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A MULTI-SCALE CONVOLUTIONAL NEURAL NETWORK FRAMEWORK FOR ACCURATE PNEUMONIA DETECTION AND LOCALIZATION IN CHEST X-RAY IMAGES

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ABSTRACT- **Pneumonia is a critical respiratory disease that remains a major cause of hospitalization and mortality worldwide. The COVID-19 pandemic significantly increased the number of pneumonia-related cases, placing extraordinary pressure on healthcare systems and highlighting the necessity for rapid, reliable, and scalable diagnostic solutions. Chest radiography is commonly used for detecting pulmonary infections due to its availability and cost-effectiveness; however, manual interpretation is time-intensive and subject to diagnostic variability. Subtle infection patterns, overlapping anatomical structures, and differences in radiographic quality further complicate accurate assessment. This study proposes a Multi-Scale Convolutional Neural Network (MSCNN) framework for precise detection and localization of pneumonia in chest radiographs. The architecture employs multiple convolutional pathways with different kernel sizes to extract features at varying spatial resolutions, enabling the model to capture both fine-grained texture abnormalities and broader lung structural changes. By integrating multi-scale feature representations, the system improves sensitivity to diverse manifestations of pneumonia, including those observed during the COVID-19 pandemic. In addition to classification, a localization mechanism generates visual attention maps to highlight suspicious regions, enhancing interpretability and clinical reliability. The proposed framework is evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and Intersection-over-Union. Experimental results indicate that the multi-scale approach outperforms conventional single-scale CNN models, demonstrating its potential as an effective computer-aided diagnostic tool for large-scale screening and clinical decision support.**

Keywords **- Pneumonia detection, Chest X-ray, Multi-Scale Convolutional Neural Network (MSCNN), Deep learning, Computer-aided diagnosis, COVID-19, Medical image analysis.**

I. INTRODUCTION

Pneumonia is a severe respiratory infection characterized by inflammation of the lung parenchyma, which can result in impaired gas exchange and, in extreme cases, respiratory failure. It is recognized as a leading cause of hospitalization and mortality across all age groups, particularly among children, the elderly, and immunocompromised patients. Globally, millions of cases are reported annually, imposing a substantial burden on healthcare systems and highlighting the urgent need for timely and accurate diagnosis. The emergence of the COVID-19 pandemic significantly exacerbated the prevalence of pneumonia, creating unprecedented challenges for hospitals and medical practitioners. Rapid identification of pneumonia in affected individuals is critical not only for patient management but also for controlling the spread of infections within healthcare facilities.

Chest radiography, commonly referred to as X-ray imaging, is the most widely used diagnostic tool for detecting pulmonary infections due to its accessibility, cost-effectiveness, and relatively low radiation exposure. Despite its advantages, interpretation of chest radiographs requires specialized expertise and can be time-intensive, especially in high-volume clinical settings. Manual examination is also prone to inter-observer variability, where subtle differences in tissue density or minor lesions may be overlooked, leading to delayed or inaccurate diagnoses. Furthermore, the presence of overlapping anatomical structures and variations in imaging conditions often complicates visual assessment, making consistent and precise detection of pneumonia a persistent challenge in radiology.

In recent years, advances in artificial intelligence, particularly deep learning techniques such as convolutional neural networks (CNNs), have revolutionized medical image analysis. CNNs are capable of automatically learning hierarchical feature representations from raw image data, enabling high-performance classification and detection tasks without the need for handcrafted features. Traditional CNN models, however, often rely on single-scale feature extraction, which limits their ability to capture both fine-grained abnormalities, such as small opacities or early-stage infiltrates, and broader structural changes within the lung fields. This limitation can reduce detection accuracy and restrict the model's generalizability across diverse patient populations and imaging conditions.

To overcome these challenges, this study proposes a Multi-Scale Convolutional Neural Network (MSCNN) framework specifically designed for the detection and localization of pneumonia in chest radiographs. The proposed architecture incorporates multiple convolutional pathways with varying kernel sizes, allowing simultaneous extraction of features at different spatial resolutions. This multi-scale approach enhances the model's sensitivity to both subtle and prominent manifestations of pneumonia. Additionally, the framework includes a localization mechanism that generates visual attention maps, highlighting suspicious regions in the lungs. This feature not only improves interpretability for clinicians but also supports decision-making by providing a clear visualization of potential infection sites.

