Gray Level Co-occurrence Matrix based Fully Convolutional Neural Network Model for Pneumonia Detection

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Abstract *– This study presents a new method to improve the detection ability of a convolutional neural network (CNN) in pneumonia detection using chest X-ray images. Using Gray-Level Co-occurrence Matrix (GLCM) analysis, additional channels are added to the original image data provided by Guangzhou Children's Hospital in Guangzhou, China. The main goal is to design a lightweight, fully convolution network and increase its available information using GLCM. Performance analysis is performed on the new CNN model and GLCM-enhanced CNN model, and results are compared with Transfer Learning approaches. Various evaluation metrics, including accuracy, precision, recall, F1 score, and AUC-ROC, are used to evaluate the improved analysis performance of CNN. The results showed a significant increase in the ability of the model to detect pneumonia, with an accuracy of 99.57%. In addition, the study evaluates the descriptive properties of the CNN model by analyzing its decision process using Grad-CAM.*

Keywords*:* *CNN, Pneumonia, Chest X-ray, Diagnostic, Explainability, GLCM*

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1. INTRODUCTION

Pneumonia is a leading cause of infant death globally. Hence, a precise diagnosis is essential for successful treatment. The current standard of care for diagnosing pneumonia consists of imaging techniques and physical examination, with chest X-rays and computed tomography (CT) scans being the most common imaging procedures. Radiologists are tasked with interpreting these images, using their training to spot signs of pneumonia and inform further decisions about patient care. However, radiologists' views of this procedure vary, making it subjective. Furthermore, there are disadvantages to relying solely on human interpretation, and the healthcare system faces difficulties due to the growing need for diagnostic imaging. More objective, scalable, and practical techniques for pneumonia detection are required because of the limitations associated with subjectivity, human factors, and technological limits [1].

Convolutional Neural Networks (CNNs) are a powerful method of deep learning techniques that can identify complex patterns in images [2-4]. A typical CNN has many layers of artificial neurons, frequently with different kinds of layers for various purposes. They are extensively used in the medical imaging diagnosis and classification of a wide range of diseases, from brain tumors to skin lesions and, more recently, respiratory illnesses, including pneumonia. Even with their efficacy, there are still many obstacles to overcome. One major obstacle is the large amount of computational power required to train reliable CNN models. Large-scale datasets or complex models may require complex and time-consuming training methods, which call for sophisticated systems that aren't always readily available.

Models for transfer learning, like VGGNet, AlexNet, MobileNet, and ResNet, have been widely used for various applications, including the classification of medical images. Although these models have shown to be successful, their original architectures were intended for multiclass classification on datasets such as Imagenet, which has more than 100 classes. These models are considered excessive for applications such as pneumonia detection, where input images are frequently grayscale with a single channel, and there are just two classification classes. Their larger number of channels and intricate network architecture also lead to bulkier model sizes, which require significant processing power. As a result, there is an increasing need for low-complexity, lightweight models, especially for resource-constrained setups. This paper explores a novel strategy for creating a lightweight X-ray image classification model that uses point-wise convolution and max-pooling to achieve progressive dimension reduction and channel count reduction. This research also examines the combination of the Gray-Level Co-occurrence Matrix (GLCM) to improve the detection power of CNN models. By incorporating additional data channels from the GLCM into the original image.

The main idea of this work is to show that a small and robust CNN model may produce predictions that are comparable to or better than those produced by current techniques, even though it is much smaller in size. Additionally, adding texture feature information from images can further improve this performance.

The key contributions of this manuscript include:

- Creation of a lightweight fully convolutional CNN model for pneumonia classification
- Performing necessary preprocessing on the Xray images
- Extracting GLCM-based channels from the given images and appending them to original images for the classification task
- Experimentation with channel dimensions and counts while keeping crucial spatial information for precise predictions
- Comparison of the proposed model's classification performance to transfer learning models (trained on the same dataset), such as VGG and ResNet

The sections that follow are arranged as follows: The findings of the literature review are shown in Section 2. In Section 3, the dataset used and methods are described in detail. The results are shown and discussed in Section 4. The manuscript is concluded in Section 6, after Section 5 examines potential future developments.

2. LITERATURE REVIEW

Souid et al. [5] used a modified MobileNet V2 model to make predictions from radiographic images. They applied transfer learning and metadata integration, extracting data from the NIH Chest-Xray-14 database. The performance of their method is evaluated using the AUC statistic, giving an average AUC of 0.558 and achieving an accuracy of more than 90%.

