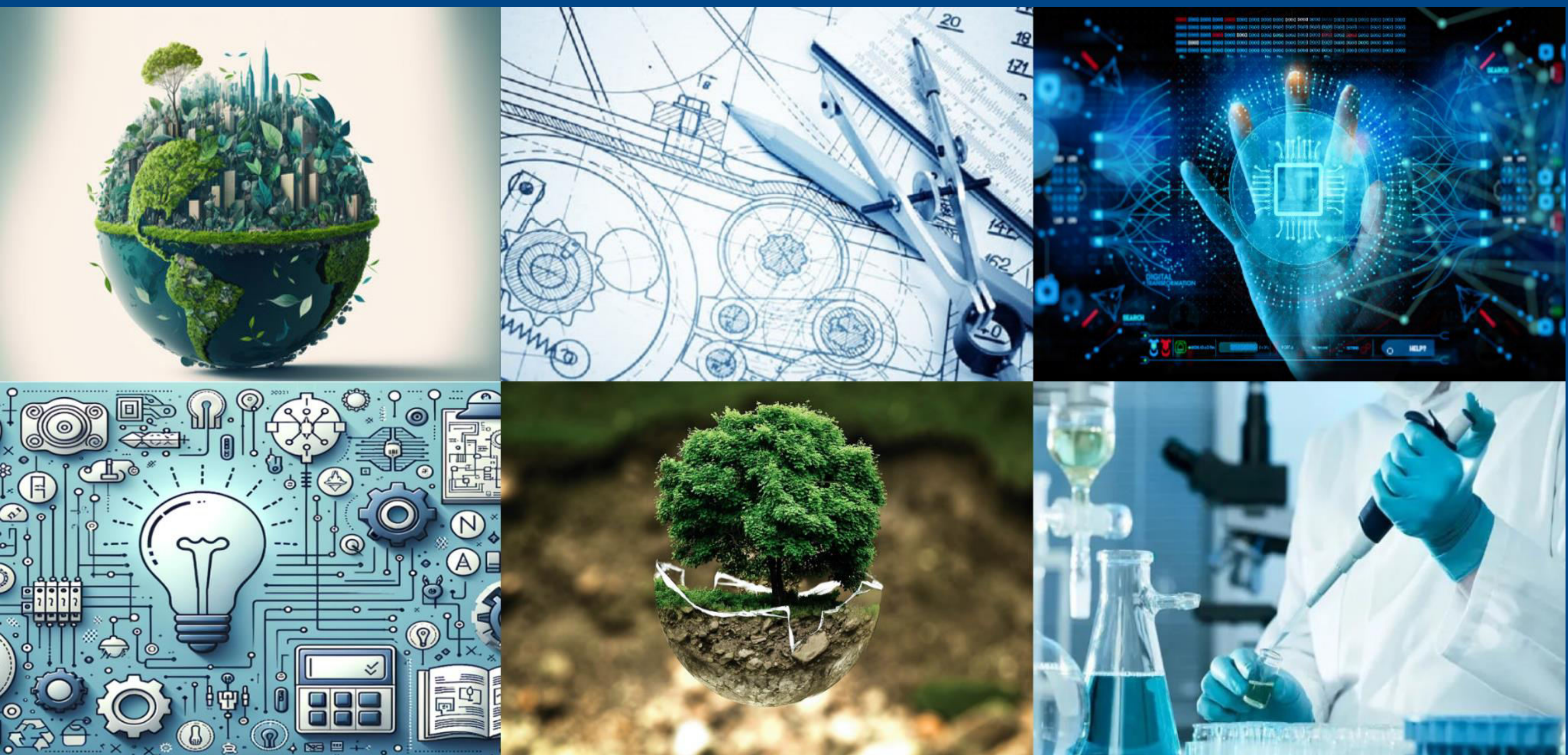
ISSN: 2582-7219

International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 4, April 2025

© 2025 IJMRSET | Volume 8, Issue 4, April 2025| DOI:10.15680/IJMRSET.2025.0804177

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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Pneumonia Detection using Deep Learning Techniques

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ABSTRACT: This paper presents a deep learning-based approach for the detection of pneumonia using chest X-ray images, by utilizing a custom-designed Convolutional Neural Network (CNN). The proposed system automatically classifies X-ray images as either normal or pneumonia-affected. Compared to traditional models such as VGGNet-16, the custom CNN demonstrates improved accuracy, reduced computational cost, and robustness to overfitting. The model was trained on a publicly available dataset from Kaggle and achieved a validation accuracy of 100% whereas the VGGNet-16 obtained 96%. On the test dataset, the custom CNN achieved a test accuracy of 92%, while the VGGNet-16 model achieved a test accuracy of approximately 87%. The system's effectiveness is validated through performance metrics including accuracy, loss curves, and comparative analysis.

