Detecting pneumonia from chest X-rays using deep learning based neural networks: an hybrid approach

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ABSTRACT

Pneumonia a disease which occurs when the alveoli (air sacs) in the lings fill with fluidlike substance it can be due to infectious agents like virus, bacteria especially in an environment with contaminated air is often considered as lethal disease because the deaths associated with is high. There are several factors which contribute to this disease like age as their immune systems are not fully developed making it easier to get attacked by infections, chronic health conditions like asthma or weak immune systems may worsen the situation. Machine learning (ML) algorithms have tend to perform better while images are given, however compared to them deep learning (DL) algorithms have shown good promising results especially when images are given as an input this is because they have upper hand in identifying key features and loss optimization makes them best suited for this tasks. The significance of this research is to make an extensive review on the pneumonia and early detecting pneumonia by utilizing DL based neural networks.

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1. INTRODUCTION

Pneumonia can be caused by many organisms based on the type of organisms and the area of the lungs it affects. Here is a detailed description provided below:

a) Based on cause
- Bacterial pneumonia: it is disease in which lungs get affected by bacteria it leads to irritation in lungs symptoms include high fever, cough with yellow or green mucus.
- Viral pneumonia: it is a disease in which lungs get affected by virus it leads to fluid accumulation in lungs symptoms include fever, dry cough, muscle pain, weakness.

b) Based on location of acquisition
- Community-acquired pneumonia (CAP): it is type of disease that occurs outside area of hospital due to getting in contact with other people who are having harmful pathogens. People who suffer from this disease may have trouble in breathing.
- Hospital-acquired pneumonia (HAP): it is type of disease that occurs inside of the hospital after a certain point of time after getting admitted into the hospital. It is usually caused by medical equipment inside the hospital. Symptoms include fever.

c) Based on area of lungs affected

– Lobar pneumonia: it is a type of disease in which a lobe (a large area) of lung gets affected it is due to presence of bacteria in such cases the air sacs fill with fluid the lobe area's blood vessels gets swollen leading to increase more blood on lobe area.
– Interstitial pneumonia: it is disease in which the space (the tissue and space around the air sacs of the lungs) area gets affected and causes swelling in the area due to this normal gas exchange does not take place properly as a result oxygen intake gets less and carbon dioxide retention gets increase's so there will be uneven distribution of gas leading to difficulty in breathing

Figure 1 is the pictorial representation of the different types of pneumonia.