In their study, Oh et al. [6] introduced a deep neural network model based on patch-based analysis. They trained the model on a small data set and based their decisions on broad observations from random lung patches. In addition, they introduced the Grad-CAM saliency map for detailed information.

Khan et al. [7] developed a CoroNet model using the Xception architecture to train it on a dataset containing X-ray images of COVID-19 and pneumonia. Their model achieved an accuracy of 89.6% and a precision and recall rate of 90% and 89.9%, respectively, for COVID-19.

Ozturk et al. [7] proposed a new model in their study to improve the diagnosis of COVID-19. This model achieved a good accuracy of 87% in two variable classifications.

Wijaya et al. [8] used K-Nearest Neighbor and Gray Level Co-Occurrence methods, achieving the highest accuracy of 66.20% for K=5.

Polsinelli et al. [9] designed a lightweight CNN based on SqueezeNet, which correctly detected COVID-19 in CT chest scans with 85.03% accuracy,

Joshi et al. [10] conducted a study where a CNN model called LiMS-Net was proposed to solve the problem of overfitting in training samples and the detection of COVID-19 by CT scans. With 2.53 million parameters, the model outperformed the transfer learning approaches and achieved 92.11% accuracy and 92.59% F1 score, demonstrating its effectiveness even with small CT data.

Several other studies [11-13] were also performed to identify pneumonia using machine learning and X-ray images of the chest, thus reinforcing the critical role of machine learning and deep learning in automatic detection.

3. MATERIALS AND METHODS

This study uses X-ray images showing different pneumonia patterns as the dataset to build and validate our model. We designed a simple CNN model to handle the complexity of pneumonia diagnosis, carefully considering the balance between model complexity and diagnosis accuracy within the limits of a real clinical setting. Our dataset is divided into training, validation, and testing sections to evaluate the model's performance. In addition to creating and evaluating the model, we use Grad-CAM visualization to see the areas in the image that contribute more to pneumonia classification.

The proposed framework and workflow are shown in Fig. 1. The first step in the process is loading the images, which are then resized to 224 by 224 pixels and normalized. These images are then processed using a feature extractor to extract different texture-based GLCM feature channels. After that, the extracted channels are added back to the original image. Now that this enhanced image has 1+9 channels, we train our lightweight CNN model. A loss computation is done, and the network weights are modified following the resultant computed loss.

3.1. DATASET

The dataset used for this study consisted of chest X-ray images of two kinds: one representing pneumonia and the other showing normal conditions. These radiographic images were provided by Guangzhou Children's Hospital, China [14]. The dataset is publically available and can be accessed using this link: https://data.mendeley.com/datasets/rscbjbr9sj/3. A pneumonia case includes images that show different levels and degrees of the disease, while a normal case includes images without any signs of pneumonia. This diverse dataset serves as a reliable basis for developing and evaluating our simple CNN model for diagnosing pneumonia. The image has different dimensions in the study, although the majority is 255 x 255 pixels with a depth of 24 bits, and the images are in PNG format.

Table 1. Train and test split for dataset

Class label	Training	Testing
Normal	1340	3874
Pneumonia	224	241

3.2. PREPROCESSING

In the study, all images were processed by resizing them to a size of 224 x 224 pixels. The main goals of resizing were to enhance model performance and computational efficiency. First, resizing ensures consistency in the data provided to the network by helping to standardize input dimensions throughout the dataset. This uniformity is essential for the CNN to efficiently learn and generalize patterns. Additionally, resizing lessens the computational effort. This is particularly useful when training big models on hardware that is constrained. Apart from this, resizing also allows effective comparison of results.

Next, we normalize the pixel values in the image; Normalizing improves the training stability and convergence of the model. Normalizing guarantees that features in various channels are on a similar scale and helps reduce pixel intensity variances. By avoiding problems like vanishing or exploding gradients. Additionally, it strengthens the network's resistance to variations in lighting and enhances its capacity to recognize patterns in various images. The calculation of normalized pixel values is performed using the formula [15]:

$$normalized\_value(z) = (pixel\_value(x) - average\_value(\mu)) \,/\, standard\_deviation(\sigma) \quad (1)$$

3.2.1. Gray-Level Co-occurrence Matrix (GLCM)

Apart from resizing the images, we also apply the GLCM method to extract and create nine additional channels, including Mean, Standard Deviation, Contrast, Dissimilarity, Homogeneity, Angular Second Moment, Energy, Maximum, and Entropy values. These additional channels are appended back to the original image (refer to Fig. 2), and the image is then converted into a tensor object for model training.

