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A revolutionary convolutional neural network architecture for more accurate lung cancer classification

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ABSTRACT

This research aimed to investigate a breakthrough in convolutional neural network (CNN) architecture with the potential to revolutionize lung cancer classification. The proposed method is a comparative optimization model of ResNet architecture, with accuracy rate of 99.68% in identifying and categorizing lung cancer types. The results showed that the use of innovative methods in CNN architecture, such as multi-dimensional convolutional layers and the integration of specific lung cancer features, effectively provided highly accurate and reliable outcomes. These showed a positive impact on the development of medical diagnostic technology, offering promising potential to enhance prognosis and response to treatment for lung cancer patients. With high accuracy rate, this breakthrough presents opportunities for further advancements in lung cancer management through artificial intelligence-based methods.

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1. INTRODUCTION

Lung cancer is among the most prevalent and deadly types of cancer globally, occurring from uncontrolled growth in lung tissue forming tumors [1]–[3]. This disease does not often show symptoms in the early stages, leading to late diagnosis when treatment becomes more challenging. The main risk factors for lung cancer include exposure to carcinogenic substances such as cigarette smoke, air pollution, and radon [4], [5]. Therefore, there is a need for continuous research and innovation in the field of lung cancer diagnostic and treatment aiming at improving the prognosis as well as life quality of patients. Several strategies have been implemented to develop more sensitive and accurate diagnostic methods, along with effective and curative therapies to address the global burden of lung cancer [4]–[7]. Other preventive and management steps include campaigns to avoid major risk factors such as smoking and increasing awareness of early detection [8]. Consequently, this research focuses on the application of artificial intelligence technology in the development of a revolutionary convolutional neural network (CNN) architecture to improve accuracy in lung cancer diagnosis often hindered by morphological and genetic variations that are difficult to identify using conventional methods [9]–[11].

This research applies various methods including the use of multi-dimensional convolutional layers and the integration of specific lung cancer features into CNN architecture. In the development of CNN, several popular architecture that have successfully been effective in various image processing and classification tasks include LeNet-5, AlexNet, visual geometry group network (VGGNet), GoogLeNet (Inception), residual network (ResNet), MobileNet, EfficientNet, and DenseNet [12]–[17]. LeNet-5 has made significant contributions to CNN development, while AlexNet, developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, is known for its deeper architecture and larger convolution layers. Furthermore, VGGNet, developed at the University of Oxford, is known for very deep structure using relatively small convolution blocks, consisting of 16 or 19 layers, depending on the variant used. GoogLeNet, developed at Google, introduces the "Inception" module which uses multiple filter sizes in one layer to capture features at various scales and improve representation skills [18], [19]. ResNet was developed by Kaiming He and the team at Microsoft Research, using residual blocks that allow deeper model training without experiencing vanishing gradient problems. MobileNet is designed for mobile device applications, optimizing speed, and computational requirements using depthwise separable convolutions. EfficientNet combines scaling methods to optimize model efficiency regarding size, speed, and accuracy. Densely connected convolutional network (DenseNet) is developed to address the vanishing and exploding gradient problems, using closer connections between layers in the form of "dense blocks". Each architecture has specific characteristics, which are used according to required tasks and needs. Meanwhile, the selection of CNN architecture can significantly influence the performance and results of the developed model [18]–[22].

Regarding the popular architecture in previous research [23], several significant advantages have been documented. The proposed ensemble learning of ResNet, EfficientNet, and Inception-v3 with weighted voting (ELREI) method successfully addresses limitations and leverages the strengths of each CNN architecture, namely ResNet, EfficientNet, and Inception-v3. This method achieves excellent results of more than 98% accuracy, precision, recall, and F1-score, with the potential to overcome overfitting, which is often encountered in CNN architecture. This research also provides a performance comparison of the ELREI method with previous results, showing excellent performance in classifying lung disease based on chest X-ray (CXR) images. However, one identified limitation is the lack of discussion regarding model testing on different datasets or cross-dataset testing. Although the results obtained are more than 98%, there is no information regarding model testing on external datasets or cross-datasets. Meanwhile, in other research machine learning model, particularly SVM and decision tree classifiers have been used to classify abnormal breath sounds such as wheezes and crackles [24]. This method shows potential in diagnosing respiratory diseases more accurately and objectively using patient demographic data and chest region to obtain more comprehensive information. However, the research has several identifiable limitations including the absence of in-depth explanation in comparison with previous research. Information on limitations or constraints is also not available, which can help readers better understand the context and interpret the results.