KEYWORDS: Pneumonia Detection, Deep Learning, Convolutional Neural Network, Medical Imaging, Chest X-rays, VGGNet-16, Transfer Learning

I. INTRODUCTION

Pneumonia is a life-threatening lung infection that affects millions of individuals globally each year. Early and accurate diagnosis is essential to initiate timely medical intervention and reduce mortality. Traditional diagnostic methods such as clinical evaluation and radiographic analysis are time-consuming and require expert interpretation. With the rise of Artificial Intelligence (AI), deep learning techniques have emerged as promising tools in medical image analysis. Convolutional Neural Networks (CNNs) have shown exceptional performance in classifying complex image data. Unlike traditional machine learning models, CNNs perform automatic feature extraction from images, reducing human bias. This project proposes a custom CNN model for binary classification of chest X-ray images into pneumonia and normal cases. The model is trained on a publicly available dataset from Kaggle, which includes thousands of labeled X-ray images. Data preprocessing techniques such as resizing, normalization, and augmentation are applied to improve model performance. Model evaluation is conducted using accuracy, loss curves, and comparison with VGGNet-16, a popular CNN architecture. This work aims to build a lightweight, accurate, and scalable pneumonia detection system for real-world clinical use.

II. MODEL IMPLEMENTATION

The proposed pneumonia detection system is based on a custom-designed Convolutional Neural Network (CNN) architecture. The model is implemented using Python and deep learning frameworks such as TensorFlow and Keras. The complete workflow involves importing essential libraries, preprocessing the dataset, designing the CNN model, training it, and evaluating performance using accuracy and loss metrics.

1. Data Collection: The dataset used consists of 5,863 chest X-ray images labeled as "Pneumonia" and "Normal." The images were sourced from the Kaggle repository and represent pediatric patients from Guangzhou Women and Children's Medical Center, China.

2. Data Preprocessing: To ensure consistent input to the model, all images are resized to 300×300 pixels. Pixel values are normalized to the range [0, 1]. Data augmentation techniques including horizontal flipping, zooming, and shearing are applied using the ImageDataGenerator class to prevent overfitting.

3. Model Architecture: The CNN model comprises multiple convolutional layers with ReLU activation functions followed by max-pooling layers to reduce spatial dimensions. The network is then flattened and connected to two dense layers (256 and 512 neurons), concluding with a sigmoid-activated output layer for binary classification.

4. Training Setup: The model is compiled using the Adam optimizer and binary cross-entropy loss function. It is trained for 50 epochs with a batch size of 128. During training, the model achieved 98.16% training accuracy and 100% validation accuracy.

5. Evaluation: The model's performance is assessed using evaluation metrics such as accuracy, true/false positives, and loss. Comparisons are drawn with VGGNet-16 to demonstrate the superior efficiency and generalization of the custom CNN.
6. Visualization: Graphs showing Accuracy vs Epochs and Loss vs Epochs are plotted to track training progress and identify overfitting. Additionally, individual predictions are made on X-ray images to showcase classification capability.