Gray-Level-Co-occurrence Matrix is an image texture analysis technique commonly used in image processing and computer vision. It defines the spatial relationship between pixel intensity values in a digital image. A GLCM is constructed by counting the occurrences of two pixels with strong values at different distances and directions in the image.

3.3. DEEP NEURAL NETWORK CLASSIFIER

The proposed CNN model is suitable for pneumonia classification, distinguishing between normal and pneumonia conditions. Its purpose is to diagnose pneumonia in patients by analyzing chest x-ray images. The following sections will provide a detailed description of this CNN model and go into the details of its development and analysis of its results.

3.3.1. Components of Model

The proposed CNN model is designed to classify pneumonia, with the primary goal of distinguishing between normal and pneumonia-related conditions from chest X-ray images. This model uses layers with filters of different sizes (kernels), such as 3x3 or 5x5, to extract essential features from the input image. These filters combine, creating feature maps representing different parts of the original image [16]. Batch Normalization is used after every layer. It involves normalizing the intermediate feature maps within a batch of training samples to have zero mean and unit variance. By applying BatchNorm, the network becomes less sensitive to variations in the distribution of inputs, leading to improved training stability and faster convergence [17].

We can define the normalization formula of Batch Norm as:

$$Z^n = (\frac{Z - m_z}{s_z}) \quad (2)$$

where m_z and s_z represent the mean and standard deviation

Non-linearity is introduced by using an activation function, namely ELU, which is given by the following formula [18]:

$$f(x) = \{ x, if\ x > 0\ and\ -\alpha * (exp(-x) - 1),\ if\ x < 0\} \quad (3)$$

In addition, the model uses a reduction method, namely Max pooling, to reduce space dimensions while maintaining essential features. It divides the feature map into non-overlapping areas and selects the maximum value in each area, preserving the essential features and removing the less important details. Global Average Pooling (GAP) is used at the end to reduce an entire channel to one value.

Finally, during training, the model uses Softmax activation and negative log loss as a function to transform the existing values into a probability distribution with a wrong prediction penalty, thus making predictions more accurate [19].

3.3.2. Architecture of the Proposed Model

The proposed CNN model comprises convolutional layers, pooling layers, and GAP layers. The PyTorch library is used to design the model in Python. This model follows the process of compression and expansion to add channels and consists of two types of blocks: convolutional and transition blocks.

In convolutional block, the input or feature maps are convolved over by a 3x3 filter with a stride of 1 and padding of 0, the number of channels in the filter progressively increases twice (e.g., 16,32,64), and then the transition block is applied to bring the channels back to the starting value (e.g., 16). In the study, we have trained the same CNN model twice, once with the original image of 3 channels and again with GLCM images of 3+9 channels. Thus, the number of input channels varies for both cases.

In a convolutional block, we have used a 3x3 kernel to create feature maps of channel sizes 16, 32, and 64; after every convolution, a batch normalization and ELU are added. Once the model reaches 64 channels, the dimension of the feature map is reduced by using max-pooling. Additionally, the size of the channels is also reduced using point-wise convolution.

This transition block can be understood with the help of Fig. 3. Suppose we have an input of Channels (C) x Width (W) x Height (H). On this input, we apply max-pooling, which reduces the dimension of the image by a factor of r (generally 2). Thus, the resulting output will become C x W/r x H/r. Note that the number of channels are still the same, just the dimensions of the image are reduced. Next, we use point-wise convolution to reduce the number of channels.

This is done by using a filter of C x 1 x 1. Now, this filter can be used multiple times depending on the channels we need as output. Thus, the output after every transition block will become C/p x W/r x H/r where r is the reduction factor for dimension and p is the reduction factor for a number of channels.

This transition prepares the model for another cycle of increasing channels using a convolutional block. This cycle is repeated four times until the image size is down to 11x11 with 16 channels. After this, we convolve using 3x3 filters twice with channel size increasing to 32 and 64, and then Global Average Pooling is applied, which gives an output of 64x1x1. We apply point-wise convolution to reduce this to 2x1x1, our final output before softmax.

The step-by-step operation is shown in the model summary table below.