This research investigates the effect of improving the ResNet50 model CNN architecture to improve image classification accuracy in lung cancer, while previous studies have explored the impact of using the ResNet model CNN architecture, but they have not explicitly discussed the effect on improving classification and the use of the ResNet architecture model is not explained. So that, this research presents a breakthrough, identifying the strengths and weaknesses of each method. Strengths include accuracy and efficiency improvements, while weaknesses consist of computational complexity and large data requirements for model training. To address these weaknesses, effective solutions are required, showing the potential application of the proposed method more efficiently [25], [26]. Issues in the selected method in this research include the potential limitation of training data reflecting the full variation of lung cancer. The proposed method is devised as an improvement proposal that includes strategies to enhance training data diversity and minimize potential biases arising from these limitations. The results are expected to provide higher accuracy in classification, opening opportunities for significant improvements in accurately identifying lung cancer types [21], [26]–[28]. Therefore, this research aimed to develop CNN architecture capable of overcoming diagnostic constraints of lung cancer, improving classification accuracy, and positively contributing to the advancement of medical diagnostic technology. The development is carried out to achieve significant improvements in lung cancer detection, expedite the diagnosis process, and enhance the prognosis as well as treatment of patients affected by lung cancer.

2. METHOD

This research evaluates CNN optimization techniques for classifying bone fractures using X-ray CT scan data. The study processes fracture data for CNN models to detect and classify fractures, showing significant performance improvements with appropriate optimizations. Comparative analysis reveals insights into each technique's strengths and weaknesses. The findings advance image-based medical diagnosis and offer practical guidance for optimizing CNN models in healthcare.

2.1. Data description

The dataset used in this research consisted of CT scans from patients with lung diseases, various stages of cancer, and healthy subjects. IQ-OTH/NCCD slides, annotated by experts, were sourced from Kaggle [29]. This dataset, collected in autumn 2019, includes 150 lung images from the Oncology Teaching Hospital of Iraq/National Center for Cancer Diseases. The data was split 80:20 for processing. The workflow of this research is shown in Figure 1.

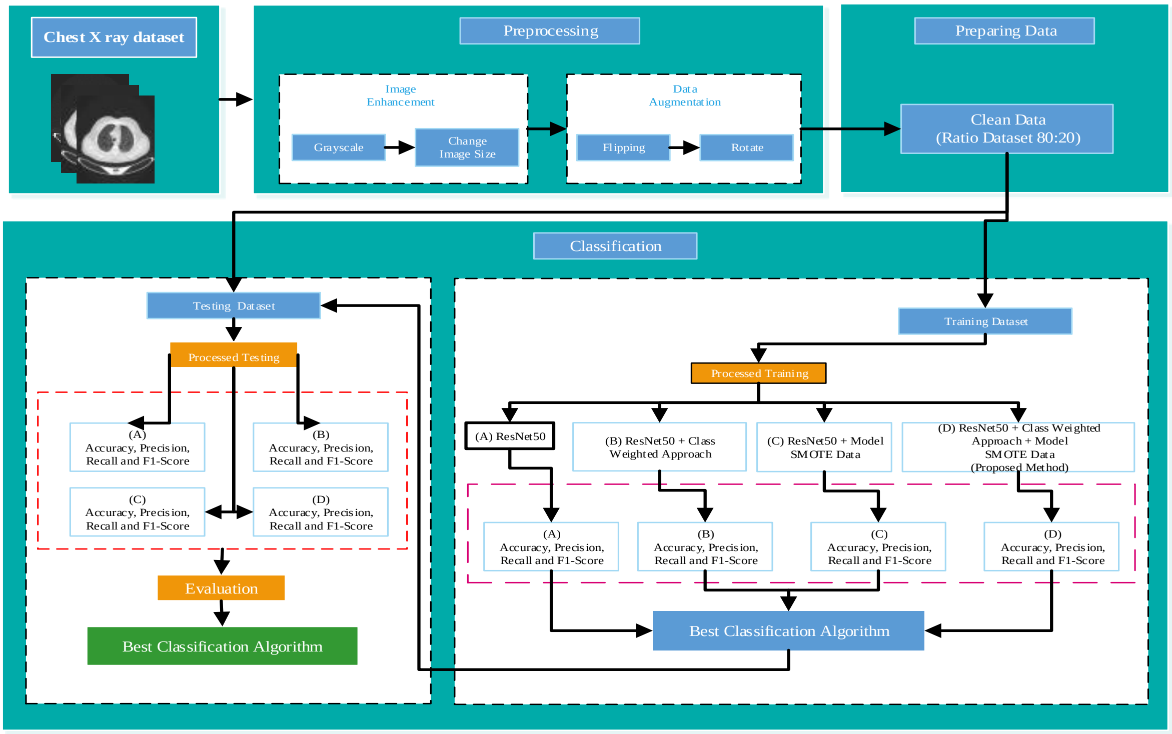


Figure 1. Research workflow in lung disease image classification process

Figure 1 illustrates the data analysis process for chest x-ray images, including preprocessing, model testing, and performance evaluation of various classification methods. Metrics such as accuracy, precision, recall, and F1 score assess model performance. Methods used include ResNet50, ResNet50 with class weighted approach, ResNet50 with synthetic minority oversampling technique (SMOTE), and a combination of ResNet50 with class weighted approach and SMOTE (proposed method). The dataset was cleaned and split 80:20 for training. The evaluation identifies the best algorithm for optimal diagnostic results.

