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Accuracy Improvement of Convolutional Neural Network with Ghost Weight Normalization for Pneumonia Classification

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ABSTRACT

Pneumonia is a critical respiratory condition that requires accurate and timely diagnosis to ensure effective treatment. In this study, we propose the integration of Ghost Weight Normalization (GWN) into a Convolutional Neural Network (CNN) to enhance the accuracy and performance of pneumonia detection. The dataset used was derived from the Kaggle repository, comprising 5,856 chest X-ray images divided into two classes: Normal and Pneumonia. The CNN + GWN model demonstrated improved classification metrics with an accuracy, precision, recall, and F1-score of 95%, outperforming the CNN-Based model, which achieved 92%. While the CNN + GWN model required slightly longer training time and more epochs to achieve its best performance, the trade-off resulted in more robust and reliable predictions. The enhanced performance is attributed to the ability of GWN to normalize weights effectively, providing diverse normalization variations and improving training stability. These results underscore the potential of the CNN + GWN model for reliable pneumonia detection and highlight its capability to address the limitations of conventional CNN architectures.

1. Introduction

Pneumonia is one of the leading respiratory diseases contributing to significant morbidity and serving as a major cause of mortality worldwide, particularly among vulnerable groups such as children, the elderly, and individuals with weakened immune systems (Pettigrew et al., 2020). The World Health Organization (WHO) identifies pneumonia as a critical public health issue, responsible for approximately 14% of all deaths in children under five years old globally, despite being a preventable and treatable condition. In addition to its direct health impact, pneumonia places a substantial burden on healthcare systems, with high rates of hospital admissions and intensive care requirements. Data from Community-Acquired Pneumonia (CAP) indicate that the in-hospital mortality rate due to pneumonia is 18.5%, with monthly and yearly mortality rates of 22.9% and 44.5%, respectively (Theilacker et al., 2021). These alarming statistics highlight the urgency of developing more effective diagnostic tools to identify and treat pneumonia at earlier stages, thereby reducing both mortality rates and the economic strain on healthcare providers. Early diagnosis is a key strategy to prevent severe complications and improve patient survival rates (Crosby et al., 2022). However, conventional methods, such as chest radiograph analysis, are costly, require expert involvement, are time-consuming, and may be prone to human error. Therefore, there is a pressing need for technological advancements to improve the detection of pneumonia.

Recently, Artificial Intelligence (AI) has been increasingly used in a variety of ways (Armaeni et al., 2024). One of them is widely used in image data analysis, especially in the medical field (Baihaqi, Wahyudi, et al., 2024; Khajuria et al., 2023). One of the algorithms frequently used for this task is Convolutional Neural Network (CNN). CNN is known as a model capable of extracting important features from images automatically and efficiently. The main advantage of CNN lies in its computational efficiency, especially when compared to more complex CNN-based models with deeper layers (Kuang, 2021). This makes CNN an ideal choice for applications requiring rapid diagnosis, such as early detection of pneumonia. A study employing CNN for pneumonia detection achieved a high accuracy of 91% (Chowdhury et al., 2021). In comparison, another study using DenseNet, an advanced development of CNN, only achieved an accuracy of 86.6% (Salehi et al., 2021). Additionally, the time required to train other complex deep learning models is significantly longer than that of CNN. Therefore, CNN not only offers superior accuracy but also faster processing time, making it a more practical choice for rapid diagnostic applications such as pneumonia detection. This highlights that, in the context of quick and reliable detection, basic CNN models can outperform more complex CNN variants.

However, to reduce errors in pneumonia detection using the CNN model, it is necessary to improve accuracy so that the likelihood of model errors can be minimized. One of the approach that can be applied to enhance the accuracy of the CNN model is by using weight normalization techniques, which help the model achieve stability during the training process and improve overall detection performance. These techniques work by ensuring that the model's weights are adjusted more effectively, leading to faster convergence and a more stable training process. By addressing issues such as vanishing or exploding gradients, weight normalization can make the model more robust and improve its generalization to new, unseen data. In this context, weight normalization techniques not only help the model learn faster but also contribute to better performance on classification tasks. In a study, weight normalization techniques were shown to increase CNN accuracy by 2% for classification tasks (Heeger & Zemlianova, 2020), demonstrating their potential to significantly enhance model reliability. By refining the model's weight adjustment process, these techniques help improve both the accuracy and stability of the model, making it a more reliable tool for pneumonia detection and other medical diagnoses (Zhang et al., 2021).