Table 2. Model Summary

Layer	Kernel Size	Input Shape	Output Shape
Input	-	-	[3, 224, 224]
Conv2d	3x3	[3, 224, 224]	[16, 222, 222]
Conv2d	3x3	[16, 222, 222]	[32, 220, 220]
Conv2d	3x3	[32, 220, 220]	[64, 218, 218]
MaxPool2d	2x2	[64, 218, 218]	[64, 109, 109]
Conv2d	1x1	[64, 109, 109]	[16, 109, 109]
Conv2d	3x3	[16, 109, 109]	[32, 107, 107]
Conv2d	3x3	[32, 107, 107]	[64, 105, 105]
MaxPool2d	2x2	[64, 105, 105]	[64, 52, 52]
Conv2d	1x1	[64, 52, 52]	[16, 52, 52]
Conv2d	3x3	[16, 52, 52]	[32, 50, 50]
Conv2d	3x3	[32, 50, 50]	[64, 48, 48]
MaxPool2d	2x2	[64, 48, 48]	[64, 24, 24]
Conv2d	1x1	[64, 24, 24]	[16, 24, 24]
Conv2d (with Padding)	3x3	[16, 24, 24]	[32, 24, 24]
Conv2d	3x3	[32, 24, 24]	[64, 22, 22]
MaxPool2d	2x2	[64, 22, 22]	[64, 11, 11]
Conv2d	1x1	[64, 11, 11]	[16, 11, 11]
Conv2d	3x3	[16, 11, 11]	[32, 7, 7]
Conv2d	3x3	[32, 7, 7]	[64, 5, 5]
AvgPool2d	5x5	[64, 5, 5]	[64, 1, 1]
Conv2d	1x1	[64, 1, 1]	[2, 1, 1]

3.4. MODEL TRAINING AND TESTING

For training and testing, the dataset is divided into two parts: training and testing data. During the training phase, the CNN model is trained using the training data. Stochastic Gradient Descent has been used as an optimizer which updates the model parameters to minimize the loss function. The learning rate is set to 0.01, allowing the optimizer to control the step size during parameter updates. In addition, a momentum value of 0.9 is specified, which helps speed up the convergence during training. The epochs and batch size are set to 25 and 32, respectively. The model is trained by feeding batches through the network, calculating losses, and fitting gradients to improve model parameters. This process continues until all the epochs are over. Finally, the trained model is evaluated using test data.

Table 3. Training Hyperparameters

Hyperparameter	Value
Optimizer	SGD
Learning Rate	0.01
Momentum	0.9
Epochs	20
Batch Size	32

3.5. EXPERIMENTAL SETUP

In this study we have performed all the experiments on a machine with an NVIDIA GeForce GTX 1050 Ti GPU, 24 GB of RAM, and an Intel Core i5 8th Gen processor.

All the scripts were written and executed using Python 3.9.16 and the major libraries include PyTorch 2.0.0 with CUDA 11.8, and torchvision 0.15.1.

It is important to emphasize that a model's training time depends on the system specification hence for comparison, we have chosen to use the total number of trainable parameters in the model. Smaller parameter counts lead to faster training, especially when using transfer learning on a range of machines, as the number of parameters is directly proportional to the training time.