2.2. Explanation of the Resnet50, ResNet50+ model building with SMOTE data and ResNet50+ model building with class weighted approach

ResNet is one of the architectural models based on the concept of residual blocks, which allows the network to overcome the challenges of training very deep models. Residual blocks serve as basic units that allow direct information flow from input to output without many complex transformations, facilitating the preservation of identity information during the training process [23]. This model uses shortcut connections or "residuals" that allow training of very deep networks without degradation problems, which usually occur in deep networks. The following we will explain the 3 optimized Resnet models.

Figure 2 shows the architecture of Figure 2(a) ResNet50 model, Figure 2(b) ResNet50 with SMOTE data, and Figure 2(c) ResNet50 with class weighted approach, all of which use different blocks with the assumption that they allow the network to learn a better data representation. These layers work together to convert image input into output that can be used for classification or other tasks. ResNet50 is a powerful neural network model and is frequently used in image recognition and classification tasks due to its ability to learn better representations of data. Advantages of ResNet50: network depth: With 50 layers, this model is able to capture very complex and detailed features. Residual connections: Reduces the vanishing gradient problem, making training more efficient. Pre-trained models: Pre-trained models are available in ImageNet, so they can be adapted to various tasks quickly. Disadvantages of ResNet50: Overfitting: Can occur if the dataset is not large enough or varied. Training time: Requires quite a long training time and high computing resources.

