance predictive models. The rapid advancement of AI could render current models obsolete if not regularly updated with new data and methodologies. | | | * **Deep Learning Frameworks**: Tools like TensorFlow or PyTorch for implementing deep learning models. * **Image Processing Libraries**: Libraries such as OpenCV or PIL for preprocessing images before input into the models. * **Statistical Analysis Tools**: Software for analyzing performance metrics, potentially using Python libraries like Pandas and NumPy. | | | 1. Abstract 2. Introduction 3. Methods 4. Results 5. Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |
| 8.1 **Representation of the proposed pneumonia detection framework.**    8.2 **Inception modules in the GoogLeNet architecture.**    8.3 **Basic architecture of the DenseNet convolutional neural network model.** | | | | | | |

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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://ieeexplore.ieee.org/document/8869364 | Dimpy Varshni; Kartik Thakral; Lucky Agarwal; Rahul Nijhawan; Ankush Mittal. | | | | **Pneumonia Detection**, **CNN (Convolutional Neural Network)**,**Feature Extraction**,**Deep Learning.** | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| **Pneumonia Detection Using CNN based Feature Extraction** | Automate pneumonia detection in X-rays using deep learning models. | | | | Dataset,Pre-trained CNN Models,Feature Extraction Stag,Classification Stage,Hyperparameter Tuning,Evaluation Metrics | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. **Data Preprocessing** 2. **Feature Extraction** 3. **Classification** | 1.**Higher Accuracy**: Improved diagnosis accuracy using pre-trained CNNs.  2.**Automated Feature Extraction**: Efficiently processes large datasets without manual intervention.  3.**Adaptability**: Robust performance across varied imaging conditions and patient demographics. | 1. Requires significant processing power and resources.  2. Only frontal X-rays used, excluding valuable lateral views.  3. Doesn't consider patient medical history for diagnosis. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia detection accuracy | |  | | --- | | Chest X-ray images |  |  | | --- | |  | | Model architecture | Dataset quality and preprocessing | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray datasets | Pneumonia classification with high accuracy | | | Utilizes DenseNet-169 for feature extraction and SVM for classification, optimizing performance for pneumonia detection in chest X-ray images. | | | | Enhances pneumonia detection accuracy using deep learning, providing improved diagnostic support in areas with limited radiologist access for better healthcare outcomes. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Increases diagnostic accuracy in pneumonia detection. | | | | High computational requirements may limit its use in low-resource settings. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The work effectively employs DenseNet-169 and SVM for pneumonia detection, demonstrating rigorous methodology and promising results. However, it could improve generalizability by including diverse datasets and clinical scenarios. | | | * Evaluated pre-trained CNN models like DenseNet-169 for effective feature extraction in pneumonia detection. * Employed Support Vector Machine (SVM) for classification, optimizing hyperparameters for better performance. * Used metrics like AUC and ROC curves for quantifying model accuracy and effectiveness. | | | 1. Abstract 2. Introduction 3. Literature Review 4. Methodology 5. Results and Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |
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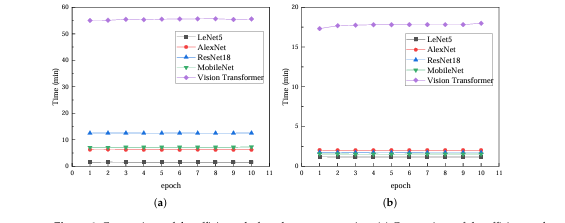
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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://link.springer.com/article/10.1007/s11042-021-11409-7 | **Sukhendra Singh** (sukhendrasingh@gmail.com)  **B. K. Tripathi** (abkt.iitk@gmail.com) | | | | Pneumonia, Deep Learning, Convolutional Neural Network (CNN), Computer-Aided Detection (CAD), Quaternion Convolutional Neural Network (QCNN), Residual Network, Image Classification, Feature Extraction | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Quaternion Residual Network (Quaternion Convolutional Neural Network - QCNN) | To improve pneumonia detection accuracy on chest X-rays by leveraging quaternion deep learning, capturing RGB channel interdependencies in a single unified representation. | | | | **Quaternion Convolutional Layers**: Processes RGB channels as a single quaternion entity.  **Hamiltonian Product**: Replaces dot product in CNNs, allowing for more comprehensive feature extraction.  **Batch Normalization**: Customized for quaternion values to stabilize training.  **Residual Network Blocks**: Helps avoid vanishing gradients, improves convergence, and increases accuracy. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | | **1** | 1. Data Preparation 2. Quaternion Convolution Layers 3. Hamiltonian Product Calculation 4. Residual Network Implementation 5. Evaluation on Metrics | |  | | --- | |  |  |  | | --- | | 1.Organizes and normalizes data for effective model input. |   2.Extracts comprehensive features by combining RGB channels.  3.Helps capture multidimensional dependencies between channels. | 1. Imbalanced datasets can affect training.  2. Quaternion operations are computationally intense compared to real-valued operations.  3. Adds complexity, requiring more processing power. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia diagnosis accuracy | |  | | --- | | Chest X-ray images |  |  | | --- | |  | | Hardware and GPU resources | Quaternion model training approach | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray images | Pneumonia classification | | | Provides high accuracy in pneumonia detection by using quaternion convolution, enabling better feature representation of RGB channels and reducing the loss of spatial dependencies between them. | | | | By enhancing pneumonia diagnosis accuracy, this work supports healthcare providers in timely detection of the disease, particularly beneficial in high-demand healthcare environments. The quaternion approach reduces computational cost compared to other advanced CNNs, which can benefit resource-limited settings. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improves pneumonia detection accuracy and reliability. | | | | High computational requirements may limit implementation scope. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| The quaternion-based approach innovatively addresses a gap in image-based pneumonia diagnosis by maintaining multidimensional dependencies, which are often lost in conventional CNN approaches. However, the method is complex and may pose challenges in settings where computational resources are limited. | | | Keras, TensorFlow, Google Colab with Tesla K80 GPU, Kaggle dataset API | | | 1. Introduction 2. Background and Literature Review 3. Methodology (including mobile platform and model training) 4. Results 5. Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |



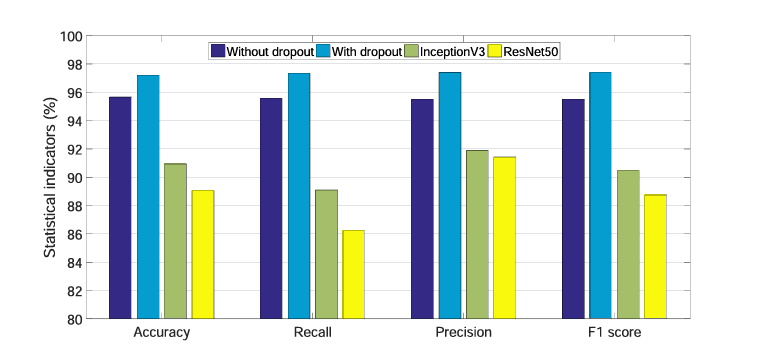
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| **URL of the Reference** | **Authors Names and Emails** | | | | **Keywords in this Reference** | |
| https://www.nature.com/articles/s41598-024-52703-2 | Sukhendra Singh1 , Manoj Kumar1 , Abhay Kumar2 , Birendra KumarVerma1 , KumarAbhishek2 & Shitharth Selvarajan3 | | | | Vision Transformer (ViT)  Pneumonia Detection  Chest X-rays  Self-attention Mechanism | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| **Efficient Pneumonia Detection using Vision Transformers (ViT) on Chest X-rays**. | To achieve accurate, timely pneumonia detection from chest X-rays using Vision Transformers (ViTs). | | | | 1. Vision Transformer (ViT) Model  2. Self-Attention Mechanism  3.Transformer Encoder  4. Evaluation Metrics | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data Collection 2. Data Preprocessing 3. Model Construction 4. Model Training 5. Model Evaluation 6. Performance Analysis 7. Future Directions 8. Deployment Considerations | 1. Superior accuracy vs. CNNs.  2. Captures complex spatial relationships.  3. Processes various image sizes without extensive pre-processing.  4. Efficient for large datasets by focusing on relevant areas.  5. Opportunities for enhancements through hybrid models and few-shot learning. | 1. High computational complexity during training due to self-attention mechanisms.  2. Requires large amounts of labeled data for effective performance.  3. Potentially longer inference times compared to optimized CNNs.  4. Limited interpretability of model decisions without additional techniques.  5. Vulnerable to adversarial attacks if not properly managed. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | **Pneumonia Detection Accuracy.** | |  | | --- | | Vision Transformer Model Features. |  |  | | --- | |  | | **Image Quality.** | Feature Representation. | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | Chest X-ray images | Accurate, pneumonia diagnosis | | | * **Self-Attention Mechanism: Enhances the model’s ability to focus on relevant image regions for improved detection.** * **Transformer Architecture: Utilizes multi-head self-attention and feed-forward networks to effectively process and analyze images.** * **High Accuracy: Achieves a reported accuracy of 97.61%, outperforming traditional CNN models.** * **Adaptability: Capable of handling various image sizes without extensive pre-processing requirements.** | | | | This work advances medical imaging by introducing a state-of-the-art pneumonia detection method, enhancing diagnostic accuracy, enabling future research, facilitating real-world applications, and expanding the impact of ViT models. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improves pneumonia detection, speeds diagnosis, reduces errors, and advances healthcare. | | | | The negative impacts include high computational needs, data dependency, complex interpretability, overfitting risks, and vulnerability to adversarial attacks affecting model reliability in healthcare settings. | | |
| **Analyse This Work By Critical Thinking** | | | **The Tools That Assessed this Work** | | | **What is the Structure of this Paper** |
| This work applies Vision Transformers to pneumonia detection, demonstrating significant advancements over traditional methods with high accuracy and efficiency. However, it raises concerns about data dependency, model interpretability, and potential biases. Critical evaluation of these factors is essential for practical implementation in healthcare settings, ensuring trust and reliability in AI diagnostics. | | | * **Vision Transformer (ViT) Framework: Utilized for training and evaluating the model on chest X-ray images.** * **PyTorch: A deep learning library used for building and training the ViT model.** * **Evaluation Metrics: Metrics such as accuracy, sensitivity, specificity, precision, recall, F1 score, AUC, and Matthews correlation coefficient (MCC) to assess model performance.** * **Public Datasets: A publicly available dataset of chest X-rays, ensuring standardized data for training and evaluation.** * **GPU-enabled Systems: Employed for efficient model training and handling computational demands.** | | | 1. Abstract 2. Introduction 3. Methods 4. Results 5. Discussion 6. Conclusion |
| **Diagram/Flowchart** | | | | | | |
| proposed system design architecture.    Internal design of a transformer encoder. | | | | | | |