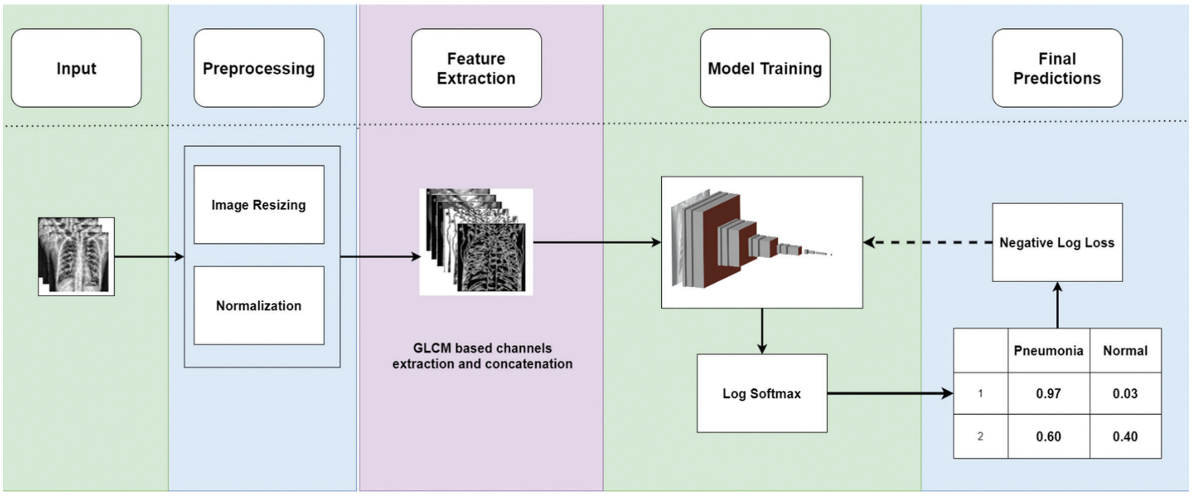

Fig. 1. Proposed framework and workflow

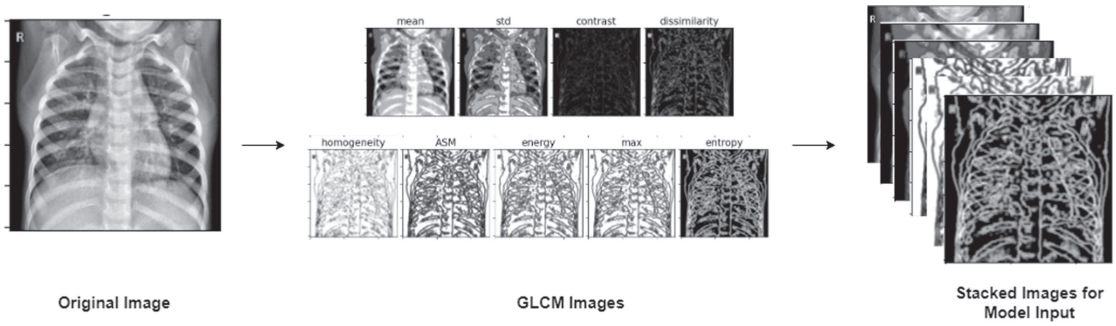

Fig. 2. GLCM-based channel concatenation

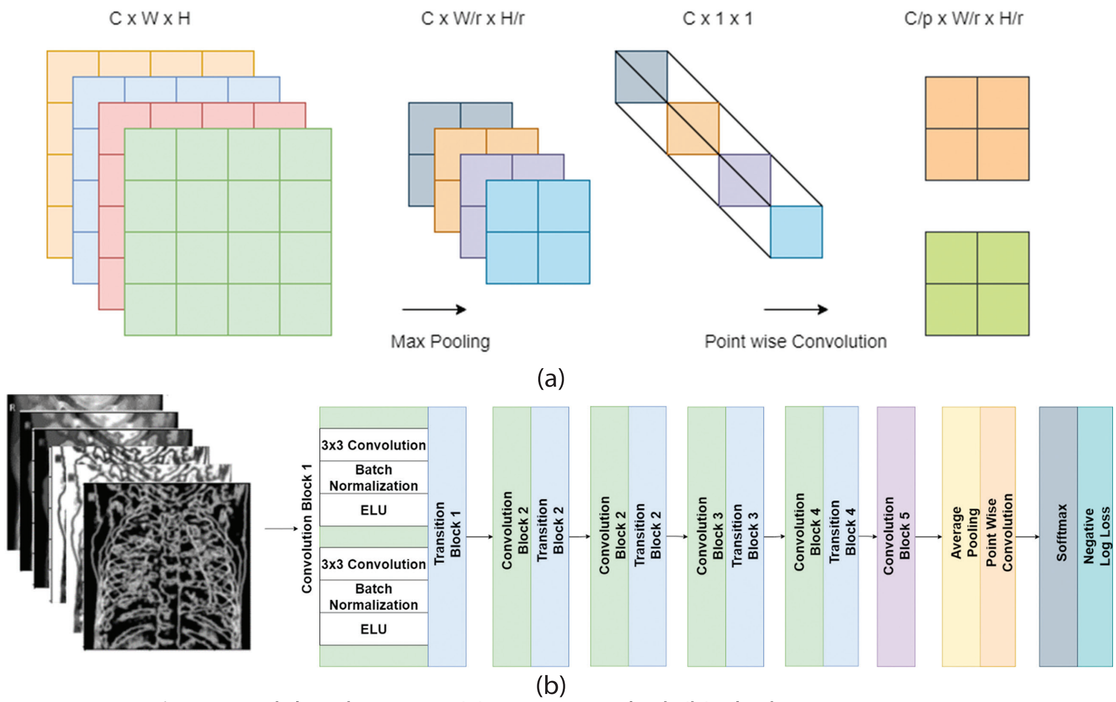

Fig. 3. Model Architecture (a) Transition Block (b) Blocks Arrangement

4. RESULTS AND DISCUSSIONS

Results from the proposed models are reported and discussed in this section and a comparative analysis is presented, highlighting the differences between our proposed models and existing models. Shown next in Table 3 and Table 4 we can see the training and test evaluation for both the CNN model.