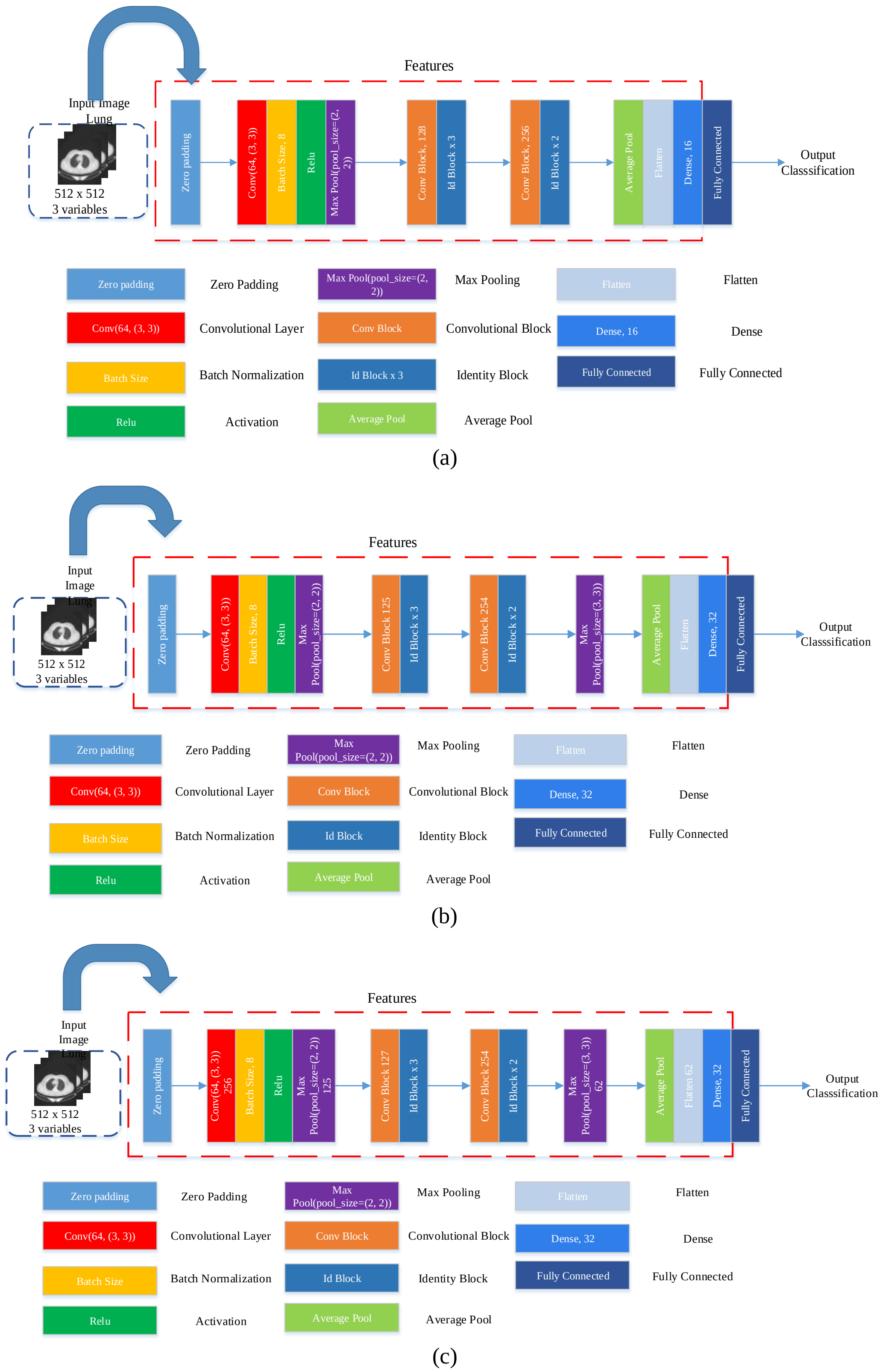


Figure 2. The architecture of (a) ResNet50, (b) ResNet50 with SMOTE data, and (c) ResNet50 with class weighted approach

ResNet50 + SMOTE: This model is the result of applying the SMOTE technique to the dataset before training the ResNet50 model. SMOTE is a data balancing technique created to address the problem of imbalanced datasets, where minority classes are improved by creating new synthetic samples based on existing minority samples. Advantages of ResNet50 + SMOTE: Data balancing: Improves representation of minority classes, helps models to learn better and reduces bias. Accuracy improvement: Typically improves model performance on minority classes, reducing misclassifying problems. Cons of ResNet50 + SMOTE: Processing time: Increasing synthetic data requires additional processing time. Overfitting: Even if the data is balanced, overfitting can still occur if the synthetic data is not diverse enough.

ResNet50 + class weighted approach this approach involves giving greater weight to minority classes during the ResNet50 model training process. Instead of increasing the sample of minority classes, the model is given a larger penalty for errors in these classes. Advantages of ResNet50 + class weighted: balancing without adding data: No need to increase the amount of data, thereby reducing the risk of overfitting. Efficiency: Usually faster than oversampling methods because there is no need to create additional samples. Disadvantages of ResNet50 + class weighted: Complex tuning: Choosing the right weights for each class can be a complex task and requires a lot of experimentation. Stability: If the weights given are too extreme, it can cause instability in model training.

2.3. ResNet50+ model building with class weighted approach + model building with SMOTE data

Innovative methods are needed to improve the performance of lung cancer classification models by combining SMOTE data, data augmentation, and model building with a class weighted approach. This method aims to overcome challenges in developing lung cancer diagnostic models. By combining these three methods, the model is expected to be able to recognize complex patterns in lung cancer images, including those in the minority class.

Figure 3 shows the architecture of the proposed method, combining ResNet50, model building with class weighted approach, and model building with SMOTE data, as well as adding softmax before the fully connected layer. The red lines show the parts of the proposed method. The use of SMOTE data, data augmentation, and model building with a class weighted approach in this research was proven to increase the accuracy and sensitivity of the lung cancer classification model. The proposed method is effective for recognizing complex patterns in lung cancer images, thereby improving the performance of lung cancer classification models.

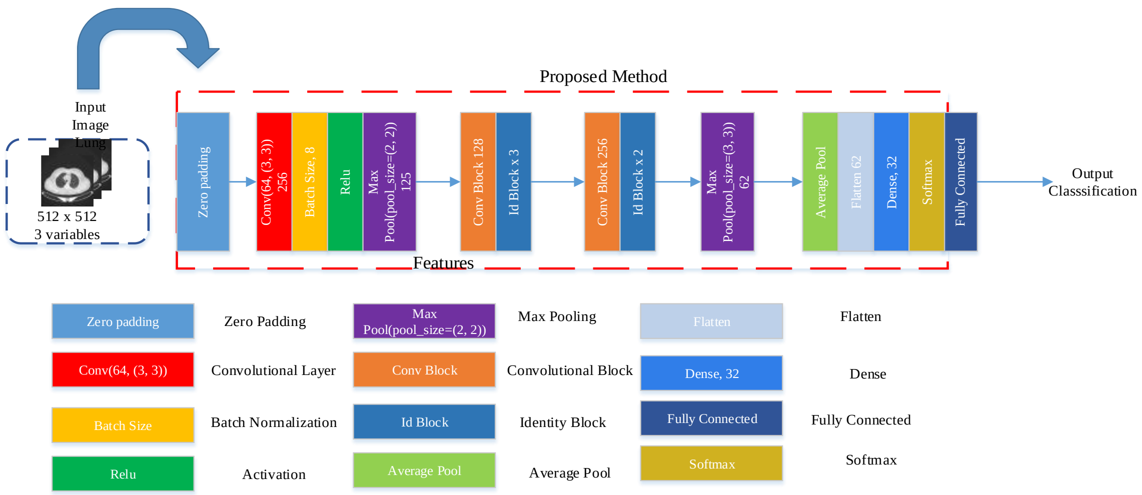


Figure 3. Illustration of the proposed method in lung CT scan image classification process