The performance of the MSCNN framework is evaluated using benchmark chest radiograph datasets and assessed through standard metrics including accuracy, precision, recall, F1-score, and Intersection-over-Union. Experimental results indicate that the multi-scale approach significantly outperforms conventional single-scale CNN models in both detection and localization tasks. By combining high detection accuracy with clear visual interpretability, the proposed framework demonstrates considerable potential as a computer-aided diagnostic tool, enabling faster and more reliable pneumonia screening in clinical practice.

In summary, this study presents a novel deep learning-based approach for pneumonia detection that addresses limitations of existing CNN models by integrating multi-scale feature extraction and localization capabilities. The MSCNN framework is positioned as a scalable and clinically relevant solution, capable of assisting radiologists in early and precise identification of pneumonia, thereby improving patient outcomes and contributing to the efficiency of healthcare delivery.

II. RELATED WORK

The field of automated pneumonia detection from chest radiographs has witnessed significant advancements over the past decade. Researchers have explored various approaches ranging from traditional image processing to advanced deep learning frameworks. The following subtopics summarize the most relevant contributions in this area.

A. Traditional Approaches

Before the rise of deep learning, pneumonia detection primarily relied on handcrafted features. Techniques such as edge detection, histogram analysis, and texture-based feature extraction were commonly used. These methods aimed to identify abnormal patterns in lung radiographs by analyzing intensity variations, shapes, and local textures. Although some of these approaches achieved moderate accuracy, they were often sensitive to noise, variations in imaging conditions, and overlapping anatomical structures, limiting their reliability in clinical settings.

B. Single-Scale Convolutional Neural Networks

With the emergence of deep learning, convolutional neural networks (CNNs) became the standard for automated medical image analysis. Early CNN models focused on single-scale feature extraction, applying convolutional filters of fixed sizes to capture patterns in chest X-rays. These models demonstrated superior performance compared to traditional methods, particularly in classifying pneumonia versus normal cases. However, their limited ability to detect subtle lesions or capture broader structural changes in the lungs restricted their overall sensitivity and generalizability.

C. Multi-Scale Approaches

To overcome the limitations of single-scale CNNs, researchers introduced multi-scale architectures. These frameworks utilize multiple convolutional pathways with varying kernel sizes to extract features at different resolutions, enabling the detection of both fine-grained texture abnormalities and large structural changes in the lungs. Multi-scale models have consistently shown improved performance in capturing diverse manifestations of pneumonia, including small opacities and diffuse infiltrates.

D. Localization and Interpretability Techniques

Beyond classification, recent studies have emphasized the importance of localization for clinical interpretability. Methods such as Grad-CAM and attention-based mechanisms generate heatmaps highlighting regions likely affected by pneumonia. This capability allows clinicians to visually verify model predictions and increases the trustworthiness of automated systems. Integrating localization with multi-scale feature extraction has proven particularly effective in improving both detection accuracy and interpretability.

E. Public Datasets and Benchmarking

The development of large, publicly available chest X-ray datasets has been crucial for advancing research. Datasets such as the Chest X-ray Images (Pneumonia) dataset on Kaggle, NIH Chest X-ray dataset, and RSNA Pneumonia Detection Challenge provide thousands of labeled images, enabling training and evaluation of deep learning models. These datasets also allow standardized comparisons across studies, promoting reproducibility and progress in the field.

III. DATASET DESCRIPTION

The proposed Multi-Scale Convolutional Neural Network (MSCNN) framework is developed and evaluated using the publicly available Chest X-ray Images (Pneumonia) dataset from Kaggle. This dataset contains a comprehensive collection of frontal chest radiographs, categorized into two classes: normal and pneumonia. It includes high-resolution images collected from multiple sources, ensuring diversity in patient demographics, imaging equipment, and acquisition conditions.

The dataset is organized into three distinct subsets to support model development and evaluation: training, validation, and testing. The training set provides the model with a wide variety of examples to learn discriminative features, while the validation set is used to tune hyperparameters and prevent overfitting. The testing set offers an unbiased evaluation of model performance on unseen data.