One of the weight normalization techniques that excels in providing greater normalization variations is Ghost Weight Normalization (GWN). GWN operates by dividing the entire weight into several smaller segments, each of which is then normalized separately for more precise control. This segmentation allows each individual weight segment to undergo a more specific and targeted adjustment process, which significantly enhances the model's training stability and efficiency (Baihaqi, Shalsadilla, et al., 2024). Unlike traditional normalization methods that apply a single adjustment to the entire weight, GWN's approach ensures that each part of the model's weight is optimized based on its specific requirements. Once all the weight segments are normalized independently, they are reassembled into the main weight, preserving the integrity and structure of the original weight while benefiting from the individualized adjustments (Baihaqi, Setiawan, et al., 2024). This process enables multiple normalization cycles within a single weight, thereby allowing the model to refine and fine-tune its parameters more effectively. Unlike Batch Normalization (BN), which relies on batch statistics and can suffer from reduced performance when using small batch sizes or imbalanced datasets, GWN directly normalizes the weights themselves, making it more robust to varying batch sizes and complex data patterns (Z. Yao et al., 2021). The flexibility provided by GWN not only improves the efficiency of the training process but also contributes to optimizing the model's performance. With enhanced flexibility and the ability to better accommodate varying data patterns, GWN proves to be a powerful technique in boosting model accuracy and reliability, particularly in complex scenarios (Baihaqi & Setiawan, 2024; Muflikhah et al., 2024).

Therefore, this study will use Ghost Weight Normalization to normalize the weights in a CNN model for pneumonia detection as GAP research. With high accuracy, the model can reduce the error rate, making it more reliable for early diagnosis. By incorporating this advanced normalization technique, the model not only enhances its performance but also improves its ability to generalize across diverse datasets, ensuring more consistent and trustworthy results. This approach will contribute to the development of a more efficient and accurate diagnostic tool, with the potential to significantly aid in the timely detection and treatment of pneumonia, ultimately improving patient outcomes.

2. Literatur Review

A. Pneumonia

Pneumonia is an inflammatory condition of the lung parenchyma, primarily caused by infections that lead to inflammation in the alveoli. The most common pathogens responsible for pneumonia include bacteria, viruses, and fungi, with Streptococcus pneumoniae being one of the leading bacterial causes. Other bacterial causes include Haemophilus influenzae, Staphylococcus aureus, and Mycoplasma pneumoniae. Viral infections, particularly influenza viruses, respiratory syncytial virus (RSV), and coronaviruses (including SARS-CoV-2), also contribute significantly to pneumonia incidence. Pneumonia can range from mild to severe and may result in complications such as pleural effusion or respiratory failure, particularly in vulnerable populations such as the elderly, immunocompromised individuals, and children under five years of age (Kanwal et al., 2024).

The risk factors for developing pneumonia include smoking, chronic lung diseases (such as COPD), weakened immune systems, and conditions like diabetes. Vaccination, early detection, and appropriate antibiotic or antiviral therapy are crucial in managing the disease effectively. Recent studies emphasize the importance of using machine learning and artificial intelligence techniques to diagnose pneumonia at an early stage, improving outcomes through faster treatment and intervention (Stokes et al., 2022). Advances in imaging techniques, such as chest X-rays and CT scans, combined with computational methods, have facilitated early detection and better prediction of pneumonia progression

B. Convolutional Neural Network

Convolutional Neural Networks (CNN) are a type of deep learning network specifically designed for processing image data. Their operation combines convolutional layers, which use filters to extract features such as edges and textures, and pooling layers that reduce spatial dimensions while preserving essential information (Kattenborn et al., 2021). CNN are widely applied in various fields, including object recognition, object detection, and medical image analysis, due to their ability to discern complex patterns within images. The mechanism of CNN involves three main stages: convolution, pooling, and classification. Convolutional layers detect basic features using filters, while pooling layers reduce spatial dimensions to optimize computational efficiency. Finally, the fully connected layer integrates these features to perform accurate classification, making CNN powerful tools in image-based tasks (X. Yao et al., 2022).