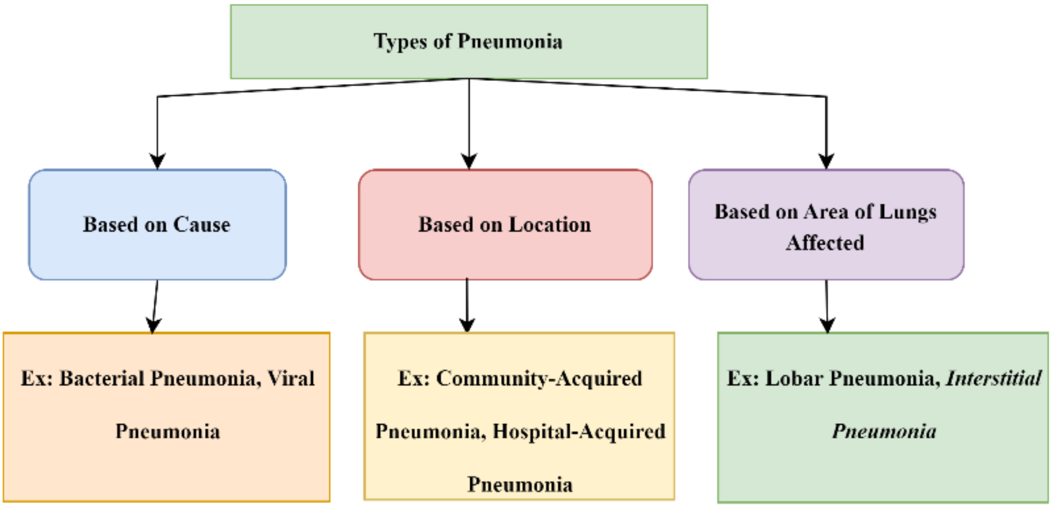

Figure 1. Different types of pneumonia

2. LITERATURE SURVEY

Asnaoui *et al.* [1] utilized several deep learning (DL) models to automatically identify the pneumonia, initially the images were pre-processed by using normalization through which pixel values are adjusted to a common scale which in terms leads to consistent gradient update leading to faster and more efficient convergence during training. Amone all the models DenseNet has achieved higher accuracy due to it unique architecture that ensured feature reuse so each layer is connected to every other layer instead of passing output of one layer to other, here the preceding layer take input from all previous layers through which it can able to capture detailed and complex features from X-ray images and achieved an accuracy of 96%.

Chandra and Verma [2] used several machine learning (ML) classifiers as the data is images, they have initially extracted key features by using histogram of oriented gradients (HOG) where HOG captures the direction in which the intensity of pixels is changing by analyzing the gradient of the image then a feature vector representing features is generated to describe overall shape and structure of the image. Additionally, to capture local patterns neighboring pixel intensities are captured. Among all the ML model's random forests have shown good results due to its nature of correcting mistakes at previous step and achieved an accuracy of 90%.

Praveen and Khan [3] developed a supervised learning model to enhance the accuracy of prediction models initially resizing was done to ensure input images have similar dimensions as it helps ML models fit according to expected input size. Key features were extracted by using principal component analysis (PCA) and independent discriminant analysis (IDA) where it is used to reduce dimensionality by transforming the data into a lower-dimensional space while preserving important information. Then data is divided into training and testing cross validation techniques were done prior to testing to make the predictions more generalized as the model gets to trained on different subsets of data and obtained accuracy of 94%.

Al Mamlook *et al.* [4] utilized multiple ML classifiers and applied preprocessing techniques like data augmentation as the data available on pneumonia is limited it creates more training samples from the existing data, helping to overcome this limitation, also helping to overcome the class imbalance. After a comparison is made among them neural networks performed well this is due to better feature extraction and can handle images at high dimension by processing them through multiple layers, each layer capturing different levels of abstraction. And obtained 90% accuracy.

Ibrahim *et al.* [5] developed a DL algorithm to distinguish between pneumonia caused by covid and other forms of pneumonia so many data enhancing procedure were used like rotation as chest X-rays images are taken at different angles by using this it make model more prepared to such images moreover these methods increase the training data without need of additional labelled data while training the model parameters were finetuned like adjusting weights to minimize loss thereby improving prediction accuracy to achieve an accuracy of 98%. Kundu *et al.* [6] developed a ensemble of DL models and considered a dataset which consists of three types of class one is healthy lungs and the other two classes are types of pneumonia. Then created a combination of DL models because instead of relying on a single model while combining predictions from multiple models helps to overcome the weakness of individual models and during model training neural network weights are adjusted thereby mitigating loss and final prediction is made by selecting class with the most votes as the final output. It achieved a 95% accuracy.

Das *et al.* [7] proposed a ML based approach and focused extensively of normalization and data augmenting as it helps to equal the pixel intensity to a similar range and helps in attaining faster convergence because the gradients take larger steps by moving towards convergence, reduces these variations by allowing the model to generalize better across different datasets. It is observed that while validating the model. The novelty is features extracted by convolutional neural network (CNN) are then fed into ML classifiers and attained an accuracy of 90%. Naralasetti *et al.* [8] utilized the concept of neural networks by considering labelled images as of image improvement pixel values are converted to a similar range this helps when loss optimization is made then weight updates are more balanced and even additionally this uniform range of inputs helps the neural network learn more effectively as there is no need of adjusting to varying input values as during training pre trained models were used which helped reduce the training time and achieved an accuracy of 90%.