Table 3. Training evaluation for CNN and GLCM CNN models

Model	Accuracy	Precision	Recall	F1
GLCM CNN	0.999	0.999	0.999	0.999
Base CNN	0.999	0.999	0.999	0.99

Table 4. Test evaluation for CNN and GLCM CNN models

Model	Accuracy	Precision	Recall	F1
GLCM CNN	0.9784	0.9785	0.9784	0.978
Base CNN	0.974	0.974	0.974	0.974

Based on the tables presented above, the GLCM-based CNN model performs slightly better than the base CNN model. Throughout the training process for both models, we consistently monitored accuracy for each epoch to ensure no over fitting. The results for the same can be seen below in Fig. 4 and Fig. 5.

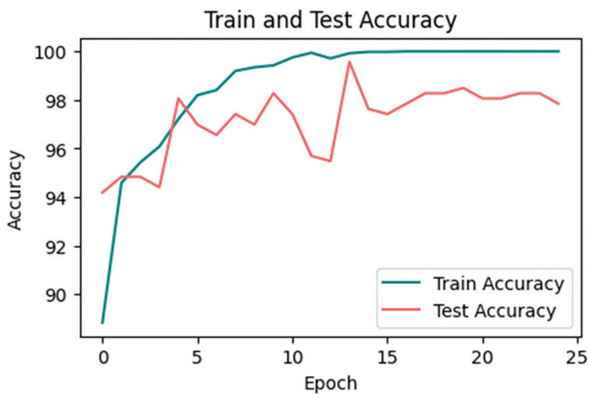

Fig. 4. Train and test accuracy for GLCM-based CNN model

Fig. 5. Train and test accuracy for base CNN model

It can be seen in the above image that fluctuations in test accuracy is lot lesser in GLCM CNN model in comparison.

Below is the comparison of test results of both the models with transfer learning approaches. The size of the models is also shown (K denotes 1000, and M denotes 100000).

Table 5. Comparison with transfer learning approaches

Model	Accuracy	Precision	Recall	F1	Size
GLCM CNN	0.9784	0.9785	0.9784	0.978	129 K
Base CNN	0.974	0.974	0.974	0.974	129 K
MobileNet V2	0.96	0.96	0.96	0.96	22.26 M
Resnet34	0.95	0.95	0.95	0.95	21.28 M
AlexNet	0.97	0.97	0.97	0.97	57.01 M
VGG-16	0.97	0.97	0.97	0.97	134.26 M

It can be seen from the table above that the proposed models perform better than transfer learning approaches, although there is a huge difference in model size. Hence, it can be concluded that the proposed models are more compact and comparable in diagnostic capabilities.

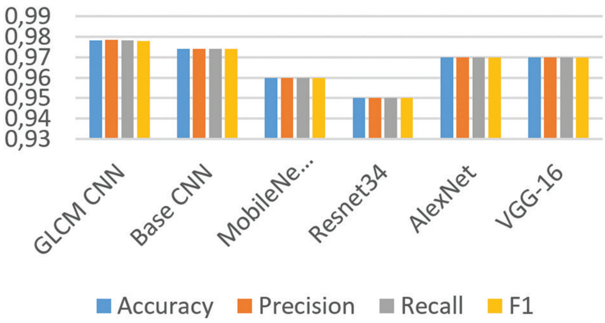

Fig. 6. Comparison with transfer learning approaches

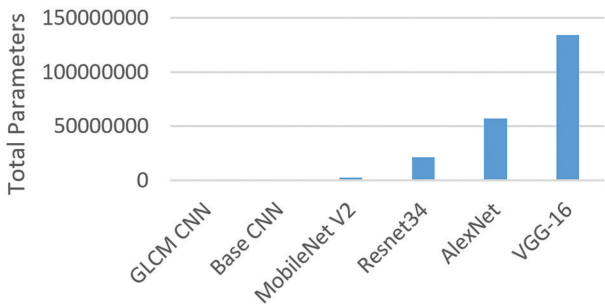

Fig. 7. Size comparison of different models

Fig. 8 shows a heat map generated using the Gradient-weighted Class Activation Mapping (GradCAM) technique, which is applied to predict pneumonia in a given input image. These heat maps serve as a critical medium, providing vital information about some regions of the input image that are critical to influencing the predictions of our Deep-learning model. By identifying these essential areas of the input image, Grad-

CAM allows decision-makers to better understand how the model approaches its predictions.