2.4. Evaluation

In the evaluation stage, the performance results of single-classification models are compared using ResNet50, ResNet50 built with SMOTE data, and ResNet50 built with a class-weighted approach. Subsequently, the proposed method, which is a revolutionary CNN architecture for more accurate lung cancer classification, is created and evaluated using performance measures such as accuracy, sensitivity, specificity, and F1-score. The results of this method are further compared with other research in the field, demonstrating its effectiveness in enhancing the precision of lung cancer detection.

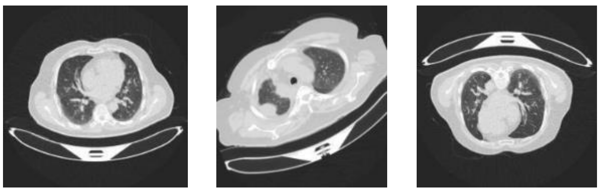
3. RESULTS AND DISCUSSION

The model training results presented in this article include crucial insights into the performance of the optimized CNN model for lung cancer classification, specifically using the CNN architecture for high-accuracy image classification with the ResNet50 Plus model as the proposed model, compared to the ResNet50 standard. In this revolutionary CNN architecture for more accurate lung cancer classification. Figure 3 provides a detailed explanation of the results obtained for each epoch, highlighting the advancements and improvements in model performance throughout the training process.

3.1. Image quality improvement

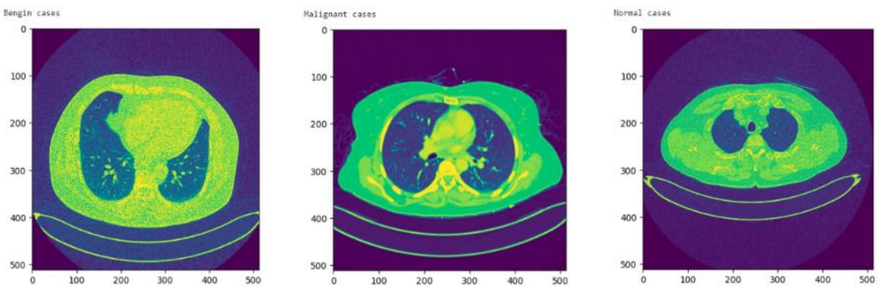
In this research, the initial stage is improving image quality to enhance the quality of lung CT scan images. A total of three lung CT scan images is shown side by side with labels "Normal," "Malignant," and "Benign" as shown in Figure 4. The image labeled "Normal" shows an axial (cross-sectional) slice of the chest CT scan without significant abnormalities. Moreover, lung structures appear clean with a normal air pattern, no nodules or masses, and an absence of fluid buildup. The image labeled "Malignant" shows an axial slice of the chest CT scan with irregular masses or nodules in lung. The masses appear denser than the surrounding normal lung tissue, showing a possible malignant tumor. The image labeled "Benign" shows an axial slice of the chest CT scan with lesions or nodules that are more defined and appear regular compared to the "Malignant" image. These lesions have clearer boundaries, showing the tendency for benign growths. These images can be used for educational or demonstration purposes on how medical images are used to differentiate between normal lung conditions, malignancy (cancer), and benign growths.

Figure 5 shows three lung segmentation images seemingly generated from a CT scan. The Figure 5(a) is labeled "Bengali case", which shows lung slice with a color scale ranging from blue to yellow. Brighter areas (yellow) show higher tissue density or areas of focus for analysis, with the segmentation emphasizing specific textures or patterns within lung. The Figure 5(b) is labeled "Polycystic case", where lung segmentation is performed to allow for a clearer view of the internal lung structures. Furthermore, there are contour lines following the shape of lung and blood vessels (bronchi), with a diverse color range showing various tissue densities or types, where bright green areas show cysts or other abnormalities. The Figure 5(c) is labeled "Normal case", showing lung slice that appears normal with segmentation indicating uniform tissue distribution. The color scale is similar to the first image but with fewer variations, showing a possible lack of significant abnormalities. All three images have coordinated scales, with values showing pixel positions. This is common for medical image analysis, where the location and size of specific areas are essential for diagnosis and evaluation. These images can be used by healthcare professionals to assess lung conditions, detect diseases or abnormalities, and monitor the progression of medical conditions. The segmentation shown aids in identifying and visualizing lung structures in more detail.