Yee and Raymond [9] used ML models on X-ray images to treat pneumonia in highly effective manner and performed data cleaning steps to ensure data which gets feeded have good combination both classes such that model gets trained on adiversified data. This process helped them to train the model equally during back propagation parameters like weight and bias are updated to minimize the loss and enhancing its ability to generalize to new data. This helped to achieve an accuracy of 95%.

Hashmi *et al.* [10] identified that pneumonia detection is time consuming and invasive process and the risk of getting intense is high. So to overcome that a neuron model proposes where initially flipping image is done which tilts the image into variety poses helped to create additional data and pretrained models were used as they can detect complex patterns and features in chest X-rays. Moreover these models reduce the need for large amounts of labelled data, prior to training fine tuning is done to make the model adaptive to a specific dataset which can extract edges and textures in images to obtain an accuracy of 96%.

Rahman *et al.* [11] utilized the concept of pre trained models which are trained on large datasets as it helps models reducing training time since those models have knowledge of large datasets while getting trained on a specific dataset identifying key patterns gets easier. Inception V3 model is used since it can extract features at different convolutions which helped to identify pneumonia-related patterns at various sizes which helped to enhance the ability to identify and classify pneumonia effectively. Thereby obtained 95% accuracy.

Hashmi *et al.* [12] developed a hybrid model that combines multiple CNN layers in which the number of filters, layers in the network, input image size are adjusted or scaled down which helped to learn more features by capturing more complex patterns by providing more detailed information. However, it also provided compound scaling allowed good steady growth. Then loss is measure during training by taking difference between the predicted class probabilities and the true class labels and shown accuracy 95%. Alsharif *et al.* [13] developed a neural network with a greater number of convolutional layers to represent hierarchical representation of data as this is better way to capture basic to advanced deep features where disease traces are found this model has shown good results by obtaining an accuracy of 96%.

Ortiz-Toro *et al.* [14] used ML models initially enhancement is done to improve quality and reduce noise, which is crucial for accurate feature extraction. For better analyzing structure using gray level co-occurrence matrix (GCLM) pixel arrangement and positioning is extracted which helped to capture healthy lung area versus diseased lung area. However there is need to verify GCLM as it can vary with respect to change in image resolution. Finally using ML classifier accuracy obtained is 92%.

Sharma and Guleria [15] utilized large dataset and a dl based pre trained model which is having more convolutions since features can be extracted while the convolutional filters are low. This is because it helps architecture to be deeper so more layers can be added and it can learn more complex features from the data. Also, it leads to fewer parameters compared to larger filters this helped them prevent overfitting and makes the model easier to train then validation is made to obtain an accuracy of 95%.

Muhammad *et al.* [16] introduced a hybrid model based by combining ML and DL, models is used for building neural networks which extracts features from the highly processed images without having noise.

These neural networks are pre trained on large datasets and are fine tuned to chest X-ray dataset because these models allow faster convergence as they already learned general features from a large dataset, so they require less time to adapt to a new task. Moreover, training a DL model from scratch requires lot of data. These pretrained models overcame this and finally classification is made using a ML classifier and obtained an accuracy of 94%.

Jain *et al.* [17] utilized transfer learning to detect pneumonia in chest X-ray images. A pretrained model which is a combination of multiple dl models is chosen which is already trained on larger dataset to leverage the knowledge of the model to much smaller datasets and the dl based pre trained model is finetuned by adjusting weights and parameters by making the model suitable for this task and then final phase of training is made and these models have shown good performance as it reduced the time taken to train it from scratch and achieved 97% accuracy.

Salehi *et al.* [18] utilized transfer learning and build a pre trained neuron model it is because since these models have better knowledge and have extracted relevant information while fine tuning it to a specific task it requires fewer epochs to train it apart from that they perform better with smaller datasets because they start with a pre-existing knowledge and obtained accuracy 96%. Gülgün and Erol [19] utilized DL models to classify pneumonia from chest X-rays for that multiple DL models were used it is observed that resent 50 model have shown good performance. It is because of inception modules which are nothing but convolution filters which can be adjusted according to level of convolution then to evaluate it roc is used as it represents the both correct and incorrect cases which are identified by the model and it has achieved better accuracy of 94%.