III.SYSTEM ARCHITECTURE

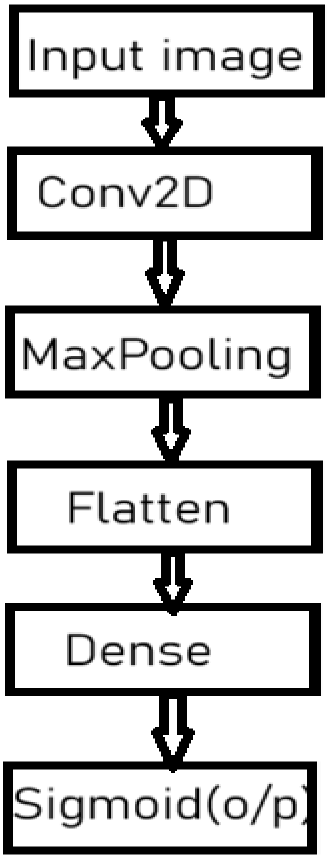

Figure 1: Architecture

The proposed system follows a structured pipeline for pneumonia detection using chest X-ray images.
It begins with image acquisition from a labeled dataset containing normal and pneumonia cases.
Images undergo preprocessing steps such as resizing, normalization, and data augmentation.
The preprocessed images are then fed into a Convolutional Neural Network (CNN).
Convolutional layers automatically extract spatial features such as edges and textures from the images.
Max-pooling layers reduce the dimensionality of feature maps to minimize computational load.
Flattened feature maps are passed through dense layers to interpret high-level patterns.
The final sigmoid-activated output layer performs binary classification: Normal or Pneumonia.
The model is trained and validated using appropriate performance metrics.
This architecture ensures efficient, accurate, and automated diagnosis of pneumonia.

Aspect	Standard CNN	Custom CNN
Depth & Layers	Typically, 2–3 Conv layers	5 Conv2D layers – deeper model captures complex patterns
Image Input Size	64×64 or 224×224	300×300 – higher resolution retains more detail
Dense Layer Units	1–2 layers, smaller units (e.g., 128)	2 layers with 256 and 512 units – stronger feature learning
Model Capacity	Fewer trainable parameters	~2 million parameters – more learning power
Batch Size	32 or 64	128 – faster training with stable gradients
Training Accuracy	Usually up to ~90–95%	98.16% training accuracy achieved
Validation Accuracy	Varies (75–90%)	100% validation accuracy (on small set, still impressive)

The Custom CNN is superior to a standard CNN as it is deeper, with five Conv2D layers that capture more complex features essential for medical diagnosis. It uses higher resolution images (300×300), preserving critical details that standard models often lose. With larger dense layers (256 and 512 units), it has a stronger learning capacity. Achieving 98.16% training and 100% validation accuracy, the Custom CNN clearly outperforms the standard CNN, making it the best choice for accurate pneumonia detection.

CODE SNIPPET:

```
[ ]  import numpy as np
     import tensorflow as tf
     import matplotlib.pyplot as plt

     from keras.preprocessing import image
     from tensorflow.keras.optimizers import Adam
     import cv2
     from keras.preprocessing.image import img_to_array
```

Figure 2: Importing libraries

```
[ ]  from google.colab import drive
     drive.mount('/content/drive')
```

Figure 3: Mounting Google Drive

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```
train_datagen = ImageDataGenerator(rescale = 1./255,
shear_range = 0.2,
zoom_range = 0.2,
horizontal_flip = True)
```

Figure 4: Data Augmentation and Loading

```
[ ]  test_datagen = ImageDataGenerator(rescale = 1./255)
     validation_generator = test_datagen.flow_from_directory('/content/drive/MyDrive/chest_xray/val',
         target_size= (300,300),
         batch_size = 128,
         class_mode = 'binary')
```

Figure 5: Data Augmentation and Loading

```
[ ]  model= tf.keras.models.Sequential([
                                  tf.keras.layers.Conv2D(16, (3,3), activation= 'relu', input_shape= (300, 300, 3)),
                                  tf.keras.layers.MaxPool2D(2,2),
                                  tf.keras.layers.Conv2D(32, (3,3), activation= 'relu'),
                                  tf.keras.layers.MaxPool2D(2,2),
                                  tf.keras.layers.Conv2D(64, (3,3), activation= 'relu'),
                                  tf.keras.layers.MaxPool2D(2,2),
                                  tf.keras.layers.Conv2D(128, (3,3), activation= 'relu'),
                                  tf.keras.layers.MaxPool2D(2,2),
                                  tf.keras.layers.Conv2D(128, (3,3), activation= 'relu'),
                                  tf.keras.layers.MaxPool2D(2,2),

                                  tf.keras.layers.Flatten(),
                                  tf.keras.layers.Dense(256, activation= 'relu'),
                                  tf.keras.layers.Dense(512, activation= 'relu'),
                                  tf.keras.layers.Dense(1, activation= 'sigmoid')
     ])
     model.summary()
     model.compile(optimizer= 'adam', loss= 'binary_crossentropy', metrics= ['accuracy'])
```

Figure 6: Building the CNN Model