Normal Malignant Benign

Figure 4. Data augmentation results using rotation transformation



(a) (b) (c)

Figure 5. Example of clean data images (a) bengali case, (b) polycystic case, (c) normal case

3.2. CT scan image classification

In image classification stage, the data used include the segmentation result of CT scan image, which are divided into training and testing data. The training data process is further divided into training and validation data. At this stage, 1097 data are used consisting of 70% (768 training data) and 30% (329 validation data).

3.2.1. Convolutional neural network classification architecture

At this stage, image classification is performed separately using architecture ResNet50, ResNet50+class weighted approach, ResNet50+model SMOTE data, and ResNet50+class weighted approach+ SMOTE data. Figure 6 shows the comparison of accuracy results obtained by each architecture on training and validation data. The blue line represents accuracy value for training data, while the orange line shows validation data accuracy as shown in Figures 6(a) to 6(d).

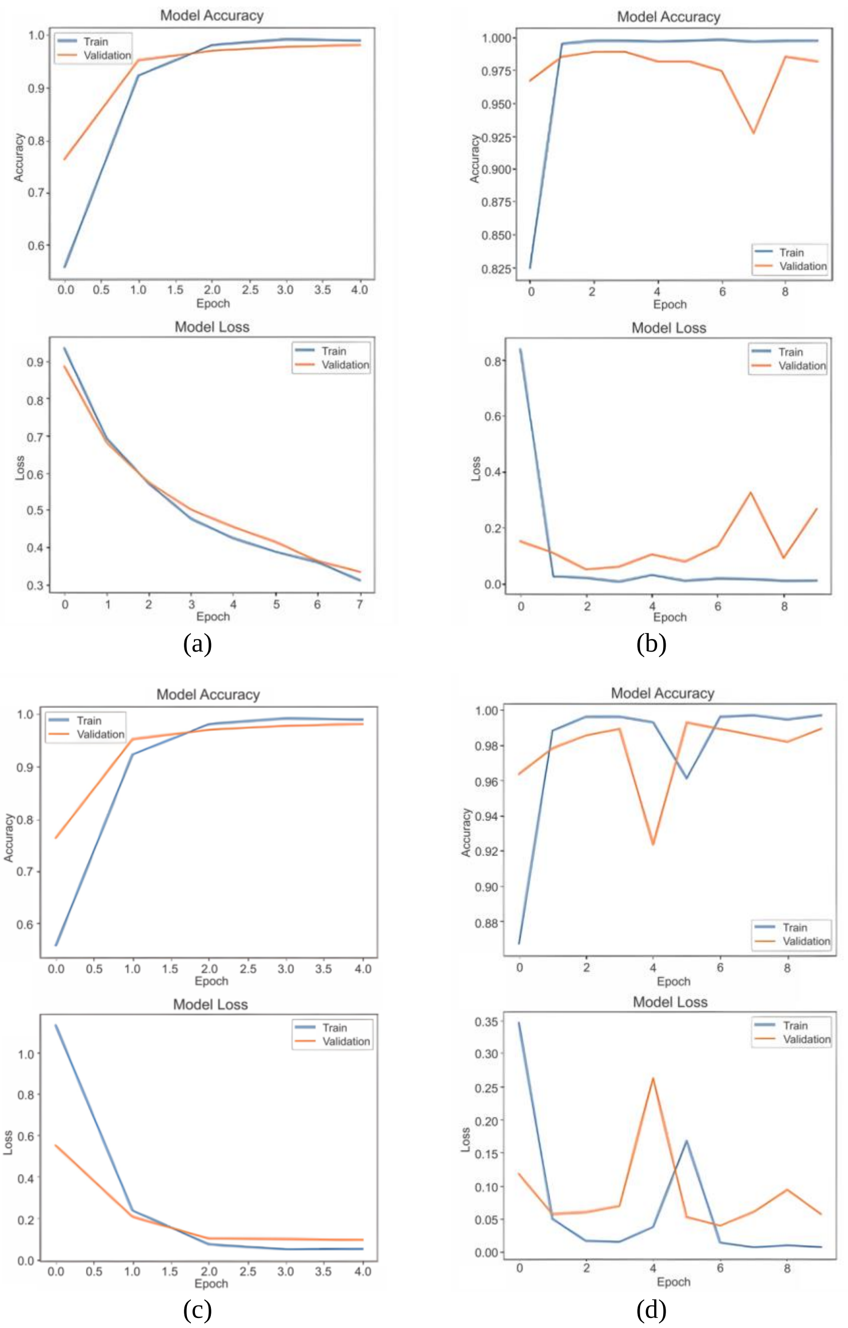


Figure 6. Graph of accuracy and loss for the CXR image classification training process using architecture: (a) ResNet50, (b) ResNet50+SMOTE data, (c) ResNet50+class weighted approach, (d) ResNet50+SMOTE data+class weighted approach