Masad *et al.* [20] introduced a hybrid model where multiple dl models were combined to get good performance as medical data is diverse in terms of quality and patient's data these models can adapt to diverse data characteristics better than single-model approaches. Additionally, these are having capability to focus on most important regions where key features are there by considering similarity scores and achieved an accuracy of 92%. Račić *et al.* [21] used DL and build a CNN model as it is best suitable for image classification tasks by considering a dataset which contains images of patients which are both positive and negative to Pneumonia then data augmentation is done after that a neural network is build to extract key features by reducing dimensionality and several convolutional layers followed by pooling layers is built allowing loss optimization and obtained accuracy 93%.

Zein *et al.* [22] used transfer learning as it involved using a already trained model on larger datasets for much smaller and domain specific tasks like detecting pneumonia. For this model as the network is already built hyperparameters like weight updating and adjustments were done, and performance measurement is made it is shown accuracy of 96%. Sharma *et al.* [23] utilized a neural network-based CNN model the novelty is more number of convolution layers were used to extract finest features. While training dropout were used, it helped to overcome overfitting by reducing certain percentage of neurons where they cannot be active this prevents the network from relying too heavily on any one node and batch normalization to overcome distribution of inputs these helped to attain a good accuracy of 95%.

Zhang *et al.* [24] introduced a CNN model by enhancing internal architecture by adding more convolution layers, changing data cleaning steps and novelty is by using a gradient mechanism where a heatmap is generated and average of gradients is considered to identify important features which makes convolutional layers easier to give better results by obtaining accuracy of 96%. Manickam *et al.* [25] used DL model to extract fine features. Initially a pre trained transfer learning model is considered as it is already trained on a large-scale dataset the task became much simpler to extract features by making model fit for this task. Post training many optimizers were used to adjust learning rate which tells how large weight adjustments need to be and considered a small learning rate because small weight updates lead to better convergence and obtained an accuracy of 94%.

3. METHOD

3.1. Dataset details

The dataset used for this purpose is chest X-ray images (pneumonia) which is predominantly used for pneumonia detection it consists of three directories in which training, testing and validation files are found where in each file again it subclassified in normal consists of X-ray images of healthy lungs. And pneumonia disease X-ray images of lungs affected by pneumonia., consists more than 5,000 images which are having dimensions around 1,200×1,500 pixels. Figure 2 shows the normal image of lungs taken by X-ray and Figure 3 shows pneumonia affected lungs taken by X-ray.

3.2. Data preprocessing

It is an important stage before give data for training the model because it ensures model is generalized well. Preprocessing helps to achieve better accuracy at later stages of any method. For that many methods have performed, and they are described below.

Figure 2. Normal image of lungs taken by X-ray

Figure 3. Pneumonia affected lungs taken by X-ray

3.2.1. Image rescale

This process involves converting images whose intensity are different to 0 to 1, it is necessary as it helps stabilizing and speeding up the training process. This conversion can be made by dividing pixel value by 255. Histogram representation shown in Figure 4.

3.2.2. Shear and zoom

It transforms image along one side through a certain angle which is defined in terms of probability. It is essential some images are sheared in certain directions in such cases detecting them becomes easier while zoom involves making image size bigger as some images might have different size. So, making the model to train with different zoom size helps to become invariant to the scale of the objects.

3.2.3. Flipping

This operation involves flips the image along the vertical axis where left side of the image becomes the right side this helps model to become generalized to flipping. And can detect objects irrespective of their orientation. Different flipped images can be seen in Figure 5.