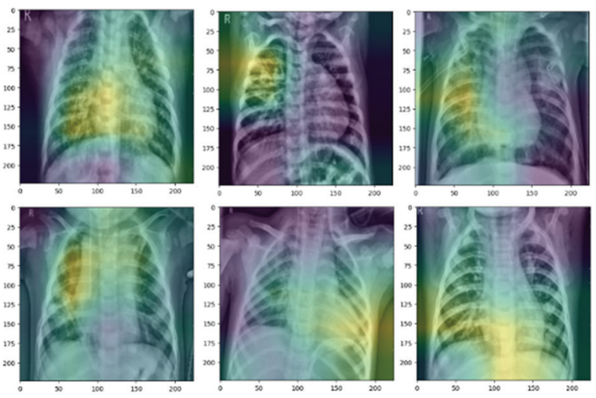

Fig. 8. GradCAM output

In Table 4, we assess the performance of our proposed model using the test dataset and compare it to previous studies. We have only shown the studies that have used the same dataset. It can be seen from the table below that the GLCM CNN model performs better in terms of all the evaluation metrics compared to work done by Moujahid et al. [20] and Zhang et al. [21]. Study conducted by Singh et al. [22] and Srivastav et al. [23] did not report all the metric however our model still shows better Accuracy and F1 Score.

Table 4. Model comparison

	Accuracy	Precision	Recall	F1Score
GLCM CNN Model	**0.9784**	**0.9785**	**0.9784**	**0.978**
Moujahid et al. [20]	0.9681	0.91	0.97	0.94
Zhang et al. [21]	0.9607	0.9441	0.9082	0.9258
Singh et al. [22]	0.9375			0.9405
Srivastav et al. [23]	0.945			

In summary, better model performance scores and less test accuracy fluctuations show that the GLCM-based CNN model performs marginally better in pneumonia identification than the base CNN model. Furthermore, the proposed models perform better than transfer learning strategies, demonstrating their effectiveness and diagnostic potential. Notably, even if the GLCM-based CNN produces better results, the base CNN might make sense when resources are limited because of its comparable performance.

5. LIMITATIONS AND FUTURE SCOPE

Although the current GLCM-based CNN model gives better accuracy than the base CNN model. The preprocessing and Model training time for the GLCM-based CNN model is huge. Further work is required to reduce time and make the process more efficient. It is suggested to adapt our base CNN model if the decision time required is less. Additionally, while the current approach only uses the GLCM method, further improvement of performance is possible by incorporating different texture-based features.

6. CONCLUSION

Our research has led to the creation of a novel model for pneumonia detection. We have developed a simple, Fully Convolutional Neural Network (CNN) algorithm that handles the difficult task of detecting pneumonia. The CNN model showed exceptional performance in pneumonia detection. The evaluation metrics demonstrated the model's ability to distinguish between pneumonia and non-pneumonia. The CNN model based on the Gray-Level Co-occurrence Matrix (GLCM) performed the best, achieving training and testing accuracy of 99.99% and 97%, respectively. Although the base CNN model achieved less accuracy, it significantly takes less time to train and predict. From a broader point of view, this study not only shows an advanced approach but also a bright future for AI-based healthcare. Although we focused on pneumonia, the models and principles applied in this research have great potential to address similar challenges in healthcare.

7. REFERENCES

[1] G. Labhane, R. Pansare, S. Maheshwari, R. Tiwari, A. Shukla, "Detection of Pediatric Pneumonia from Chest X-Ray Images using CNN and Transfer Learning", Proceedings of the 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things, Jaipur, India, 7-8 February 2020, pp. 85-92.

[2] D. Saida, K. K. Vardhan, P. Premchand, "Effective Brain Tumor Classification Using Deep Residual Network-Based Transfer Learning", International Journal of Electrical and Computer Engineering Systems, Vol. 14, No. 6, 2023, pp. 625-634.

[3] S. Tounsi, K. Boukari, A. Souahi, "The impact of collarette region-based convolutional neural network for iris recognition", International Journal of Electrical and Computer Engineering Systems, Vol. 13, No. 1, 2022, pp. 37-47.

[4] Y. Dahdouh, A. A. Boudhir, M. B. Ahmed, "A New Approach using Deep Learning and Reinforcement Learning in HealthCare: Skin Cancer Classification", International Journal of Electrical and Computer Engineering Systems, Vol. 14, No. 5, 2023, pp. 557-564.