Figure 6 contains four line graphs, each representing model accuracy over several epochs. Specifically, each graph is labeled differently, showing the type of model or data processing used. Figure 6(a) is titled "ResNet50", showing two lines with one representing training accuracy (orange) and the other indicating validation accuracy (blue). Both lines show an upward trend, showing an increase in accuracy as the number of epochs rises. Training accuracy starts slightly above 0.6326 and ends near 0.8783, while validation accuracy commences approximately below 0.6145 and concludes above the training accuracy at 0.8436. Figure 6(b) is titled "SMOTE data", showing lines for training and validation accuracy. Training accuracy commences slightly above 0.8246 and experiences a little decrease below 0.9968. Meanwhile, validation accuracy commences at approximately 0.9673, rising to meet the training accuracy in the middle of the graph, but diverges and ends slightly below 0.9273. Figure 6(c) is titled "class weighted approach", which is similar to the first graph characterized by two lines for training and validation accuracy. Training accuracy commences at 0.5572 and rises to slightly below 0.9903, while validation accuracy starts around 0.7636 and increases to 0.9818. Figure 6(d) shows two graphs depicting accuracy and loss of the proposed model. Accuracy on both training and validation data tends to increase with an increasing number of epochs. Training accuracy is 0.9968 and validation accuracy is in the high range of 0.9891. Furthermore, the loss values for both training and validation data tend to decrease with an increasing number of epochs, with a loss of 0.0075 and a val_loss of 0.0577. This shows that the model is capable of reducing loss value as the training progresses.

The graphs show that the proposed model is capable of improving accuracy and reducing loss as the training progresses. The validation accuracy approaching or exceeding the training accuracy shows that the model can generalize well to new data, showing good performance. All graphs have the x-axis labeled "Epoch" and the y-axis labeled "Accuracy." The x-axis shows the progress of epochs, although the exact number is not specific. The y-axis shows accuracy, ranging from around 0.65 to slightly above 0.9 in all graphs with accuracy values fluctuating and legend showing a line that represents training and validation. These graphs are commonly used to evaluate the performance of machine learning model, focusing on the effectiveness of generating unseen new data (validation accuracy) compared to the performance of training data. The proposed model overcomes limitations and leverages the advantages of different CNN architecture (ResNet50, class weighted approach, and model SMOTE data) by combining various classification results. Furthermore, the proposed model works during the training phase, which allows checking the performance results of the weights at each epoch on training and validation data to handle overfitting. Our research shows that the highest performance achieved by the proposed method is not only limited to near-perfect accuracy levels, but also to very high precision, recall, and F1 score. This can be interpreted to mean that high accuracy is not always associated with poor performance in other aspects such as precision, recall, and F1 score. The proposed method can benefit from the class weighted approach, SMOTE data, and ResNet50 architecture without adversely impacting the model performance in terms of lung cancer detection. The evaluation results show that this combination of methods is able to improve overall performance without sacrificing other important aspects in lung cancer classification.

3.2.2. Confusion matrix

In training CNN model with ResNet50, ResNet50+SMOTE data, ResNet50+class weighted approach, and ResNet50+SMOTE data+class weighted approach (proposed method), an important evaluation tool called the confusion matrix is used for performance measurement. The confusion matrix provides a detailed overview of how well the model can classify each category. This matrix consists of four main parts, namely true positive (TP), true negative (TN), false positive (FP), and false negative (FN). TP represents the number of samples correctly classified into the correct class, while TN includes samples correctly classified into the negative class. FP is the number of samples mistakenly classified as positive, while FN is the number of samples mistakenly classified as negative. In Figure 7(a) to (d) you can see the following.

As shown in Figure 7, the use of confusion matrix facilitates the calculation of several important evaluation metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the ability of model to correctly predict classes overall. Precision measures accuracy of model's positive predictions, while recall measures the ability to find all actual positive cases. Furthermore, the F1-score is a combination of precision and recall. Through the analysis of confusion matrix and evaluation metrics, deep insights into the performance of CNN model with ResNet architecture can be obtained. Meanwhile, adjustment or fine-tuning is made to improve classification results where necessary, as shown in Table 1.