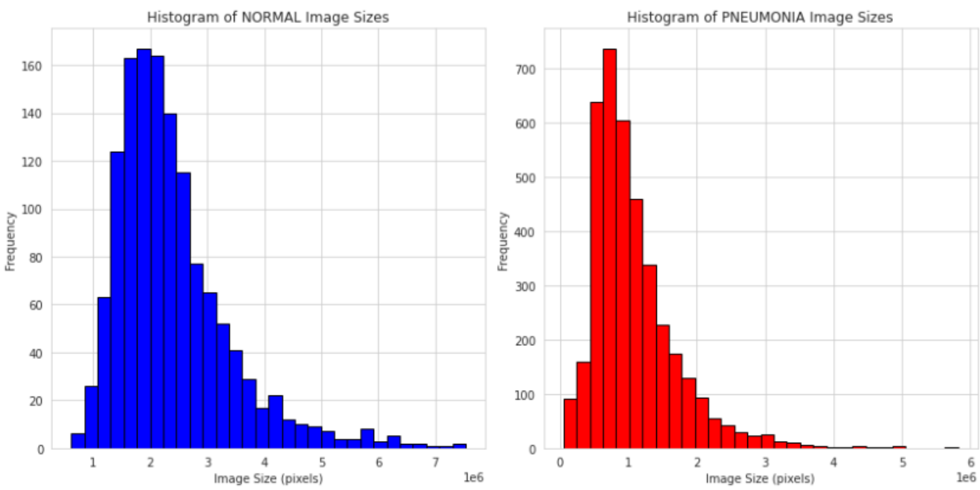

Figure 4. Represents histogram of normal and pneumonia image size distribution

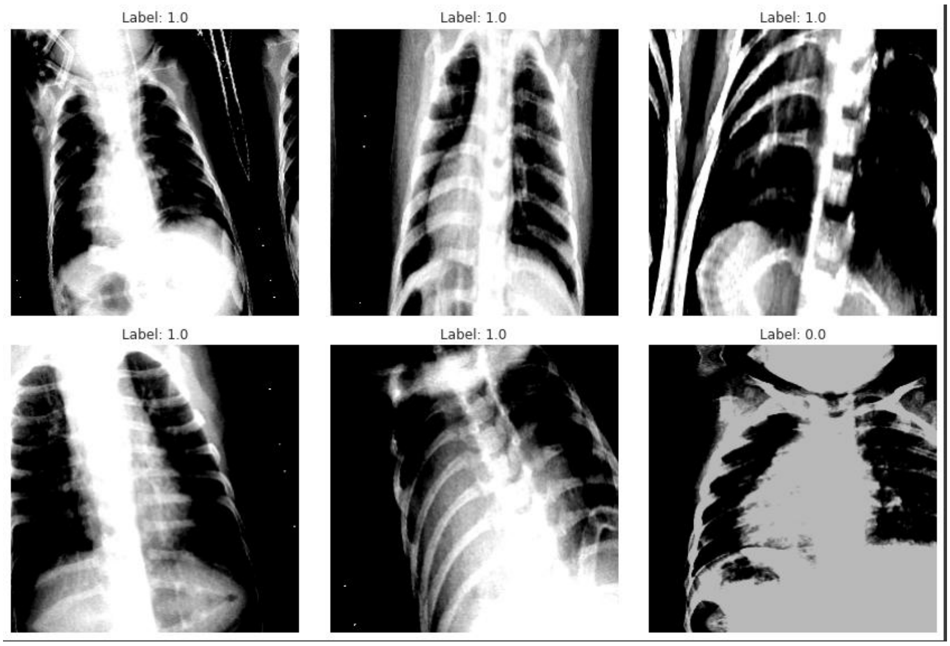

Figure 5. Labelled images of normal and pneumonia case

3.3. ResNet 50 model

It is a dl based neural network which consists of 50 layers considered as four staged networks with residual block which helps in avoiding gradient issues. Each stage is convolutional layers where the filters are getting increased to extract even finest features making it best suitable for medical image identification tasks. Moreover, bottleneck design helps to maintain depth of network while reducing unwanted parameters and reducing complexity. Architecture shown in Figure 6.