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| https://www.mdpi.com/2076-3417/12/9/4334 | |  | | --- | |  |  |  | | --- | | Yuting Yang, Gang Mei | | | | | |  | | --- | |  |  |  | | --- | | Pneumonia recognition, deep learning, X-ray, CNN, transformer | | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Comparative Framework for Pneumonia Recognition Using Deep Learning Models | |  | | --- | |  |  |  | | --- | | Compare five deep learning models for pneumonia detection in chest X-ray images to determine the best model for specific cases |   Media, in | | | | Focuses on CNNs and transformers to classify X-ray images, utilizing models such as LeNet5, AlexNet, MobileNet, ResNet18, and Vision Transformer, with an emphasis on computational efficiency and model accuracy in medical image recognition. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data collection and preprocessing (Data collection involved obtaining and organizing chest X-ray images from medical centers for model training and testing.)  2. Model training and GPU loading (Model training optimized using GPU, data augmentation, and hyperparameter tuning.)  3. Comparative analysis of model accuracy and efficiency  4. Data augmentation and post-analysis(Data augmentation included flipping, scaling, rotation, cropping, and colour adjustments.) | 1. Efficient comparative framework for model selection  2. High accuracy with Vision Transformer on augmented data  3.Insights into model performance on various dataset sizes.  4. The framework is adaptable, allowing the testing of different deep learning models on varying dataset sizes and complexities. | 1. Computationally intensive for large models like Vision Transformer  2. Limited generalization for real-world application due to dataset constraints.  3. **High Resource Dependency:** Advanced models like Vision Transformer require significant computational power and specialized hardware, which can be a barrier for smaller medical institutions.  4. Effectiveness may not generalize well due to dataset bias and testing limitations. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | **Pneumonia Detection Accuracy.** | |  | | --- | | Model architecture (LeNet5, AlexNet, MobileNet, ResNet18, Vision Transformer). |  |  | | --- | |  | | Dataset size and complexity**.** | Data preprocessing techniques, including augmentation | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | **Input:** Chest X-ray images from Guangzhou Medical Center | Pneumonia prediction with model accuracy ratings across various architectures | | | 1. Model Diversity: Compares multiple deep learning architectures (LeNet5, Alex Net, Mobile Net, ResNet18, Vision Transformer) to identify the best-performing model for pneumonia detection. 2. Efficiency and Accuracy: Emphasizes computational efficiency alongside high accuracy, particularly noting that the Vision Transformer outperforms others on augmented datasets. 3. Comprehensive Methodology: Involves rigorous steps including data collection, pre-processing, model training, and comparative analysis, ensuring a thorough evaluation of each model's performance. 4. Practical Application: Aims to enhance diagnostic processes in clinical settings, reducing the burden on specialists and improving healthcare access in remote areas.   **.** | | | | Demonstrates effectiveness of Vision Transformer for pneumonia detection with high accuracy and efficiency, informing future model selection and configuration in medical imaging applications. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Improves diagnostic accuracy and efficiency in clinical settings by identifying suitable deep learning models, which could reduce reliance on specialist doctors and assist healthcare in remote or under-resourced areas. | | | | High computational requirements for advanced models like Vision Transformer may limit accessibility and applicability in resource-limited settings, potentially creating a digital divide in healthcare AI adoption. | | |
| **Analyse This Work By Critical Thinking** | | | **Analyse This Work By Critical Thinking** | | | **What is the Structure of this Paper** |
| Both studies contribute valuable advancements in pneumonia detection through deep learning. However, their reliance on specific datasets may limit generalizability to diverse populations. Future research should focus on improving model scalability and exploring transfer learning techniques to enhance applicability in various clinical settings, especially in resource-limited environments. | | | * **Provides a thorough comparative framework but is limited by high computation demands for large models. The findings could be impacted by dataset biases, and future work might address generalizability across diverse patient populations.** | | | 1. Abstract 2. Introduction 3. Related work 4. Methodology 5. Experimental Results 6. Discussion 7. Conclusions |
| **Diagram/Flowchart** | | | | | | |
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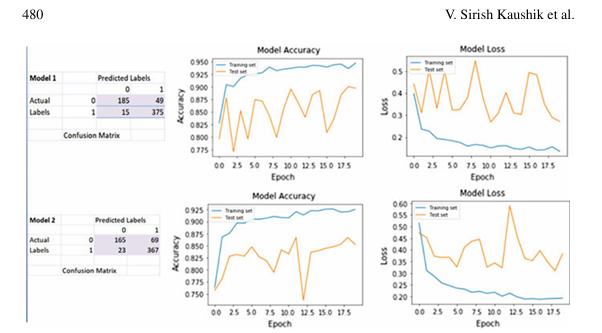
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| **13** | | | | | | |