Table 1. Comparison of lung CT scan image classification performance using ResNet

Method	Accuracy	Precision	Recall	F1-score
ResNet50	0.8783	0.7400	0.9700	0.8400
ResNet class weighted approach	0.9903	0.9800	0.9800	0.9800
ResNet SMOTE data	0.9952	0.9800	0.9800	0.9800
Proposed method	0.9968	0.9900	0.9900	0.9900

```
9/9 [==============================] - 71s 8s/step
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        37
           1       0.95      0.98      0.97       130
           2       0.74      0.97      0.84       108

    accuracy                           0.84       275
   macro avg       0.56      0.65      0.60       275
weighted avg       0.74      0.84      0.79       275

[[  0   3  34]
 [  0 127   3]
 [  0   3 105]]
```

(a)

```
9/9 [==============================] - 15s 2s/step
              precision    recall  f1-score   support

           0       1.00      0.93      0.97        30
           1       0.98      1.00      0.99       141
           2       0.98      0.97      0.98       104

    accuracy                           0.98       275
   macro avg       0.99      0.97      0.98       275
weighted avg       0.98      0.98      0.98       275

[[ 28   0   2]
 [  0 141   0]
 [  0   3 101]]
```

(b)

```
9/9 [==============================] - 20s 2s/step
              precision    recall  f1-score   support

           0       0.93      0.93      0.93        30
           1       0.99      0.99      0.99       141
           2       0.98      0.98      0.98       104

    accuracy                           0.98       275
   macro avg       0.97      0.97      0.97       275
weighted avg       0.98      0.98      0.98       275

[[ 28   0   2]
 [  1 140   0]
 [  1   1 102]]
```

(c)

```
9/9 [==============================] - 13s 1s/step
              precision    recall  f1-score   support

           0       1.00      0.93      0.97        30
           1       1.00      0.99      1.00       141
           2       0.97      1.00      0.99       104

    accuracy                           0.99       275
   macro avg       0.99      0.98      0.98       275
weighted avg       0.99      0.99      0.99       275

[[ 28   0   2]
 [  0 140   1]
 [  0   0 104]]
```

(d)

Figure 7. Confusion matrix (a) ResNet50, (b) ResNet50+SMOTE data, (c) ResNet50+class weighted approach, (d) ResNet50+SMOTE data+class weighted approach

3.2.3. Evaluation

In this research, lung CT scan image classification is performed using ResNet model, and the results are compared with the previous investigation. The comparison of lung CT scan image classification results with other researchs are presented in Table 1. The evaluation results in Table 1 show the performance comparison among the four tested methods. Based on the results, ResNet50 model without specific adjustments provides accuracy of 87.83%, precision of 74.00%, recall of 97.00%, and F1-score of 84.00%. When applying the class weighted approach to ResNet, a significant improvement is observed with 99.03% accuracy, and 98.00% for precision, recall, and F1-score, respectively. The use of SMOTE data on ResNet provides the highest accuracy of 99.52% with consistent precision, recall, and F1-score at 98.00%. However, the proposed method, consisting of class weighted approach, SMOTE data, and ResNet architecture, shows the most superior performance with accuracy of 99.68%, and 99.00% for precision, recall, and F1-score, respectively. These results show that the proposed method can positively contribute to improving lung cancer detection through machine learning model. The proposed method shows the highest performance with approximately perfect accuracy as well as very high precision, recall, and F1-score. This shows the successful combination of the class weighted approach, SMOTE data, and ResNet50 architecture in improving lung cancer classification.

This research explores the use of combination methods such as the class weighted approach, SMOTE data, and the comprehensive ResNet50 architecture in improving the performance of lung cancer classification models. However, further and in-depth studies may be needed to confirm the superiority of this method in practical scenarios involving more complex and diverse data, especially regarding the generalization of the results to never-before-seen test data. Our study shows that our proposed approach, namely a combination of class weighted approach, SMOTE data, and ResNet50 architecture, is more robust to class imbalance and variation in lung cancer datasets. Future studies could explore deeper integration of data augmentation techniques such as data augmentation to expand the generalization of the model across various medical datasets, thereby producing more reliable and defensible results. Recent observations show that the integration of class imbalance handling strategies such as class weighted approach and data SMOTE into the ResNet50 architecture not only improves model performance in terms of accuracy, precision, recall and F1 score, but also provides conclusive evidence that these phenomena are related to changes in the structure of the dataset and class distribution, not due to an artificial or synthetic increase in the number of minority class samples.

4. CONCLUSION

In conclusion, this research showed that the addition of specific methods such as the class weighted approach and SMOTE data to ResNet50 architecture significantly improved the performance of the proposed model. Based on the results, ResNet50 model without specific adjustments showed good performance, specifically in recall but encountered challenges in precision. The implementation of the class weighted approach provided a significant improvement in accuracy and precision without sacrificing recall, while the use of SMOTE data resulted in the highest accuracy. The proposed method showed the most superior performance with accuracy, precision, recall, and F1-score approaching perfect values with accuracy of 99.68% and precision of 99.00%. Therefore, the integration of class imbalance handling strategies and ResNet50 architecture development in the proposed model showed significant potential in improving accuracy of lung cancer diagnosis through machine learning model.

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