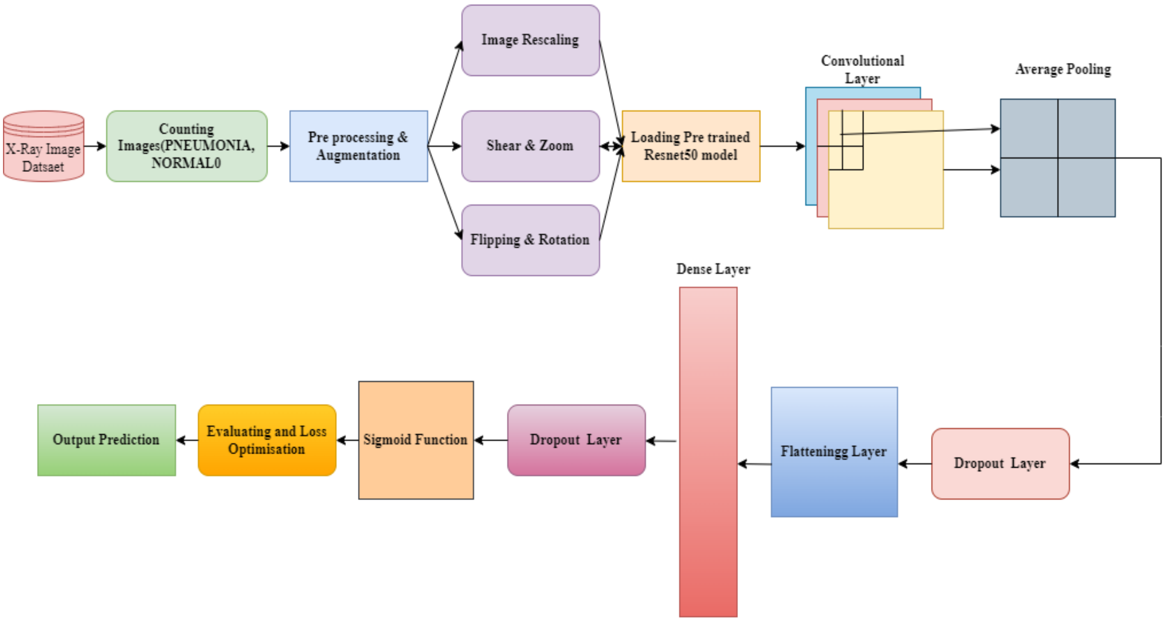

Figure 6. Architectural representation of the proposed ResNet 50 model

3.4. Global average pooling

Images are represented in terms of feature map where features are represented it is important to reduce unwanted features by retaining important information. So, this technique takes the average of the feature maps and represents them as a single feature which helps to avoid overfitting, here is the heatmap shown in Figure 7.

3.5. Pooling, early stopping and dropout

It is used to stop model training after certain point of time when there is no improvement in performance ins such cases if model doesn't stop it may prone to overfitting so to avoid that early stopping is used. While dropout removes a certain percentage of neurons as the model becomes more heavier it becomes difficult to train so to avoid that this is used image distribution in Figure 8.