C. Ghost Weight Normalization

Ghost Weight Normalization (GWN) is a normalization technique designed to offer more diverse adjustments within a single weight structure. The process involves dividing the entire weight into smaller sections called GW Batches, with the number of batches determined by a predefined GWN size (Baihaqi & Setiawan, 2024). Each GW Batch undergoes normalization independently using a specific normalization method, as indicated in Equation 1. After normalization, the GW Batches are concatenated to reconstruct the original weight. This approach enables each GW Batch to be individually normalized, enhancing flexibility and stability in model training. The GWN architecture is illustrated in Fig. 1.

An additional advantage of GWN is its capacity to handle large-scale weight matrices efficiently by breaking them into smaller, manageable components, reducing computational overhead. Moreover, by normalizing at the batch level, GWN mitigates the risk of overfitting and improves the generalization capability of the model. This unique structure supports robust learning in deep neural networks, particularly in tasks requiring high precision and stability

$$Norm = \frac{K}{\sum_{j=1}^{n} |K_{ij}|} \tag{1}$$

Description:

K = Represent the kernel matrix of size m x n

K_{ij} = Denote the element in the I row and j column of K

|K| = Matrix absolute values of K

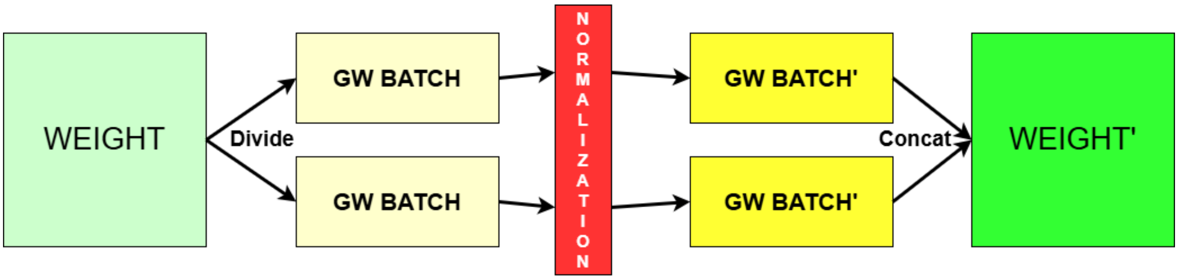

Fig. 1. Ghost Weight Normalization Architecture

3. Method

A. Dataset

The dataset used in this study is the Chest X-Ray Images (Pneumonia) dataset obtained from Kaggle, consisting of image data as illustrated in Fig. 2(a). This dataset comprises two classes: Normal and Pneumonia. The Normal class contains 1583 samples, while the Pneumonia class contains 4273 samples. The dataset is imbalanced, with the distribution percentages shown in Fig. 2(b), where the Normal class constitutes 27% of the data, and the Pneumonia class constitutes 73%, making Pneumonia the majority class.