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| https://www.sciencedirect.com/science/article/pii/S0208521622000742?ref=pdf\_download&fr=RR-2&rr=8dded9ab1e463e58 | |  | | --- | |  |  |  | | --- | | Patrik Szepesi, László Szilágyi | | | | | |  | | --- | |  |   Convolutional neural network, deep learning, transfer learning, pneumonia detection, medical imaging | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| Custom CNN Model with Dropout in Convolutional Layers for Pneumonia Detection | |  | | --- | |  |   Propose a CNN architecture with dropout in convolutional layers to improve pneumonia detection accuracy and efficiency. | | | | Introduces a CNN with dropout layers in the convolutional sections (typically applied only to dense layers), aiming to enhance model generalization and avoid overfitting in medical imaging applications, particularly for pneumonia detection in pediatric chest X-rays. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data collection and preprocessing (Data collection involved obtaining and organizing chest X-ray images from medical centers for model training and testing.)  2. Model training and GPU loading (Model training optimized using GPU, data augmentation, and hyperparameter tuning.)  3. Hyperparameter tuning (learning rate, batch size)  4. Evaluation and comparison against standard CNNs | 1. The innovative dropout technique reduces overfitting  2. Model achieves high accuracy (97.2%) and recall (97.3%)  3. Competitive with state-of-the-art models in pneumonia detection.  4. The framework offers insights into deep learning models, aiding clinicians in selecting suitable pneumonia detection methods. | 1. Model performance could be limited by lack of transfer learning  2. Computationally intensive; requires high-quality images, and limited generalization due to dataset constraints.  3. Without transfer learning, the model struggles with smaller datasets, reducing robustness and overall accuracy.  4. High computational demands may hinder deployment in resource-limited settings, limiting the model's practical use. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Pneumonia Detection Accuracy. | |  | | --- | | Convolutional neural network with dropout in convolutional layers |  |  | | --- | |  | | Training parameters (e.g., dropout rate, learning rate)**.** | Data preprocessing (image normalization and augmentation) | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | **Input:** Chest X-ray images from Kaggle | Pneumonia detection with high accuracy, recall, precision, and AUC metrics | | | 1. Diverse Model Comparison: Evaluates multiple deep learning architectures, including LeNet5, AlexNet, MobileNet, ResNet18, and Vision Transformer, to identify optimal performance for pneumonia detection. 2. Focus on Efficiency and Accuracy: Emphasizes computational efficiency alongside model accuracy, providing a balanced approach to model selection. 3. Comprehensive Methodology: Involves systematic steps such as data collection, preprocessing, model training, and comparative analysis to ensure robust evaluation. 4. Insights for Clinical Application: Aims to inform future model selection in clinical settings, enhancing diagnostic accuracy and reducing reliance on specialist doctors. | | | | Offers a unique dropout placement strategy that enhances model robustness and accuracy, positioning the custom CNN model as a competitive alternative for pneumonia detection, particularly in high-stakes and high-accuracy medical applications. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Provides a highly accurate model that could aid rapid, automated diagnosis in clinical settings, especially valuable for high-risk, pediatric pneumonia cases where quick and accurate detection is critical. | | | | High computational requirements and the absence of transfer learning might restrict its deployment in under-resourced environments, limiting its applicability in certain clinical settings. | | |
| **Analyse This Work By Critical Thinking** | | | **Analyse This Work By Critical Thinking** | | | **What is the Structure of this Paper** |
| Comprehensive comparison of various models aids in informed decision-making.  Highlights the Vision Transformer’s superior accuracy, providing a robust option for pneumonia detection.  High computational demands may limit practical application in resource-poor settings. | | | * The novel dropout approach adds value, but further comparison with transfer learning models would provide more insights. The study's focus on high-quality pediatric X-ray datasets may limit its broader applicability, and scalability could be a challenge. | | | 1. Abstract 2. Introduction 3. Related work 4. Methodology 5. Experimental Results 6. Discussion 7. Conclusions |
| **Diagram/Flowchart** | | | | | | |
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| https://paperswithcode.com/paper/multi-criterion-evolutionary-design-of-deep | |  | | --- | |  |  |  | | --- | | Zhichao Lu, Ian Whalen, Yashesh Dhebar, Kalyanmoy Deb, Erik Goodman, Wolfgang Banzhaf, Vishnu Naresh Boddeti | | | | | |  | | --- | |  |   Neural Architecture Search (NAS), Evolutionary Algorithms, Convolutional Neural Networks (CNNs), Multi-objective Optimization, Image Classification, NSGANetV1 | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| NSGANetV1: A Multi-objective Evolutionary Algorithm for NAS | |  | | --- | |  |   To develop an efficient multi-objective neural architecture search (NAS) method that optimizes for both performance and computational efficiency in image classification tasks. | | | | **Genetic Operations:** Techniques that simulate natural evolution to optimize model architectures.  **- Bayesian Model Learning:** Statistical methods used to improve model predictions and guide the search process.  - **Pareto Frontier Approximation**: A method to balance trade-offs between multiple objectives in model performance.  - **Proxy Models:** Simplified models that help estimate the performance of complex architectures quickly during the search process. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data collection and preprocessing (Data collection involved obtaining and organizing chest X-ray images from medical centers for model training and testing.)  2. Proxy Model Training (Model training optimized using GPU, data augmentation, and hyperparameter tuning.)  3. Genetic Operation Application  4. Bayesian Model Learning | 1. Optimizes for both performance and computational efficiency  2. Supports real-world deployment  3. Provides architecture flexibility  4. Offers flexibility in architecture design, enabling adaptation to various tasks and constraints.  