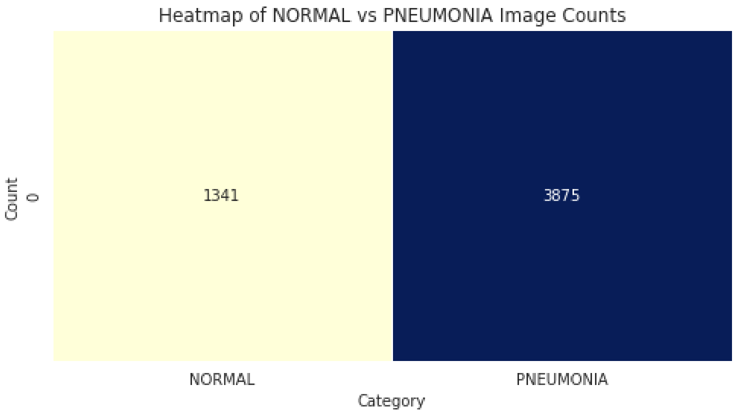

Figure 7. Heatmap distribution of both cases

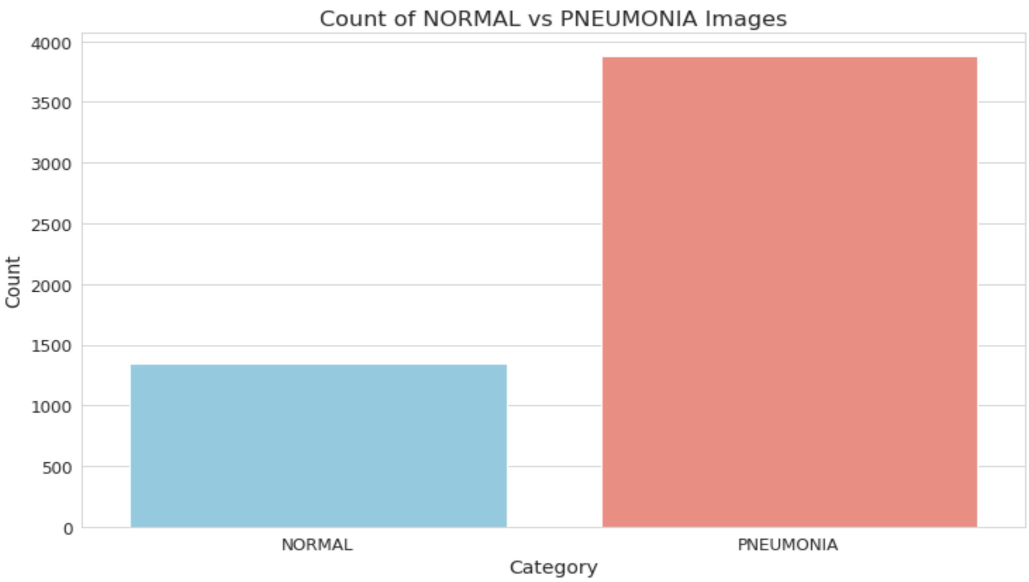

Figure 8. Normal vs pneumonia image distribution

Below is the detailed description of the implemented algorithm in a step-by-step manner:

a) Importing the libraries: importing required libraries for data handling, visualization, and model building.
b) Define dataset directories: set paths for the training, validation, and test datasets.
c) Count and display images and visualization: it is important to count total number of images in each directory as it helps to know what type of data it is. By plotting heatmaps helps in visualizing data distribution.
d) Data preprocessing and augmentation: this stage is important as it cleans the data required for training and makes the model generalized so necessary techniques like rescaling, shear, zoom and flipping were performed.

e) Building ResNet 50 model: loading the pretrained model which is trained on a larger data and set it as non-trainable.
f) Defining callbacks: to avoid overfitting a call-back function is used through which after achieving a certain accuracy the loop gets terminated and prevents the model from learning too much.
g) Training the model: model tends to get trained on a 80-20 scale, Average pooling is preferred as it reduces number of parameters and training time.
h) Dropouts and loss optimization: dropout is preferred as it reduces model's complexity by minimizing neurons and post training loss optimization were done by fine tuning the parameters.
i) Testing and visualization: then the model is tested and achieved an accuracy of 90% and showed good accurate results.

4. RESULTS AND DISCUSSION

The ResNet model performed better than traditional methods because it can learn complex features effectively. Its residual blocks help maintain strong performance by learning residual functions. As a result, it achieved an overall accuracy of 90%.

5. CONCLUSION

It is observed that ResNet50 has performed well and achieved an accuracy of 90%. This is due to it is having residual blocks through which even finest features are observed as each residual block stage number of filters and convolutions gets increased. ResNet 50 training requires powerful GPUs and large amounts of memory, so in future it is necessary to handle as new data becomes available, the model may need to be fine-tuned to maintain its performance.

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AUTHOR CONTRIBUTIONS STATEMENT

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Vissamsetty Srikanth				✓		✓					✓			
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available at Kaggle: https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia.

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