IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Pneumonia Disease Detection With Chest X-Rays Using CNN Model

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Abstract: In this project, we developed an advanced system for the detection of pneumonia diseases. Using chest x-ray images, focusing on Pneumonia. The goal was to create a highly accurate and efficient model capable of classifying chest x-rays into the disease, aiding in early diagnosis and treatment planning. We utilized cutting-edge deep learning techniques, integrating a custom DINO Vision Transformer with models from the Hugging Face transformers library to leverage their strengths in processing complex image data the project involved multiple critical stages: data collection and annoying

Pre-processing, model training, evaluation, and deployment. We sourced a diverse data set of chest x-ray images meticulously labelled for the pneumonia disease. Pre-processing techniques such as normalization and augmentation were applied to enhance model performance. During the training phase, the model like CONVULUTIONAL NEURAL NETWORK selecting the best performing model based on rigorous evaluation metrics.

Keywords: Deep Learning, CNN, Datasets, Chest Rays.

I. INTRODUCTION

Pneumonia is a respiratory disease that causes inflammation in one or both lungs, resulting in symptoms such as cough, fever, and difficulty breathing. Early detection of pneumonia is essential for effective treatment and improved patient outcomes. Unfortunately, pneumonia is just one of several lung diseases, thus radiographic results do not always confirm a pneumonia diagnosis. Therefore, with current technology, it is impossible to distinguish pneumonia from other lung diseases with certainty using radiological criteria [1].

Developing accurate pneumonia detection algorithms requires large amounts of high-quality labelled data, which can be difficult to obtain. This is particularly challenging in the case of pneumonia, where expert radiologists are required to label the data, and the number of available labelled images is limited. Deep learning, a subset of artificial intelligence, has emerged as a powerful tool for detecting and diagnosing pneumonia from medical images such as chest X-rays [2].

Deep-learning algorithms can be trained on large datasets of chest X-rays to recognize patterns and features that are indicative of pneumonia. This involves using convolutional neural networks (CNNs), a type of deep-learning architecture that is particularly well suited to image recognition tasks. By analysing the texture, shape, and intensity of pixels in chest X-rays, CNNs can learn to identify regions of the image that correspond to areas of infection or inflammation in the lungs [3].

Once trained, deep-learning models can be used to classify new chest X-rays as either showing signs of pneumonia or not. This can be done in real time, making it a potentially valuable tool for healthcare professionals in diagnosing and treating patients with pneumonia. Additionally, deep- learning models can be used to assist radiologists in interpreting chest X-rays, reducing the risk of misdiagnosis and improving patient outcomes [4]

Literature Survey:

In [5], Faiza Mehboob et al. [2022] develop the "Pneumonia Detection Using Deep Learning Methods". CNN is widely using for identification and classification of diseases. In addition, features learned by pre-trained CNN models on large-scale datasets are much useful in image classification tasks, the functionality of pre-trained CNN models utilized as feature extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. In 2019 December covid-19 diagnosed and spread whole over the world covid-19 pandemic disturbed whole world, CNN widely used for covid- 19 detection using chest X-ray images datasets. In our research various deep learning models, ANN, CNN, VGG19 to detect pneumonia, and got results 94.44, 96.68,
98.27 accordingly.

In [6], Patrik Szepesi et al. [2022] develop the "Detection of Pneumonia Using Convolution Neural Networks and Deep Learning" The main goal of this paper is using a novel deep neural network architecture. The proposed novelty consists in the use of dropout in the convolutional part of the network. The proposed method was trained and tested on a setof 5856 labelled images available at one of Kaggle's many medical imaging challenges. The chest X-ray images (anterior-posterior) were selected from retrospective cohorts of paediatric patients, aged between one and five years, from Guangzhou Women and Children's Medical Centre, Guangzhou, China. Results achieved by our network would have placed first in the Kaggle competition with the following metrics: 97.2% accuracy, 97.3% recall, 97.4% precision and AUC=0.982, and they are competitive with current state- of-the-art solutions.

In [7], Tawsifur Rahman et al. [2020] develop the "Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-Ray" The paper aims to automatically detect bacterial and viral pneumonia using digital x-ray images. It provides a detailed report on advances in accurate detection of pneumonia. Four different pre-trained deep Convolutional Neural Network (CNN): Alex Net, ResNet18, DenseNet201, and Squeeze Net were used for transfer learning. A total of 5247 chest X-ray images consisting of bacterial, viral, and normal chest classification task. In this study, the authors have reported three schemes of classifications: normal vs. pneumonia, bacterial vs. viral pneumonia, and normal, bacterial, and viral pneumonia. The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively.