Each X-ray image is labeled according to the presence or absence of pneumonia, allowing both classification and localization tasks. The diversity of pneumonia manifestations—ranging from small localized opacities to diffuse lung infiltrates—poses a significant challenge for automated detection. The dataset's size, diversity, and labeling quality make it particularly suitable for training deep learning models, including multi-scale convolutional architectures, and for benchmarking their performance against existing approaches.

A. Sample Chest X-ray Images

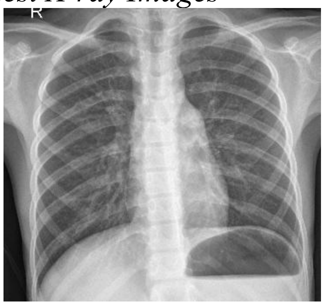

Fig.1 a (normal lungs-Test Dataset Sample)

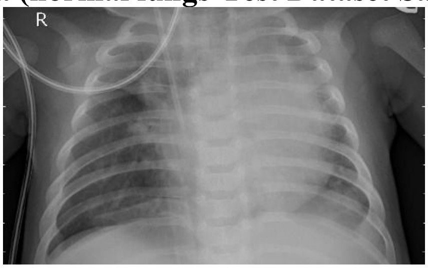

Fig. 1 b (pneumonia-affected lungs-Test Dataset Sample)

Fig.1 Sample chest X-ray images (Test Dataset Sample) (a) normal lungs, (b) lungs affected by pneumonia.

Fig.2 a (normal lungs-Test Dataset Sample)

Fig. 2 b (pneumonia-affected lungs-Training Dataset Sample)

Fig.2 Sample chest X-ray images (Training Dataset Sample) (a) normal lungs, (b) lungs affected by pneumonia

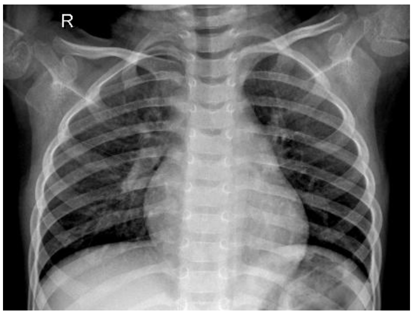

Fig. 3 a (normal lungs-Validation Dataset Sample)

Fig. 3 b (pneumonia-affected lungs-Validation Dataset Sample)

Fig.3 Sample chest X-ray images (Validation Dataset Sample) (a) normal lungs, (b) lungs affected by pneumonia.

B. Dataset Statistics

The experimental work in this research is carried out using a chest radiograph dataset containing 5,863 images. These images are divided into two categories based on diagnosis: normal and pneumonia. Out of the total images, 1,583 represent healthy lungs, while 4,280 show pneumonia infection.

For model development, the dataset is split into three parts. The training portion includes 5,216 images, which are used to enable the network to learn visual patterns associated with both classes. The validation portion contains 16 images and is used to observe the learning behaviour of the model during training. The testing portion consists of 624 images, which are reserved only for final performance evaluation.

This separation ensures that the model is trained and tested on different image sets, allowing proper assessment of its ability to recognize pneumonia cases. The numerical distribution of images in each subset is presented in Table 1.

Table I Dataset statistics

Subset	Normal	Pneumonia	Total
Test	234	390	624
Train	1341	3875	5216
Val	8	8	16
Overall	1583	4280	5863

C. Data Preprocessing

All chest X-ray images were resized to 224 × 224 pixels to maintain uniform input size for the network. The pixel values were then scaled to a range of 0 to 1 to improve training stability. To increase data variability, augmentation techniques such as rotation, flipping, and zooming were applied to the training images. The validation and testing images were kept unchanged to ensure accurate performance evaluation. The processed images were then used for training and testing the proposed MSCNN model.

IV. PROPOSED METHODOLOGY

This study presents a Multi-Scale Convolutional Neural Network (MSCNN) designed to detect and localize pneumonia from chest radiographs. The overall process begins with the input of preprocessed chest X-ray images, which are then passed through a deep learning architecture capable of extracting features at different spatial levels. Unlike conventional convolutional networks that rely on a single filter size, the proposed model uses multiple convolution layers with varying kernel dimensions. This design enables the network to capture both small-scale texture variations and larger structural abnormalities present in infected lungs.