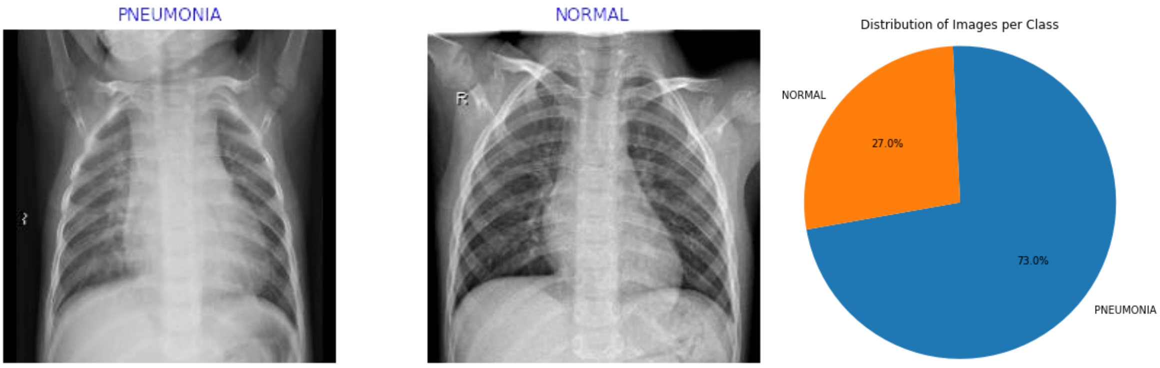

Fig. 2. (a) Dataset, (b) Distribution of Datasets

B. General System

The classification process begins with reading the Pneumonia dataset obtained from Kaggle. Subsequently, the dataset undergoes a series of data preprocessing steps. The first step involves downsampling, which is performed to address class imbalance within the dataset. The purpose of downsampling is to equalize the number of samples in each class, thereby preventing the model from becoming biased towards the majority class during training. Following this, the dataset is resized to 224 x 224 pixels and then split into training, validation, and testing datasets with proportions of 80%, 10%, and 10%, respectively. The training data is evenly distributed between the two classes, whereas the validation and testing datasets are randomized to thoroughly evaluate the model's performance and enhance its robustness.

After preprocessing, the dataset is trained using a CNN model integrated with Ghost Weight Normalization (GWN) over 100 epochs, with a learning rate set to 0.001. During evaluation, the highest validation accuracy recorded during training is selected as the best epoch. The model is then evaluated using a confusion matrix to calculate key performance metrics, including accuracy, precision, recall, and F1-score. The entire process is illustrated in Fig. 3.

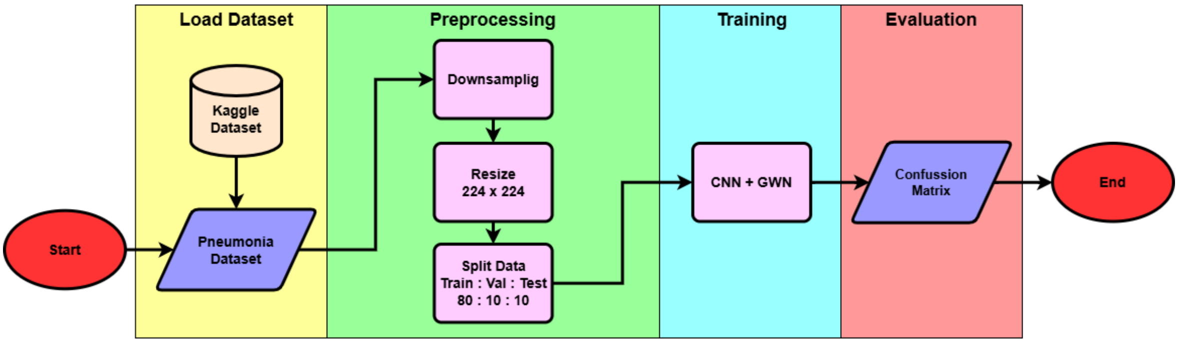

Fig. 3. General System Flow

C. Model Architecture

In Fig. 4, the model architecture consists of two blocks, followed by a flatten layer, a fully connected layer, and ends with a classification layer. The activation function used in the classification layer is softmax. The blocks in the model represent the arrangement of layers, starting with convolutional layers, followed by GWN layers, and then max pooling layers. In the first block, the convolutional layer has 128 filters, and the size of the GWN is 64. In the second block, the number of filters is 256, and the size of the GWN is 128, resulting in a total of two gw batches for each block in the GWN. The max pooling layer is then applied to extract the main features of each image.