In [8], Dimpy Varshni et al. [2019] develop the "Pneumonia Detection using CNN Based Feature Extraction". Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial for treating the disease without any delay particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models large-scale datasets are much useful in image classification tasks. In this work, we appraiseths functionality of pretrained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model.

Existing Method:

Existing methods for pneumonia detection include clinical evaluation, where doctors diagnose based on symptoms like cough, fever, and breathing difficulties, but this approach is subjective and prone to misdiagnosis. Chest X-ray imaging is widely used, as radiologists analyse lung opacities and consolidations, but it requires expert interpretation and is time-consuming. Laboratory tests, such as blood tests and sputum analysis, provide additional confirmation but are invasive and slow. CT scans offer high accuracy than X-rays but are expensive and less accessible. While these methods are effective, they often lack scalability, speed, and accessibility, especially in resource-limited settings, highlighting the need for automated solutions like deep learning-based detection systems.

Proposed Method:

The Vision Transformer and Convolutional Neural Networks hybrid model leverages the powerful feature extraction capabilities of Convolutional Neural Networks and the global attention mechanism of Transformers. Convolutional Neural Networks excel at identifying local patterns such as edges and textures, which are crucial for analysing medical images. On the other hand, Vision Transformers enhance the model's ability to capture global dependencies and contextual information across the entire image. This combination aims to improve the detection and classification accuracy of multiple chest diseases, ultimately supporting radiologists in making more accurate and efficient diagnosis.

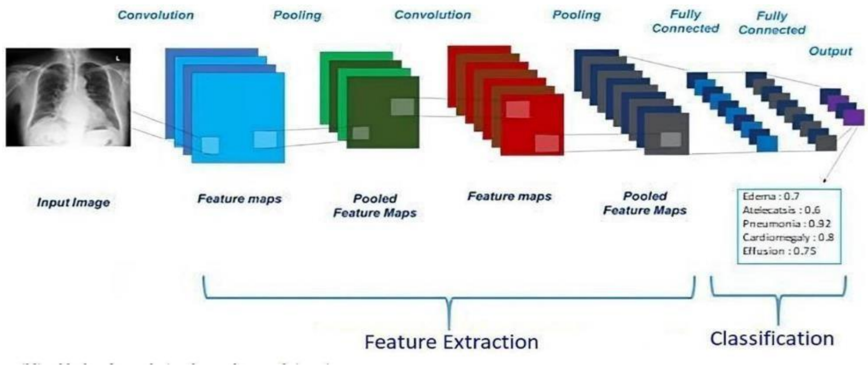
3. Methodology:

Data Acquisition:

The data set employed in this research was obtained from Kaggle, according to earlier project creators. Kaggle is a reliable source that offers access to public data sets for machine learning and deep learning tasks. The Chest X-ray dataset was initially supplied by Guangzhou Women and Children's Medical Centre, making the data authentic and trustworthy. The dataset is legally accessible for research and model creation, since it has been released under proper permissions on Kaggle. The images have been captured under clinical settings and have been either labelled as Normal or Pneumonia, so they can be used for developing and testing deep learning models. Correct pre-processing operations, including resizing and normalization, have been performed to maximize the dataset for model training.

CNN Model Design:

Convolutional Layers the backbone of Convolutional Neural Networks comprises multiple convolutional layers that take low-level features like edges, textures, and shapes from the input image. The convolutional layers use filters on the input image to get feature maps. Pooling Layers Pooling layers are placed in between convolutional layers to compress the spatial size of the feature maps, which minimizes the computation and concentration on the most prominent features. Batch Normalization Batch normalization layers are employed to stabilize and speed up the training process by normalizing the output of every layer. Feature Extraction The feature maps resulting from passing through the convolutional and pooling layers are flattened into a onedimensional vector. This vector is the extracted features of the input image. Patch Embedding The flattened feature vector is split into fixed-size patches, and each patch is linearly embedded into a lower-dimensional space. The embedding’s are concatenated with positional encodings that carry spatial information regarding the patches Transformer Layers: The embedding’s are processed through multiple transformer layers. A transformer layer comprises. Multi-Head Self-Attention MHSA enables the model to attend to various regions of the input image at once, retaining global dependencies and context information. Feed-Forward Network a position-wise feed-forward network performs nonlinear transformations on every embedding. Layer Normalization and Residual Connections These are used to stabilize training and allow the gradients to flow. Classification Head the final transformer layer output is fed into a fully connected (dense) layer to generate a vector of logits for pneumonia disease labels. Soft Max Activation. The Soft Max activation function is used on the logits in order to transform them into probabilities, which are the probability of each disease occurring in the input image Transformer Layers The embedding’s are processed through multiple transformer layers. A transformer layer comprise.