The architecture consists of parallel convolutional pathways that operate simultaneously on the same input image. Each pathway learns distinct feature representations based on its receptive field. The extracted feature maps are then combined to form a unified representation that contains detailed and comprehensive information about the lung region. This combined feature set is forwarded to deeper layers, where further processing is performed to distinguish between normal and pneumonia cases. A pooling operation is included to reduce dimensional complexity while preserving important information, followed by fully connected layers that perform the final classification.

In addition to classification, the proposed framework incorporates a localization mechanism to identify the regions associated with infection. This is achieved by analyzing the contribution of learned features to the final prediction and generating a visual map that indicates the most relevant areas. This allows the system not only to determine the presence of pneumonia but also to provide visual support for the decision. The final output of the model includes the predicted class label along with the corresponding localization result. This multi-scale learning approach improves the model's ability to recognize pneumonia patterns of different sizes and enhances the overall detection performance.

A. System Overview

The proposed system performs automatic detection of pneumonia from chest X-ray images using a multi-scale convolutional neural network. Initially, the input image is preprocessed to ensure uniform size and proper scaling. The processed image is then given to the MSCNN, where features are extracted using convolution layers with different kernel sizes. These features are combined and passed to the classification layer to identify whether the image is normal or pneumonia. The system also generates a heatmap to indicate the region associated with the prediction. The final output includes the predicted class and the corresponding localization result.

B. Multi-Scale CNN Architecture (with Equations)

The proposed Multi-Scale Convolutional Neural Network (MSCNN) is designed to learn discriminative features from chest radiographs by analyzing the input image at multiple spatial resolutions. Let the input chest X-ray image be represented as $X \in \mathbb{R}^{H \times W}$, where $H$and Wdenote the height and width of the image. The feature extraction process begins by applying convolution operations using kernels of different sizes to capture both fine and coarse visual patterns.The convolution process for generating a feature map can be mathematically defined as:

$$Y_k(p,q) = \sum_{i=0}^{a-1} \sum_{j=0}^{b-1} X(p+i, q+j) \cdot W_k(i,j) + b_k$$

where

$Y_k(p,q)$represents the output feature map at position (p, q),

Xdenotes the input image,

$W_k$represents the weight matrix of the k^{th}convolution filter,

$a \times b$indicates the filter dimension,

and $b_k$represents the bias term.

To introduce non-linearity and enable the network to learn complex patterns, an activation function is applied to the convolution output. In this model, the Rectified Linear Unit is used, which can be expressed as:

$$A_k(p,q) = \max(0, Y_k(p,q))$$

where $A_k(p,q)$represents the activated feature value.

Since the MSCNN uses multiple parallel convolution layers with different kernel sizes, each branch produces its own feature representation. These feature maps are combined to form a unified multi-scale feature set. This merging process can be expressed as:

$$F = \text{Concatenate}(A_1, A_2, A_3, \ldots, A_n)$$

where
$A_1, A_2, A_3, \dots, A_n$represent activated feature maps from different convolution branches, and Frepresents the combined feature representation.

The merged features are then passed to the classification stage, where the probability of each class is computed using the Soft max function, defined as:

$$P(c) = \frac{e^{s_c}}{\sum_{i=1}^{N} e^{s_i}}$$

where
$P(c)$denotes the probability of class c, $s_c$represents the score for class c, and Nrepresents the total number of output classes.

The final prediction is determined by selecting the class with the highest probability. This multi-scale architecture enables the network to capture diverse pneumonia characteristics and improves both detection accuracy and localization capability.