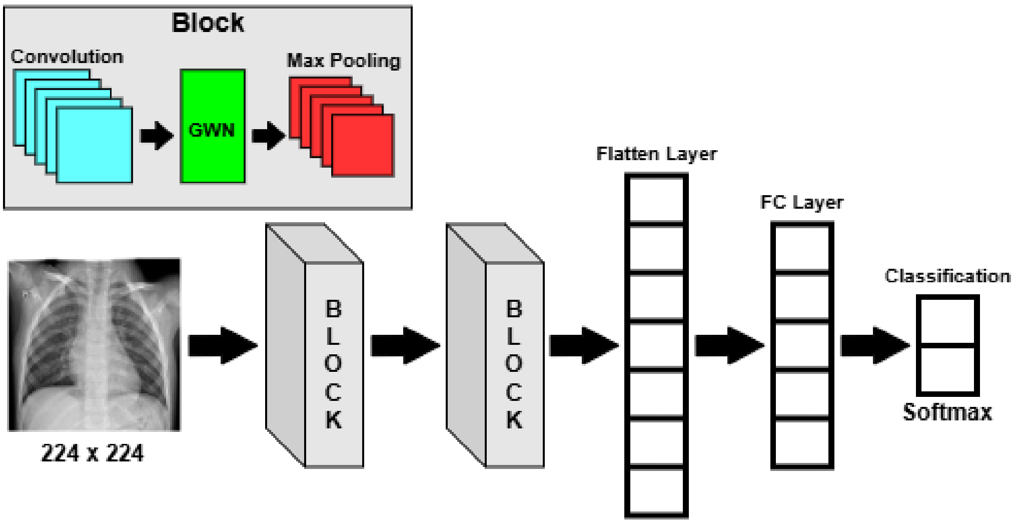

Fig. 4. Model Architecture

D. Test Scenario

Fig. 5 illustrates the testing scenario aimed at evaluating the impact of Ghost Weight Normalization (GWN) on the performance of the CNN model. The first step involves data preprocessing, following the same process as described in the preprocessing stage in Fig. 3. Next, the CNN + GWN model is compared with a CNN-based model. The CNN-based architecture used is identical to the one in Fig. 5, except it excludes the GWN layer. Both models are then evaluated using a confusion matrix, and the results compared in terms of accuracy, precision, recall, and F1-score.

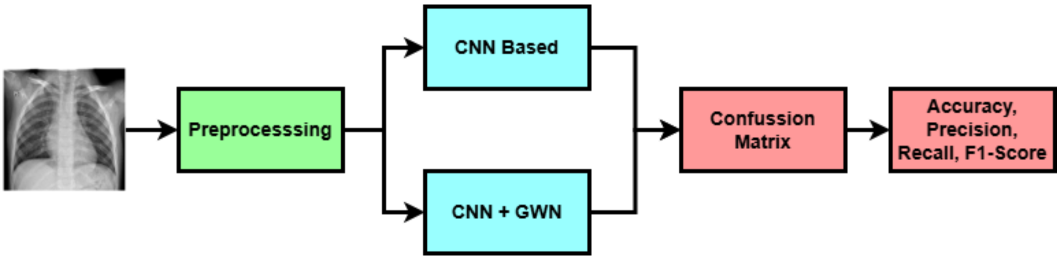

Fig. 5. Test Scenario

E. Model Evaluation

To evaluate the trained models, this study utilized a confusion matrix, a widely recognized tool for assessing classification tasks. The confusion matrix provides a detailed breakdown of prediction outcomes, including true positives or TP (correctly predicted positive samples), true negatives or TN (correctly predicted negative samples), false positives or FP (negative samples incorrectly predicted as positive), and false negatives or FN (positive samples incorrectly predicted as negative). These outcomes are essential for calculating key performance metrics such as accuracy, precision, recall, and F1-score, as outlined in Equations 2-5.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1-Score = 2 \times \frac{Recall \times Precision}{Recall+Precision} \tag{5}$$

Description:
TP = True Positive
TN = True Negative
FP = False Positive
FN = False Negative

4. Result and Discussions

A. Preprocessing Result

In the data downsampling process during preprocessing, it is observed that the minority class is the "Normal" class, with 1583 samples, while the majority class, "Pneumonia," initially contains 4273 samples. To address this imbalance, the Pneumonia class is downsampled to 1583 samples randomly. The purpose of this downsampling is to balance the data distribution between the two classes, as shown in Fig. 6. As a result, the total number of samples processed for both classes is 3116. The next step involves resizing the dataset to a standard size of 224 x 224 pixels. Following this, the data is split into three subsets: training, validation, and testing. The training dataset consists of 2532 samples, while both the validation and testing datasets each contain 317 samples.

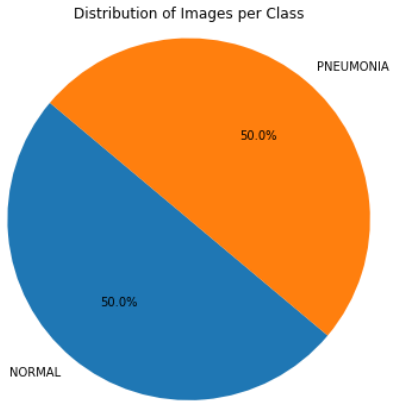

Fig. 6. Distribution of Dataset After Undersampling

B. CNN Based Result

During the training process using the CNN-Based model, the validation performance over the training epochs is depicted in Fig. 7(a). The graph indicates that over 100 epochs, the highest validation accuracy occurred at epoch 13, making it the optimal epoch. The best epoch is determined based on the highest validation accuracy achieved during the training process. Therefore, in the evaluation phase, the model weights from epoch 13 are used to ensure maximum performance. Fig. 7(b) illustrates the confusion matrix, which evaluates the model's predictive performance. During the testing phase, the model misclassified the Normal class 19 times and the Pneumonia class 6 times. Based on the confusion matrix results, the model achieved an overall accuracy, precision, recall, and F1-score of 92%