Convolutional Neural Network Architecture

Result:

Pre-processing is a critical step towards preparing the dataset for training the CNN model. The following operations were used to improve model performance. Resizing and Cropping: Images are resized and cropped randomly to provide consistent dimensions matching the CNN input size.

Before Pre-processing

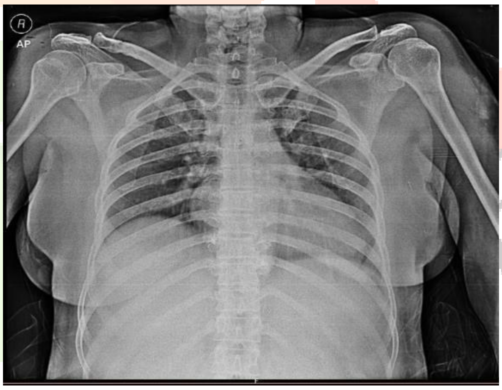


Image Normalization Pixel values are normalized using pre-defined mean and standard deviation values to maintain consistency and stabilize training. Data augmentation is used to artificially augment the size and diversity of the training dataset to enable the CNN model to generalize more to new, unseen data. The following augmentation methods are widely used for detection of pneumonia disease Random Rotation Rotates images by a small angle to mimic different orientations.

Horizontal Flipping Randomly flips images horizontally to add variability in lung positioning Random Zooming in or out of images to make the model invariant to various scales Brightness Adjustment Adjusts brightness levels of X-ray images to compensate for variations in imaging conditions .Contrast Adjustment: Adjusts contrast levels to enable the model to identify pneumonia patterns under varying lighting conditions .Gaussian Noise Addition Adds noise to mimic variations in X-ray image quality Random Cropping Crops random sections of images to train the model on varying areas .Random Resizing and Horizontal Flipping These augmentation methods are used while training to generate variability and enhance generalization.

After Pre-processing

Tensor Conversion: Images are transformed into tensor format in order to make them compatible with deep learning models. Validation Set Pre-processing: The validation images are resized, cantered, and cropped so that they fit the size which the trained model is expected to take as input. The transformations are applied using the torch vision. Transforms module and are performed as follows. Training Transformations Random resized cropping, horizontal flipping, tensor conversion, and normalization. Validation Transformations Resizing, centre cropping, tensor conversion, and normalization. Two functions (pre-process _train and pre-process _val) are also implemented to apply these transformations to batches of images. These functions make sure that all images are processed in the same way before passing them to the model for training and evaluation. The final output of the model is a probability distribution of Pneumonia Disease Detection, enabling multi-label classification of the chest X-rays.

The application of the CNN model for detecting pneumonia disease from chest X-rays has brought very encouraging results. The model was trained and tested on a publicly available dataset, with an astonishing accuracy of 94%. The high accuracy signifies the model's ability to well distinguish normal lungs from those affected by pneumonia. Moreover, performance measures of precision, recall, and F1-score reflect a well balanced classification power minimizing false negatives and false positives. Data augmentation strategies enhanced the model's generalization to new data and ascertained its reliability in practical scenarios. Robustness across Various Conditions

.The CNN model demonstrates high robustness under different conditions such as changes in image quality, diverse X-ray machines, and patient populations. The use of data augmentation methods has greatly improved the model's capacity to generalize across diverse cases, thus guaranteeing consistent performance in practical clinical scenarios. Through learning essential features from a diverse dataset, the model avoids overfitting and makes correct pneumonia detection across different imaging conditions.