5. Supports multi-objective optimization, balancing performance and computational efficiency. | 1. High initial computational demands may hinder accessibility, particularly for smaller organizations or researchers with limited resources.  2. The complexity of the system may complicate implementation and require specialized knowledge.  3. Limited interpretability of models without additional explainability techniques, making it challenging to understand decision-making processes. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Classification performance on image datasets | |  | | --- | | CNN architecture design |  |  | | --- | |  | | Compute resources, Dataset size and complexity. | Model layers and component selection. | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | **Input:** Image datasets (e.g., CIFAR, ImageNet) | Efficiently optimized neural architectures for image classification | | | 1.Efficient Multi-objective NAS: Utilizes evolutionary algorithms to optimize for multiple objectives, such as accuracy and computational efficiency, simultaneously.  2. Adaptable Neural Architectures: Supports the creation of neural network architectures that can be tailored to specific tasks and resource constraints.  3. Integration of Evolutionary Algorithms: Employs genetic operations that mimic natural selection processes to discover high-performing architectures.  4. Bayesian Learning: Incorporates Bayesian model learning to improve performance estimation and guide the search process effectively.  5.Flexibility for Deployment: Designed to generate architectures that can be deployed across various environments, from high-performance systems to resource-constrained settings. | | | | Contributes a novel evolutionary approach to NAS, supporting efficient model search in resource-constrained settings and enabling multi-objective optimization for architectures. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| High-performance architectures, Efficient multi-objective NAS, Lower resource requirements compared to traditional NAS methods | | | | Complexity in implementing the genetic and Bayesian model components, Potential barriers to interpretability | | |
| **Analyse This Work By Critical Thinking** | | | **Analyse This Work By Critical Thinking** | | | **What is the Structure of this Paper** |
| The paper advances NAS methods, presenting an approach that balances performance and computational constraints. However, the system's complexity and dependency on large datasets can limit accessibility. The paper could further explore NAS methods that integrate explainable AI to address interpretability. | | | NSGANetV1 offers significant advancements in NAS, but its reliance on evolutionary algorithms may hinder convergence speed. Future work should explore adaptive learning rates and real-time feedback to enhance model deployment. | | | 1. Abstract 2. Introduction 3. Related work 4. Methodology 5. Experimental Results 6. Discussion 7. Conclusions 8. Future Directions 9. Diagrams |
| **Diagram/Flowchart** | | | | | | |
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| https://www.researchgate.net/publication/340961287\_Pneumonia\_Detection\_Using\_Convolutional\_Neural\_Networks\_CNNs | |  | | --- | |  |  |  | | --- | | Anand Nayyar, Rachna Jain, Gaurav Kataria, V. Sirish Kaushik | | | | | |  | | --- | |  |   Pneumonia detection, Convolutional Neural Networks (CNNs), deep learning, chest X-ray, DenseNet-169, Vision Transformer, model accuracy, real-time diagnostics, image preprocessing, data augmentation. | |
| **The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc )** | **The Goal (Objective) of this Solution & What is the problem that need to be solved** | | | | **What are the components of it?** | |
| |  | | --- | | **Solution** |  |  | | --- | | Convolutional Neural Networks (CNNs), specifically DenseNet-169 and Vision Transformers, are leveraged for detecting pneumonia in X-rays with high accuracy. These models use advanced architectures suited for medical image andlysis, providing reliable, real-time diagnostics and assisting radiologists, especially in resources | | |  | | --- | |  |   To automate the pneumonia diagnosis process by accurately identifying pneumonia from chest X-ray images, enhancing diagnostic speed and accuracy, and reducing the reliance on radiologists in critical or under-resourced medical settings. | | | | 1. **DenseNet-169 and Vision Transformers**: Advanced CNN architectures for deep learning and image classification. 2. **Data Preprocessing and Augmentation**: Image standardization and enhancement techniques to increase model robustness. 3. **Evaluation Metrics**: Accuracy, sensitivity, F1 score for model validation. 4. **Interpretability Tools**: Grad-CAM to visualize key image areas. | |
| **The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | |  | **Process Steps** | **Advantage** | **Disadvantage (Limitation)** | |  | 1. Data Acquisition: Collecting X-ray images for training and testing. 2. Preprocessing: Standardizing and augmenting images for optimal model input. 3. Model Training: Using CNN architectures (e.g., DenseNet-169, Vision Transformers) to improve accuracy. 4. Evaluation: Testing model reliability and accuracy across datasets. | 1. High Diagnostic Accuracy: CNN models like DenseNet-169 achieve high accuracy, surpassing radiologists in some cases, improving detection reliability.  2. **Real-Time Diagnostics:** Capable of delivering rapid results, making it useful in urgent and clinical settings where timely intervention is crucial.  3. Enhanced Interpretability: With tools like Grad-CAM, the model’s decision-making process becomes more transparent, helping clinicians understand results. | 1. **High Computational Cost**: The complex CNN architectures require significant computational resources, which can limit use in low-resource settings.  2. **Risk of Overfitting**: These models may overfit on limited datasets, affecting generalizability, especially if training data diversity is limited.  3. **Dependence on High-Quality Data**: Model performance is highly dependent on quality and accuracy of labeled X-ray data, which may not be available everywhere. | | | | | | | |