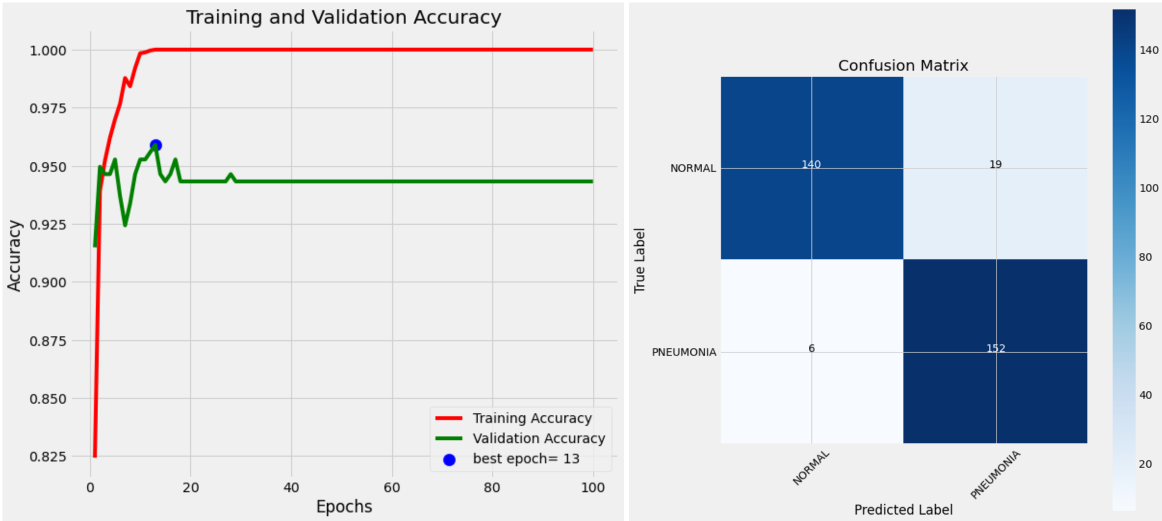

Fig. 7. (a) CNN training accuracy graph, (b) CNN Confusion Matrix Result

C. CNN + GWN Result

During the training process using the CNN + GWN model, the validation performance across 100 epochs is illustrated in Fig. 8(a). The graph highlights that epoch 24 achieved the highest validation accuracy, marking it as the optimal epoch. The best epoch is selected based on the peak accuracy recorded during training on the validation dataset. For the evaluation phase, the weights from epoch 24 are utilized to maximize the model's performance. Fig. 8(b) presents the confusion matrix for the CNN + GWN model, which serves to assess its performance. During the evaluation, the model misclassified the Normal class 8 times and the Pneumonia class 7 times on the testing dataset. Based on these results, the model demonstrated an accuracy, precision, recall, and F1-score of 95%, reflecting a notable improvement in classification performance