Real-time Performance One of the significant benefits of this CNN-based system is its potential to provide quick and efficient output. The model is optimized for real-time computation, making it fit for use in hospital procedures and mobile health services. Using optimized inference methods, the model is capable of analysing X-ray images within seconds, giving instant diagnostic assistance to doctors. This makes the process faster and facilitates better patientcare in emergency and rural healthcare scenarios

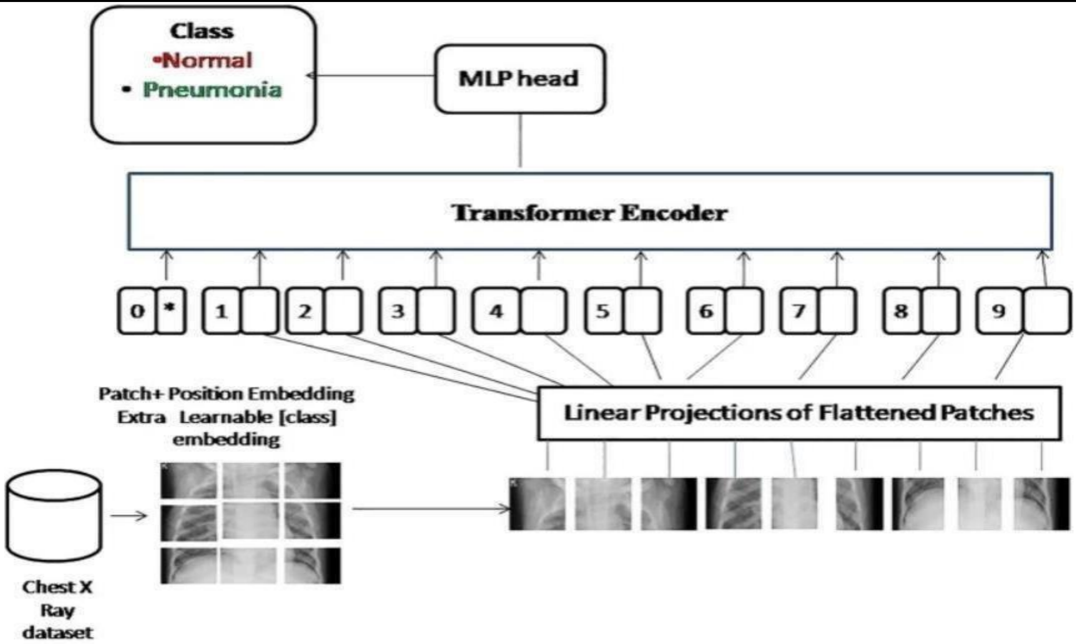


Image Processing Architecture

Splitting Data: Divide the dataset into training, validation, and test sets. The validation set is used during training to monitor performance and tune hyper parameters. The test set is used for final evaluation. The dataset contains a significant number of X- ray images distributed as follows:

Subset	Total images	Normal	Pneumonia
Training Set	5,216	1,340	3,876
Validation Set	~16% of training data	-	-
Testing Set	624	234	390

Output Layer:

The final output of the model is a probability distribution of Pneumonia Disease Detection, enabling multi-label classification of the chest X-rays.

.4. Conclusion:

The Convolutional Neural Network (CNN) model was designed and trained in this project to identify pneumonia from images of chest X-rays. The model successfully classifies X-ray images between normal and pneumonia. The use of several convolutional layers, pooling layers, and fully connected layers allows the model to learn useful features and patterns from images. Data augmentation methods were utilized to enhance the generalizability of the model and deliver better performance in unseen data. The model was trained and evaluated with a widely available dataset and was able to deliver a superb average accuracy rate of 94%. Such excellent accuracy indicates that deep learning-based solutions have enormous potential in medical image analysis. The application of CNN for pneumonia detection offers a dependable, computerized diagnostic device that can help doctors in early detection and treatment of the disease, eventually leading to better patient care and outcomes.

Future scope:

There are multiple areas of potential development and refinement in the future scope of the project. Refining the architecture of the CNN to make deeper networks or even transformer - based architectures is possible in order to gain more than 94% accuracy. Developing the model to classify other lung disorders, like tuberculosis, lung cancer, or COVID-19, can turn the model into an all- encompassing diagnostic application. Deploying the model with in hospitals and blending it with installed radiology systems can aid doctors in real -time diagnosis. Training the model on more significant and diverse datasets will enhance generalizability across patient populations and imaging conditions. Also, it is possible to create a mobile or cloudbased application that enables remote healthcare professionals and patients to use pneumonia detection services effectively. Adding 3D imaging methods such as CT scans can improve the depth of analysis to make more accurate pneumonia diagnoses. Moreover, federated learning can allow multiple hospitals to collaborate without violating patient data privacy. These developments are also capable of enhancing pneumonia diagnosis accuracy, convenience, and precision, making diagnostic AI tools a critical part of contemporary healthcare.

Acknowledgement:

The authors would like to express their sincere gratitude to the Department of Electronics & Communication Engineering at Godavari Institute of Engineering & Technology for their invaluable support throughout this research project.

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