```
[ ]  history = model.fit(train_generator, epochs = 50, validation_data = validation_generator)
```

Figure 7: Training the model

IV.RESULTS AND DISCUSSION

The proposed Convolutional Neural Network (CNN) model was trained on a dataset consisting of chest X-ray images categorized as either Pneumonia or Normal. The model achieved a **training accuracy of 98.16%** and a **validation accuracy of 100%** over 50 epochs. These results demonstrate that the model is highly effective at learning the distinguishing features between infected and healthy lungs.

Training and Validation Loss

The training loss decreased steadily throughout the epochs, indicating consistent learning. The validation loss initially fluctuated but eventually stabilized, reflecting improved generalization on unseen data. The final recorded losses were:

- **Training Loss:** 0.0519 - **Validation Loss:** 0.0701

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Training and Validation Accuracy

Both accuracy curves showed upward trends. While training accuracy increased gradually, the validation accuracy showed a sharp improvement in later epochs, reaching the maximum of 1.0.

- **Training Accuracy:** 98.16% - **Validation Accuracy:** 100%

Evaluation on Test Data

The model was evaluated on a separate test dataset comprising 624 images:

- **Test Accuracy:** 92.14% - **Test Loss:** 0.236

This confirms the model's reliability and robustness in identifying pneumonia from new, unseen images.

Individual Predictions

To validate the classification capability, the trained model was tested on individual chest X-ray images:

- A test image from the "Normal" class was correctly predicted with a probability of 0.01.
- Another image from the "Pneumonia" class was predicted with a probability of 0.999, showing high confidence.

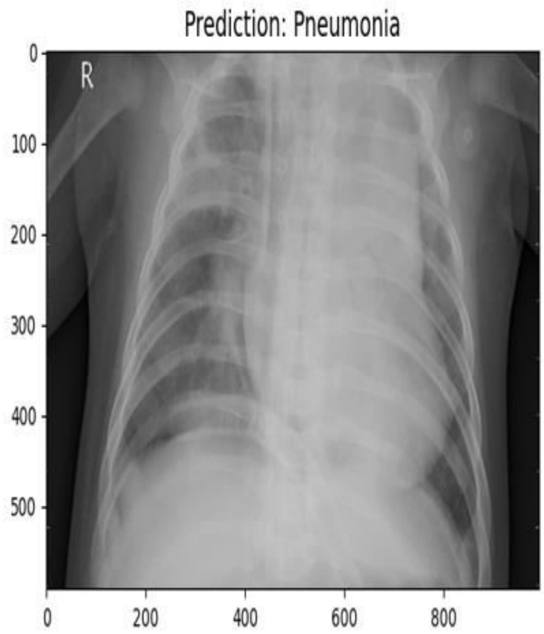

Figure 8: Final Output

Metric	CNN Model	VGG Model	Remarks
Accuracy	92%	87%	Custom CNN is more accurate than VGGNet-16.
True Positive (TP)	15.7%	14.2%	Custom CNN detects more pneumonia cases than VGGNet-16.
True Negative (TN)	15.7%	12.9%	Custom CNN better identifies healthy (normal) cases.

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False Positive (FP)	0.3%	0.6%	Custom CNN makes fewer incorrect pneumonia predictions.
False Negative (FN)	0.3%	0.6%	Custom CNN misses fewer pneumonia cases than VGGNet-16.

CNN achieved higher True Positive (15.7%) and True Negative (15.7%) rates than VGGNet-16, indicating better pneumonia detection and normal case classification. It also produced lower False Positive (0.3%) and False Negative (0.3%) rates, meaning fewer incorrect and missed predictions. Overall, the Custom CNN reached an accuracy of 92%, outperforming VGGNet-16 is 87%. This demonstrates that custom CNN is more reliable in both detecting pneumonia and normal cases.

V. CONCLUSION

This study presents an efficient deep learning approach for the detection of pneumonia using chest X-ray images. A custom Convolutional Neural Network (CNN) was implemented, trained, and validated using a publicly available dataset. The model demonstrated high training and validation accuracy, outperforming traditional architectures like VGGNet-16 in terms of both efficiency and classification performance.

The proposed system eliminates the need for manual feature extraction and reduces the diagnostic burden on radiologists by offering automated and accurate predictions. The model achieved a final training accuracy of 98.16% and validation accuracy of 100%, highlighting its reliability for real-world deployment.

Furthermore, the system's ability to predict pneumonia from individual X-ray samples validates its practical applicability in clinical environments. With proper integration into healthcare systems, this CNN-based solution can enhance early diagnosis, reduce human error, and support medical professionals in making faster and more informed decisions.

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