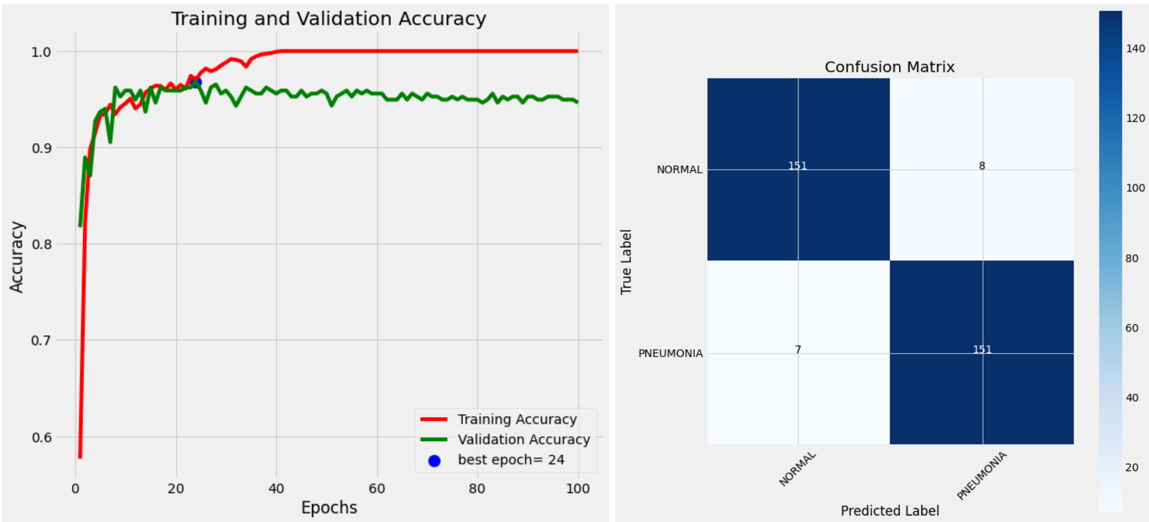

Fig. 8. (a) CNN + GWN training accuracy graph, (b) CNN + GWN Confusion Matrix Result

D. Overall evaluation

The accuracy, precision, recall, and F1-score achieved by the CNN-Based model were 3% lower, with an overall performance of 92%. In contrast, the CNN + GWN model demonstrated a superior overall evaluation score of 95%. These results indicate that GWN enhances the accuracy of the CNN model. However, during training, the CNN + GWN model required a longer training time, taking 1679 seconds, compared to the CNN-Based model's training time of 1667 seconds. This increase is attributed to the additional process in CNN + GWN, where weights are divided into gw batches and normalized separately for each batch during the feed-forward phase, leading to a slightly longer training duration. Furthermore, the best epoch for the CNN-Based model was reached faster, with the highest validation accuracy achieved at epoch 13. In comparison, the CNN + GWN model reached its best epoch at epoch 24.

Table 1. Overall Evaluation Results

Model	**Confusssion Matrix (%)**				**Best**	**Training**
	Accuracy	***Precision***	***Recall***	***F1-Score***	**Epoch**	**Time (sec)**
CNN Based	92	92	92	92	13	1667
CNN + GWN	95	95	95	95	24	1679

The delayed best epoch for CNN + GWN can be attributed to the diverse weight normalization values introduced by GWN, causing fluctuations in the validation accuracy, as observed in Fig. 8(a). This contrasts with the CNN-Based model, whose validation accuracy graph, shown in Fig. 7(a), is more stable after achieving its peak. Despite requiring more time to train and locate the best epoch, the CNN + GWN model produced higher accuracy, precision, recall, and F1-score, showcasing its superior performance compared to the CNN-Based model. The detailed comparison of results for both models is presented in Table 1. The results show that the CNN with GWN model exhibits better accuracy. The addition of GWN is a novelty in CNN to normalize the weights with more variation and is able to show better accuracy than the CNN-based model.

5. Conclusion

This study demonstrates the effectiveness of incorporating Ghost Weight Normalization (GWN) into the CNN model for pneumonia detection. Through comprehensive evaluations, the CNN + GWN model achieved superior performance compared to the standard CNN-Based model, as evidenced by an accuracy, precision, recall, and F1-score of 95%, which surpasses the 92% obtained by the CNN-Based model. The integration of GWN not only improved the overall classification performance but also contributed to better handling of model weights during training, as reflected in the model's stability and optimization. Although the CNN + GWN model required slightly longer training time and more epochs to achieve its best performance, this trade-off was compensated by the significant improvements in classification accuracy and reliability. These results highlight the potential of GWN in enhancing CNN-based models, especially in medical diagnostic tasks requiring high accuracy and reliability. However, this study has several limitations. First, the model's performance may be affected by the quality and diversity of the dataset used, which was limited to specific pneumonia images. Additionally, the CNN + GWN model's performance on larger, more diverse datasets or other medical imaging tasks is yet to be fully explored. In conclusion, the proposed CNN + GWN model presents a promising solution for pneumonia detection and can serve as a foundation for further research. Future studies may explore the application of GWN to other deep learning architectures or adapt the method for real-time diagnostic systems to improve its practicality in clinical settings.

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