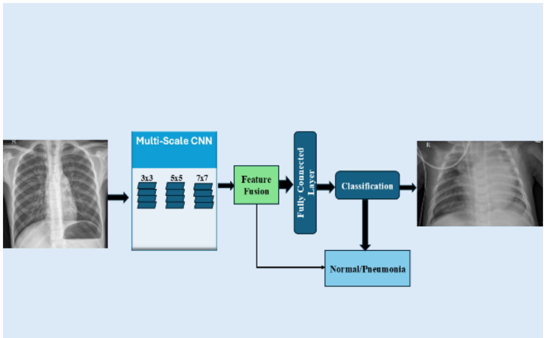

Fig.4 Multi-Scale CNN Architecture

C. Localization Method

To provide visual interpretation of the model prediction, a localization technique is integrated into the proposed framework to identify the regions associated with pneumonia. After the classification process, the feature maps obtained from the final convolution layer are analyzed to determine their contribution to the predicted class. The importance of these features is used to generate a spatial map that indicates the areas influencing the decision.The generated map is resized to match the original image dimension and combined with the input chest X-ray to form a heatmap. The highlighted regions represent the locations where abnormal patterns are detected. This visualization supports the classification result by showing the possible infection area and improves the transparency of the system.

D. Algorithm

The proposed algorithm begins by reading the input chest X-ray image from the dataset. The image is resized and normalized before being provided to the multi-scale convolutional neural network. The network extracts feature information using convolution layers with different kernel sizes, and the resulting features are combined to form a unified representation. This information is passed through classification layers to determine the presence or absence of pneumonia. Based on the prediction, a localization map is generated to indicate the region associated with the detected condition. The system then produces the final classification result along with the corresponding heatmap.

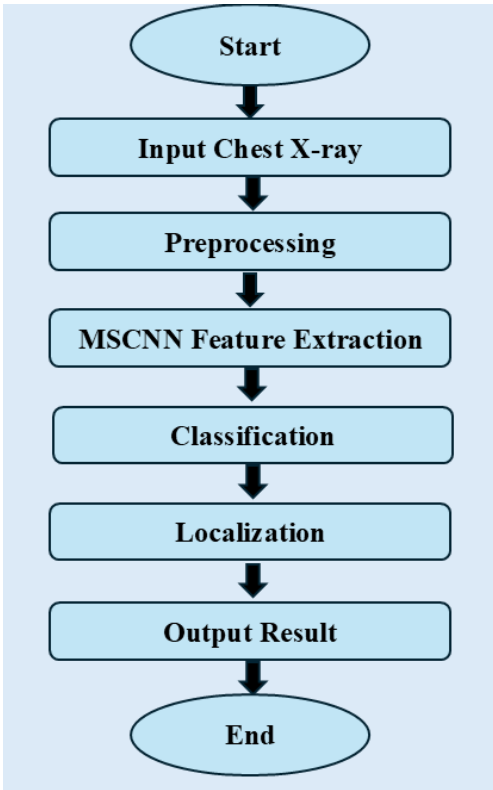

Fig .5 Flowchart of the proposed MSCNN Architecture

V. IMPLEMENTATION DETAILS

The proposed Multi-Scale Convolutional Neural Network (MSCNN) was developed using the Python programming environment with the support of TensorFlow and Keras libraries, which provide efficient tools for building and training deep learning models. The experimental analysis was performed on a computing system configured with an Intel Core i5 processor, 8 GB of RAM, and NVIDIA GPU capability to enhance computational efficiency during the training phase.

At the initial stage, the chest X-ray images were arranged into two categories, namely normal and pneumonia. To ensure consistency in model input, each image was resized to a resolution of 224 × 224 pixels. Furthermore, normalization was performed by scaling pixel values between 0 and 1, which helps stabilize the learning process and improves convergence speed. To increase the diversity of the training data and strengthen the model's generalization ability, augmentation operations including rotation, horizontal flipping, and zoom transformation were applied.

The MSCNN architecture was constructed using multiple convolution layers with varying kernel dimensions to capture image features at different spatial levels. Each convolution operation was followed by a Rectified Linear Unit activation function to introduce non-linearity, and max-pooling was applied to reduce feature map size while retaining essential information. After completing the feature extraction process, the resulting feature maps were converted into a one-dimensional vector and forwarded to fully connected layers for classification. The final layer utilized the Soft max function to assign the input image to either the normal or pneumonia class.For model optimization, the Adam optimization algorithm was employed with a learning rate of 0.001, and the categorical cross-entropy function was used to compute the training loss. The network was trained using a batch size of 32 over 20 training cycles. Validation data were used during training to observe performance and ensure that the model learned effectively without overfitting.