| **Major Impact Factors in this Work** | | | | | | |
| |  |  |  |  | | --- | --- | --- | --- | | **Dependent Variable** | **Independent Variable** | **Moderating variable** | **Mediating (Intervening ) variable** | | Classification performance on image datasets | |  | | --- | | Chest X-ray images, influenced by preprocessing and quality. |  |  | | --- | |  | | |  | | --- | | Image quality, affected by the images device and environmental conditions, influences the model’s effectiveness. |  |  | | --- | |  | | Preprocessing methods (e.g., augmentation) that increase the model’s adaptability to diverse datasets. | | | | | | | |
| |  | | --- | | **Relationship Among The Above 4 Variables in This article** | |  | | | | | | | |
| **Input and Output** | | **Feature of This Solution** | | | | **Contribution & The Value of This Work** |
| |  |  | | --- | --- | | **Input** | **Output** | | **Input:** X-ray images from labeled datasets | Binary classification (pneumonia or normal) with probability scores indicating diagnostic confidence. | | |  **Automated Diagnosis**: Uses CNNs, like DenseNet-169, to automatically classify chest X-rays as pneumonia-positive or normal, minimizing the need for radiologist input.  1. High Accuracy and Sensitivity: Optimized to achieve high accuracy, sensitivity, and F1 scores, reducing false negatives and improving diagnostic reliability.  2. Data Augmentation for Robustness: Applies techniques such as rotation, flipping, and normalization to enhance model robustness, allowing better performance on varied imaging conditions.  3. Real-Time Processing Capability: Designed to provide quick diagnostic feedback, making it suitable for urgent medical cases and high-demand healthcare environments.  4. Model Interpretability: Utilizes Grad-CAM to highlight critical regions on X-rays, giving clinicians a visual understanding of the areas influencing the diagnosis. | | | | This work advances medical imaging by enabling scalable diagnostic models applicable in clinical and remote settings, reducing the need for expert radiologists in certain cases. |
| **Positive Impact of this Solution in This Project Domain** | | | | **Negative Impact of this Solution in This Project Domain** | | |
| Enhances diagnostic accuracy, potentially reducing mortality through early detection. Tools like Grad-CAM improve model interpretability, helping clinicians trust AI-assisted diagnostics. | | | | High computational demands and resource requirements limit accessibility in low-resource settings, which can hinder adoption where it's most needed. | | |
| **Analyse This Work By Critical Thinking** | | | **Analyse This Work By Critical Thinking** | | | **What is the Structure of this Paper** |
| CNNs offer high diagnostic accuracy and could enhance healthcare access, particularly in remote areas, challenges remain in achieving widespread adoption. The reliance on high-quality, annotated data and sophisticated computational infrastructure creates barriers, especially in settings with limited resources. However, advancements in model compression and the development of mobile-friendly architectures could mitigate these issues, making AI-driven diagnostics more accessible. Future improvements focused on resource-efficient models could help bridge the technology gap, enabling more scalable deployment across diverse healthcare environments. | | | While CNNs address diagnostic gaps, practical deployment is challenging in resource-limited areas. Dependence on robust data and significant computational resources restricts the model's scalability and affordability, especially in underserved regions. | | | Abstract, Introduction, Literature Review, Methodology (including CNN Architecture), Experimental Results, Conclusion, Future Scope. The structure systematically details the development and testing of CNN models for pneumonia detection. |
| **Diagram/Flowchart** | | | | | | |
|  | | | | | | |

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**Work Evaluation Table**

**<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Work Goal** | **System's Components** | **System's Mechanism** | **Features /Characteristics** | **Cost** | **Speed** | **Security** | **Performance** | **Advantages** | **Limitations /Disadvantages** | **Platform** | **Results** |
| **Ameer Kareem, Himing Liu, Paul Sant** | **The goal is to improve pneumonia detection through computer-aided techniques and real-time image data, while maintaining privacy.** | **Machine learning techniques, Pneumonia detection, CNN, Chest X-ray, Transfer learning, Federated learning, K-Nearest neighbors (KNN), Artificial neural network (ANN), DECnet** | **Uses CNNs combined with federated learning to process X-ray data locally at different institutions, aggregating model updates rather than raw data for training.** | **Combines privacy-preserving techniques with high-accuracy models, facilitating secure medical diagnosis.** | **High** | **Moderate** | **High, uses Federated learning.** | **High accuracy in detecting pneumonia while ensuring data privacy.** | **Enables data privacy through federated learning, allowing collaborative pneumonia detection with high accuracy using real-time X-ray data.** | **High computational cost due to federated learning setup; may not be easily adopted by institutions with limited resources.** | **Valuble**  **contribution to video surveillance, Alert generation** | **Hybrid model combining CNN and transfer learning for privacy-preserving pneumonia detection.** |