[5] A. Souid, N. Sakli, H. Sakli, "Classification and Predictions of Lung Diseases from Chest X-rays Using MobileNet V2", Applied Sciences, Vol. 11, No. 6, 2021, p. 2751.

[6] Y. Oh, S. Park, J. C. Ye, "Deep Learning COVID-19 Features on CXR Using Limited Training Data Sets", IEEE Transactions on Medical Imaging, Vol. 39, No. 8, 2020, pp. 2688-2700.

[7] T. Ozturk, M. Talo, E. A. Yildrim, U. B. Baloglu, O. Yildrim, U. R. Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images", Computers in Biology and Medicine, Vol. 121, 2020, p. 103792.

[8] C. Wijaya, H. Irsyad, W. Widhiarso, "KLASIFIKASI PNEUMONIA MENGGUNAKAN METODE K-NEAREST NEIGHBOR DENGAN EKSTRAKSI GLCM", Jurnal Algoritme, Vol. 1, No. 1, 2020, pp. 33-44.

[9] M. Polsinelli, L. Cinque, G. Placidi, "A light CNN for detecting COVID-19 from CT scans of the chest", Pattern Recognition Letters, Vol. 140, 2020, pp. 95-100.

[10] A. M. Joshi, D. R. Nayak, D. Das, Y. Zhang, "LiMS-Net: A Lightweight Multi-Scale CNN for COVID-19 Detection from Chest CT Scans", ACM Transactions on Management Information Systems, Vol. 14, No. 1, 2023, pp. 1-17.

[11] S. D. Thepade, H. Jha, "COVID-19 Identification using Machine Learning Classifiers with GLCM Features of Chest X-ray Images", Trends in Sciences, Vol. 18, No. 23, 2021, p. 46.

[12] Y. J. Kim, "Machine Learning Model Based on Radiomic Features for Differentiation between COVID-19 and Pneumonia on Chest X-ray", Sensors, Vol. 22, No. 17, 2022, p. 6709.

[13] N. Dey, Y.-D. Zhang, V. Rajinikanth, R. Pugalenthi, N. Sri Madhava Raja, "Customized VGG19 Architecture for Pneumonia Detection in Chest X-Rays", Pattern Recognition Letters, Vol. 143, 2021, pp. 67-74.

[14] D. Kermany, K. Zhang, M. Goldbaum, "Large Dataset of Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images", Cell, Vol. 172, No. 5, 2018, pp. 1122-1131.

[15] S.-C. Pei, C.-N. Lin, "Image normalization for pattern recognition", Image and Vision Computing, Vol. 13, No. 10, 1995, pp. 711-723.

[16] Y. Lecun, L. Battou, Y. Bengio, P. Haffner, "Gradient-based learning applied to document recognition", Proceedings of the IEEE, Vol. 86, No. 11, 1998, pp. 2278-2324.

[17] S. Ioffe, C. Szegedy, "Batch normalization: accelerating deep network training by reducing internal covariate shift", Proceedings of the 32nd International Conference on International Conference on Machine Learning, Vol. 37, Lille, France, July 2015. pp. 448-456.

[18] D.-A. Clevert, T. Unterthiner, S. Hochreiter, "Fast and Accurate Deep Network Learning by Exponential Linear Units (ELUs)", Proceedings of the 4th International Conference on Learning Representations, San Juan, Puerto Rico, 2-4 May 2016.

[19] A. Krizhevsky, I. Sutskever, G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks", Advances in Neural Information Processing Systems, Vol. 25, 2012, pp. 1-9.

[20] H. Moujahid, B. Cherradi, O. E. Gannour, L. Bahatti, O. Terrada, S. Hamida, "Convolutional Neural Network Based Classification of Patients with Pneumonia using X-ray Lung Images", Advances in Science, Technology and Engineering Systems Journal, Vol. 5, 2020, pp. 167-175.

[21] D. Zhang, F. Ren, Y. Li, L. Na, Y. Ma, "Pneumonia Detection from Chest X-ray Images Based on Convolutional Neural Network", Electronics, Vol. 10, No. 13, 2021, p. 1512.

[22] S. Singh, B. K. Tripathi, "Pneumonia classification using quaternion deep learning", Multimedia Tools and Applications, Vol. 81, No. 2, 2022, pp. 1743-1764.

[23] D. Srivastav, A. Bajpai, P. Srivastava, "Improved Classification for Pneumonia Detection using Transfer Learning with GAN based Synthetic Image Augmentation", Proceedings of the 11th International Conference on Cloud Computing, Data Science & Engineering, Noida, India, 28-29 January 2021, pp. 433-437.