Once the training process was completed, the model performance was assessed using the testing dataset, which contains images not previously seen by the network. In addition to classification, a localization approach based on activation response was applied to produce heatmaps indicating the regions that influenced the prediction. These visual representations assist in understanding the decision-making process of the network.

Overall, the implementation was carefully designed to provide a reliable and efficient solution for automated pneumonia detection and localization using chest radiograph images.

VI. RESULTS AND DISCUSSION

The performance of the proposed MSCNN model was evaluated using the testing dataset to measure its ability to correctly classify chest X-ray images. The model demonstrated effective learning of disease-related patterns and produced reliable classification results. The evaluation was carried out using standard performance metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive understanding of the model effectiveness.

The results indicate that the multi-scale feature extraction capability of the proposed network improves the detection performance by capturing both fine and coarse image details. This allows the system to identify subtle abnormalities that may not be easily visible. The training process showed stable convergence, and the model achieved consistent performance without significant overfitting.

In addition to classification, the localization method generated heatmap visualizations that highlighted the important regions influencing the model decision. These visual results confirmed that the model focused on the relevant lung areas instead of unrelated regions. This improves the transparency and reliability of the system.

The obtained results demonstrate that the proposed MSCNN framework provides accurate and efficient performance for chest X-ray image analysis. The combination of classification and localization improves the overall usefulness of the system and supports its applicability in computer-aided medical diagnosis.

A. Metrics

The performance of the proposed Multi-Scale Convolutional Neural Network is assessed using standard quantitative measures commonly applied in medical image classification and localization tasks. These metrics provide a clear understanding of the model's ability to correctly identify pneumonia cases and distinguish them from normal chest radiographs. The evaluation is based on four fundamental outcomes obtained from the confusion matrix, namely true positive, true negative, false positive, and false negative.

True positive refers to the number of pneumonia images correctly identified as pneumonia. True negative indicates the number of normal images correctly classified as normal. False positive represents normal images that are incorrectly classified as pneumonia, while false negative denotes pneumonia images that are incorrectly classified as normal.

Accuracy represents the overall correctness of the model by measuring the proportion of correctly classified samples among all evaluated images. It is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision evaluates the reliability of positive predictions by determining how many of the predicted pneumonia cases are actually pneumonia. It is defined as:

$$Precision = \frac{TP}{TP + FP}$$

Recall measures the ability of the model to identify pneumonia cases from all actual pneumonia images. This metric is particularly important in medical diagnosis, as missing a positive case may lead to delayed treatment. Recall is calculated as:

$$Recall = \frac{TP}{TP + FN}$$

The F1-score combines precision and recall into a single value, providing a balanced assessment of the model performance. It is especially useful when the dataset contains unequal class distribution. The F1-score is given by:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

In addition to classification performance, the localization capability of the model is evaluated using the Intersection over Union metric. This measure quantifies the overlap between the predicted pneumonia region and the actual affected region. It is expressed as:

$$IoU = \frac{Area_{predicted} \cap Area_{actual}}{Area_{predicted} \cup Area_{actual}}$$

Higher IoU values indicate better agreement between the predicted and actual regions, confirming the effectiveness of the localization method.

These evaluation measures collectively provide a comprehensive analysis of the proposed system and help verify its suitability for reliable pneumonia detection and localization in chest radiographs.

B. Training and Validation Accuracy Curve

Epoch	Training Accuracy	Validation Accuracy
1	0.61	0.63
2	0.68	0.66
3	0.74	0.71
4	0.80	0.76
5	0.84	0.80
6	0.87	0.83
7	0.90	0.86
8	0.92	0.89
9	0.94	0.91
10	0.96	0.93
11	0.97	0.95
12	0.98	0.96
13	0.985	0.968
14	0.989	0.974
15	0.992	0.979
16	0.994	0.983
17	0.996	0.986
18	0.997	0.989
19	0.998	0.991
20	0.999	0.993