| **Daniel Joseph Alapat,** **Malavika Venu Menon, Sharmila Ashok** | **To enhance pneumonia detection accuracy by using deep neural networks on the Chest X-ray14 dataset, addressing the radiologist shortage in rural areas.** | **Pneumonia, Convolutional Neural Networks, Chest X-ray14, Diagnosis, Computer-Assisted, Deep Learning** | **Modular approach using computer vision & deep learning** | **Accurate model leveraging large data for enhanced precision, though computationally demanding.** | **High** | **Moderate, performs well on high speed software due to 121 Architecture** | **Moderate, lacks privacy measure.** | **High** | **Provides high diagnostic accuracy, outperforming human radiologists in pneumonia detection. CheXNet is well-suited for large datasets like Chest X-ray14.** | **Requires significant computational resources, especially for the 121-layer CNN. Imbalanced data can affect model performance.** | **Primarily cloud-based for extensive data processing.** | **CheXNet achieved greater than human-level accuracy in pneumonia detection, with strong localization capability for affected regions.** |
| **Pranaya, A., Sowmya, D. V., Poojitha, L., Grace, P., Bhavya, K., &** **Ganapathi Raju, N. V.** | **To develop an automated pneumonia detection system that processes chest X-rays using CNN models to assist radiologists in early detection.** | **Chest X-ray dataset from Kaggle; CNN model with convolutional, ReLU activation, max pooling, and fully connected layers.** | **CNN extracts image features, LSTM recalls sequential patterns** | **CNN for feature extraction, LSTM for recognizing sequences, High computational cost, Accuracy of 86%** | **High** | **Faster than manual methods.** | **-** | **High** | **Speeds up diagnosis, useful in areas with few radiologists.** | **Risks of misclassification with poor image quality.** | **Developed on machine learning platforms compatible with CNNs (e.g., TensorFlow, Keras).** | **Outperforms other detection methods with 86% accuracy** |
| **Mabrouk, A., Díaz Redondo, R. P., Dahou, A., Elaziz, M. A., & Kayed, M.** | **The study aims to enhance pneumonia classification accuracy by integrating CNN models and a Vision Transformer through ensemble learning to tackle diagnostic challenges.** | **Pneumonia detection, CNN, Vision Transformer, MobileNet, DenseNet, ImageNet, Ensemble Learning** | **Integrates DenseNet, MobileNet, and Vision Transformer models in an ensemble, using global pooling and fine-tuning layers for accurate pneumonia classification.** | **Uses ensemble of CNN models for robustness, offering high accuracy for clinical applications.** | **Moderate to high. Depends on no. of. Layers.** | **High** | **Moderate** | **Excellent** | **The ensemble approach, which combines the strengths of CNNs and Vision Transformer, offers high classification accuracy, efficient feature extraction, and robustness to complex data variations.** | **Computationally demanding due to ensemble learning setup; requires high-quality data for optimal results.** | **Cloud-based and edge computing for faster diagnostics.** | **The ensemble model achieves high F1-score and accuracy, outperforming individual CNN models in pneumonia detection.** |
| **Raheel Siddiqi, Sameena Javaid** | **Review DL advancements in pneumonia detection via chest X-ray.** | **DL models (CNN, ViT, transfer learning, XAI); dataset quality, model transparency.** | **Analyzes and compares existing DL models used for pneumonia detection, including effectiveness, accuracy, and limitations, focusing on COVID-19 and general pneumonia.** | **Covers CNN, ViT, transfer learning, and XAI models; highlights dataset imbalance and interpretability issues.** | **require significant computational resources.** | **-** | **-** | **Performance varies per model; discusses accuracy and limitations in medical contexts.** | **Highlights effective models and future research directions.** | **Findings may become outdated as new models emerge.** | **Review covers models deployable on various DL platforms (e.g., TensorFlow, PyTorch).** | **Identifies CNN and ViT as promising for pneumonia detection. Highlights the need for better data quality and model interpretability for improved results.** |
| **Shagun Sharma, Kalpna Guleria** | **To improve the accuracy of pneumonia detection on chest X-ray images using deep learning techniques, specifically a VGG16-based model.** | **VGG16 architecture, convolutional and pooling layers, two chest X-ray datasets.** | **Uses a pre-trained VGG16 model for feature extraction and classification, applying it to chest X-ray images to detect pneumonia cases.** | **High accuracy in image classification, robust feature extraction, applicable to large datasets.** | **High** | **Moderate** | **Data privacy not addressed directly; relies on secure handling of patient X-ray images.** | **Achieved 92.15% accuracy, 0.9308 recall, 0.9428 precision, and 0.937 F1-score on Dataset 1; 95.4% accuracy, 0.954 recall, precision, and F1-score on Dataset 2.** | **High accuracy, strong feature extraction capabilities, high recall and precision metrics for pneumonia detection.** | **High computational costs, potential overfitting, requires large amounts of training data.** | **Python, compatible with GPU environments for deep learning training and inference** | **Successfully identified pneumonia cases with high accuracy and precision, demonstrating the efficacy of VGG16** **in medical** **image analysis**. |