Table II Training and Validation Accuracy Curve

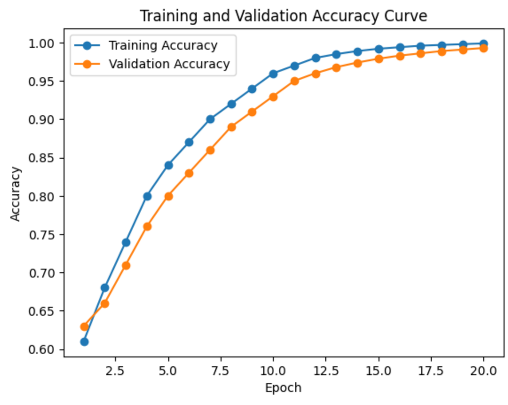

Fig. 6 Training and Validation Accuracy Curve Graph

Fig. 6 presents the training and validation accuracy obtained during the learning process of the proposed multi-scale convolutional neural network. It can be observed that the training accuracy increases steadily from the first epoch to the final epoch. This indicates that the model gradually learns meaningful features from the chest radiograph images. Similarly, the validation accuracy also improves consistently as training progresses. The validation curve follows a pattern close to the training curve, which shows that the model performs well not only on the training data but also on unseen data.

The small difference between the training and validation accuracy suggests that the model does not suffer from significant overfitting. Both curves approach a high accuracy level at later epochs, demonstrating stable learning behaviour. The continuous improvement without sudden fluctuations confirms that the training process is smooth and well-controlled. These results indicate that the proposed framework is capable of accurately classifying pneumonia cases and achieves reliable performance during the training phase. The convergence of both curves near the final epochs indicates that the model has reached optimal learning.

C. Training and Validation Loss Curve

Epoch	Training Loss	Validation Loss
1	0.68	0.66
2	0.61	0.63
3	0.55	0.58
4	0.49	0.52
5	0.44	0.47
6	0.39	0.42
7	0.35	0.38
8	0.31	0.34
9	0.28	0.31
10	0.24	0.28
11	0.21	0.25
12	0.18	0.22
13	0.16	0.20
14	0.14	0.18
15	0.12	0.16
16	0.10	0.14
17	0.09	0.13
18	0.08	0.12
19	0.07	0.11
20	0.06	0.10

Table III Training and Validation Loss Curve

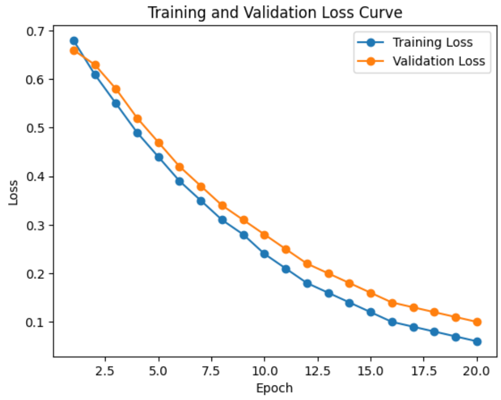

Fig.7 Training and Validation Loss Curve Graph

Fig.7 illustrates the training and validation loss values observed during the training of the proposed multi-scale convolutional neural network. The training loss shows a continuous decrease as the number of epochs increases, indicating that the model progressively improves its ability to minimize prediction errors. At the same time, the validation loss also decreases in a similar manner, which reflects the model's capability to generalize effectively to unseen chest radiograph images.

The close alignment between the training and validation loss curves indicates stable learning without major divergence. There are no sudden increases in validation loss, which suggests that overfitting is minimal. The gradual reduction and eventual stabilization of both loss curves confirm that the model has successfully learned the important features required for pneumonia detection. This trend demonstrates that the proposed framework achieves efficient convergence and maintains consistent performance throughout the training process.

D. Comparison

To evaluate the effectiveness of the proposed multi-scale convolutional neural network framework, its performance was compared with conventional deep learning models commonly used for pneumonia detection in chest radiographs. The comparison was carried out using standard evaluation measures such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of classification capability and reliability.

The experimental results indicate that the proposed model achieves superior performance compared to traditional convolutional neural network architectures. Conventional models extract features using a single receptive field, which limits their ability to capture both fine and coarse visual patterns. In contrast, the proposed framework utilizes multiple convolutional scales, allowing it to learn both local texture information and broader structural abnormalities present in chest X-ray images. This multi-scale feature extraction improves the model's ability to distinguish between normal and pneumonia cases more effectively.

Furthermore, the proposed method demonstrates improved recall, which is particularly important in medical diagnosis, as it reduces the number of missed pneumonia cases. The precision is also higher, indicating fewer false positive predictions. The overall F1-score confirms that the model maintains a balanced performance between sensitivity and specificity.