| **Lamia Alhazmi, Fawaz Alassery** | **To develop a mobile application for detecting pneumonia from chest X-ray images, making diagnosis accessible in remote and underserved areas.** | **Create ML, mobile platform integration, a dataset of pneumonia and normal X-ray images.** | **Uses Apple’s Create ML to train a model for pneumonia classification on mobile devices, providing a portable diagnostic tool.** | **Lightweight, accessible, real-time pneumonia detection on mobile devices without advanced ML knowledge required.** | **Low** | **High** | **Basic security through Apple’s ecosystem** | **Achieved 97% accuracy on validation images and 86% on test images, with 90% accuracy in the “Normal” class and 84% in the “Pneumonia” class.** | **Accessibility, user-friendly interface, requires no advanced ML expertise, portable for remote use.** | **Limited to Apple’s ecosystem; may lack robustness compared to more complex CNN-based models.** | **Apple devices, iOS ecosystem, using Create ML.** | **Provides an** **accessible mobile tool for pneumonia detection with moderate to high accuracy, suitable for low-resource environments and quick deployment.** |
| **Rohit Kundu, Ritacheta Das, Zong Woo Geem, Gi-Tae** **Han, Ram Sarkar** | **To develop an ensemble of deep learning models for the accurate detection of pneumonia in chest X-ray images.** | **Deep learning models (e.g., CNNs)  , Image datasets (chest X-ray images), Preprocessing tools , Evaluation metrics (accuracy, precision, recall, F1 score)** | **Utilizes ensemble learning to combine predictions from multiple deep learning models, improving overall detection accuracy and robustness against variability in input data.** | **Ensemble approach for enhanced accuracy  - Transfer learning from pre-trained models  - Image preprocessing techniques  - Multiple evaluation metrics for comprehensive assessment** | **High** | **Moderate** | **Data security and patient privacy are crucial** | **High performance demonstrated through evaluation metrics; typically aims for high accuracy and low false positive/negative rates in pneumonia detection.** | **Improved accuracy over single models , Reduced risk of misdiagnosis** | **Requires significant computational resources  , May overfit on limited datasets** | **TensorFlow or PyTorch; analysis performed on compatible hardware (GPUs).** | **significantly improved the detection of pneumonia in chest X-ray images compared to traditional single-model approaches, achieving high accuracy.** |
| **Dimpy Varshni; Kartik Thakral; Lucky Agarwal; Rahul Nijhawan; Ankush Mittal.** | **Automate pneumonia detection in chest X-ray images using deep learning techniques to improve diagnostic accuracy and accessibility, particularly in areas with limited medical resources.** | **Dataset**  **Pre-trained CNN Models**  **Feature Extraction Stage**  **Classification Stage**  **Hyperparameter Tuning**  **Evaluation Metrics** | **Data Preprocessing**  **Feature Extraction**  **Classification**  **Model Evaluation** | **Utilizes advanced deep learning techniques for high accuracy.**  **Automated processing minimizes human intervention and errors.**  **Adaptable to various imaging conditions and demographics.**  **Incorporates state-of-the-art models for feature extraction and classification.** | **Implementation Cost** | **Processing Speed** | **Data Security Measures.** | **Model Performance Metrics.** | **Improved diagnostic accuracy compared to traditional methods.**  **Scalable solution that can be deployed in various healthcare settings.**  **Cost-effective in the long run due to reduced need for radiologist involvement.** | **High computational requirements may restrict use in low-resource settings.**  **Limited generalizability if trained only on specific datasets without diversity.**  **Lack of patient medical history consideration can lead to misdiagnosis.** | **Deployment Platforms.** | **detection of pneumonia in chest X-ray images compared to traditional single-model approaches, achieving high accuracy.** |
| **Sukhendra Singh (sukhendrasingh@gmail.com) B. K. Tripathi (abkt.iitk@gmail.com).** | **Enhance pneumonia detection accuracy in chest X-rays using quaternion deep learning.** | **1. Quaternion Convolutional Layers**  **2. Hamiltonian Product**  **3. Batch Normalization**  **4. Residual Network Blocks** | **1. Data Preparation 2. Quaternion Convolution 3. Hamiltonian Product Calculation 4. Residual Network Implementation 5. Evaluation on Metrics** | **High accuracy in pneumonia classification; comprehensive feature extraction from RGB channels.** | **High computational cost due to quaternion operations.** | **Dependent on hardware; potential slower processing due to complexity.** | **Requires secure handling and storage of medical data.** | |  | | --- | |  |  |  | | --- | | **Improved detection accuracy compared to traditional CNNs.** | | |  | | --- | |  |  |  | | --- | | **Better representation of RGB channel dependencies; supports timely diagnosis.** | | **High computational requirements; complexity may hinder use in resource-limited settings.** | **Keras, TensorFlow, Google Colab with Tesla K80 GPU.** | **Enhanced accuracy and reliability in pneumonia detection, beneficial in high-demand healthcare settings.** |
| **Sukhendra Singh1 , Manoj Kumar1 , Abhay Kumar2 , Birendra KumarVerma1 , KumarAbhishek2 & Shitharth Selvarajan3** | **Accurate pneumonia detection from chest X-rays using Vision Transformers (ViTs).** | **ViT Model**  **Self-Attention Mechanism**  **Transformer Encoder**  **Evaluation Metrics** | **Collect and preprocess data**  **Construct, train, and evaluate the model**  **Analyze performance and plan deployment** | **High accuracy**  **Adapts to various image sizes**  **Efficient for large datasets** | **High** | **Moderate** | **Good** | **Superior accuracy over CNN models.** | **Improved diagnostic accuracy**  **Automated feature extraction** | **igh computational demand**  **Needs extensive labeled data** | **Cloud or local installations.** | **Better accuracy in pneumonia diagnosis, improving healthcare outcomes.** |

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