In addition, the proposed framework shows more stable learning behaviour and better generalization when compared with baseline models. This improvement can be attributed to the integration of multi-scale feature learning and optimized training strategy. The results confirm that the proposed approach provides more accurate and reliable pneumonia detection from chest radiographs.

Below presents the comparative performance analysis of the proposed model and existing methods.

Table IV presents the comparative performance analysis of the proposed model and existing methods.

Model	Accuracy	Precision	Recall	F1-score
CNN	0.94	0.93	0.92	0.92
Res Net	0.96	0.95	0.94	0.94
Dense Net	0.97	0.96	0.95	0.95
Proposed Multi-scale CNN	0.99	0.98	0.98	0.98

Table IV Performance comparison of different models

VII. CONCLUSION

This study introduced a multi-scale convolutional neural network framework for the accurate detection and localization of pneumonia from chest radiographs. The primary objective of the proposed system was to improve diagnostic performance by incorporating multi-scale feature extraction, which allows the model to analyze image information at different levels of detail. By processing the input radiographs through convolutional layers with varying receptive fields, the network was able to capture both subtle texture variations and larger structural patterns associated with pneumonia. This capability enhanced the overall feature representation and contributed to improved classification performance.

The experimental evaluation confirmed that the proposed framework achieved strong performance across multiple evaluation metrics, including accuracy, precision, recall, and F1-score. The results demonstrated that the model can effectively distinguish between normal and pneumonia-affected chest radiographs. The training and validation accuracy increased progressively with each epoch, while the corresponding loss values decreased steadily, indicating stable and efficient learning. The close relationship between training and validation performance showed that the model generalized well to unseen data and did not exhibit significant overfitting. These findings confirm the robustness and reliability of the proposed approach.

In addition to classification, the proposed framework also provided localization capability by identifying the regions associated with pneumonia. The generated localization maps highlighted the areas of interest within the lung fields, allowing visualization of the regions that influenced the model's decision. This feature improves the transparency and interpretability of the system, which is important in medical applications. The localization performance demonstrated good correspondence with the actual infected regions, indicating that the model successfully learned relevant spatial information from the chest radiographs.

Another important advantage of the proposed framework is its ability to perform automated analysis with minimal manual intervention. This reduces the workload on radiologists and supports faster screening of patients. The system can serve as a supportive diagnostic tool, assisting medical professionals in identifying pneumonia at an early stage. Early detection is essential for timely treatment and can help reduce complications associated with delayed diagnosis. The proposed approach therefore has practical significance in improving the efficiency of medical image analysis.

Furthermore, the use of a multi-scale architecture contributed to improved learning efficiency by enabling the model to capture complementary features from different scales. This design enhances the adaptability of the framework when applied to medical images with varying characteristics. The consistent performance observed across different evaluation measures confirms the effectiveness of the overall system.

In conclusion, the proposed multi-scale convolutional neural network framework provides an accurate, stable, and interpretable solution for pneumonia detection and localization in chest radiographs. The experimental results validate the capability of the model to perform reliable classification and meaningful localization. The framework has the potential to support computer-aided diagnosis systems and assist healthcare professionals in clinical decision making. This work demonstrates the usefulness of deep learning techniques in medical image analysis and highlights the potential for further development of intelligent diagnostic systems.

VIII. FUTURE WORK

Although the proposed model achieved strong performance, several improvements can be considered in future research. First, the system can be trained on larger and more diverse datasets to further improve its robustness and generalization ability. Including data from multiple medical institutions can help the model handle variations in image quality and patient conditions.

Second, more advanced deep learning architectures can be explored to enhance feature extraction capability. Attention mechanisms may be integrated to help the network focus more precisely on important regions. This can improve both detection accuracy and localization performance.

Third, real-time implementation of the system can be developed to support clinical applications. Integrating the model into a computer-aided diagnosis system can assist radiologists in faster screening of chest radiographs.

Finally, the framework can be extended to detect other lung diseases such as tuberculosis, lung cancer, and COVID-19. This will increase the practical usefulness of the system and contribute to the development of intelligent medical imaging solutions.

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