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Classification Of Lung Disease Images Using EfficientNetB2 Model With Random Sampling

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Abstract

The rapid advancement of deep learning in medical imaging has significantly improved lung disease diagnosis, with CNNs like EfficientNet showing strong performance on chest X-ray analysis. However, class imbalance remains a challenge, often reducing model accuracy. This study examines the impact of random oversampling compared to original and undersampled data in classifying lung diseases using EfficientNet-B2. Emphasizing its simplicity, the study evaluates whether random oversampling can match more complex methods like SMOTE. Through systematic data collection, preprocessing, and model training, performance is assessed using accuracy, precision, recall, and F1-score. Results show EfficientNet-B2 consistently outperforms MobileNetV3-Large across all sampling methods, with random oversampling achieving the best results—training accuracy of 99.61% and testing accuracy of 93.65% under a 70:30 split. While oversampling proves most effective, method selection should consider specific application needs, resource constraints, and deployment scale to ensure reliable diagnostic outcomes.

Keywords– *EfficientNet B2, MobileNet V3 Large, Lung Disease, Class Imbalance, Random Sampling.*

1. Introduction

The rapid advancement of deep learning, particularly in medical image analysis, has revolutionized the diagnosis and classification of lung diseases(Kermany et al., 2018). Convolutional Neural Networks (CNNs) have demonstrated remarkable success in detecting abnormalities in chest X-ray images, thereby assisting in the early and accurate identification of diseases(Wang et al., n.d.). Among various existing models, EfficientNet has emerged as a powerful architecture due to its scalable design and its efficiency in balancing model depth, width, and input resolution(Tan & Le, 2019). However, despite these advancements, one of the ongoing challenges in medical imaging datasets is class imbalance, where certain disease types have significantly fewer samples than others, leading to biased model performance(He & Garcia, 2009),(Alberto et al., n.d.).

EfficientNet-B2 is a variant of EfficientNet that offers an optimal balance between accuracy and computational efficiency. Compared to other variants like EfficientNet-B0 and B1, which have fewer parameters, EfficientNet-B2 achieves a top-1 accuracy of 80.1% on the ImageNet dataset with approximately 9.1 million parameters and an input resolution of 260×260 pixels. This makes it highly capable of capturing important visual features without significantly increasing model complexity(Tan & Le, 2019). While larger models such as EfficientNet-B4 to B7 do offer higher accuracy, they demand substantially more computational resources(Haixiang et al., 2017), making them less suitable for hardware-constrained environments. In various studies, EfficientNet-B2 has demonstrated good generalization, fast training, and suitability for transfer learning on medical imaging datasets, with a lower risk of overfitting. Therefore, EfficientNet-B2 is considered an ideal solution for implementing deep learning models that require a balanced trade-off between efficiency and accuracy.

Class imbalance is a well-documented issue in machine learning, especially in medical applications where rare diseases often have far fewer samples than more common ones(Johnson & Khoshgoftaar, 2019). This imbalance can lead deep learning models to be biased toward majority classes, resulting in poor

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generalization for minority classes(Chawla et al., 2002). To address this problem, various data sampling techniques have been proposed, including oversampling and undersampling(Shorten & Khoshgoftaar, 2019), (Marques et al., 2020). Random sampling, as a basic yet widely used method, offers a simple way to balance datasets either by duplicating samples from the minority class (oversampling) or by reducing samples from the majority class (undersampling). However, the effectiveness of this method in medical image classification using deep learning, particularly when combined with advanced architectures like EfficientNet, still requires further investigation(Pramudhita et al., 2023).

Recent studies have explored the use of EfficientNet in medical image classification and have shown its superior performance in tasks such as COVID-19 detection from chest X-rays(Wang et al., n.d.). However, most of these studies focus more on improving model architecture rather than addressing dataset imbalance, even though this issue can significantly impact real-world applications. While advanced techniques such as the Synthetic Minority Over-sampling Technique (SMOTE)(Shorten & Khoshgoftaar, 2019) and data augmentation(Marques et al., 2020) have been explored, random sampling remains a computationally efficient alternative that deserves deeper analysis, especially in medical imaging scenarios with limited resources.

This study investigates the impact of random sampling on the classification of lung diseases using the EfficientNet-B2 model. We evaluate how different random sampling strategies, such as random oversampling and random undersampling, affect model performance on imbalanced datasets. Our analysis builds upon previous research in deep learning for medical diagnosis(Kermany et al., 2018) and class imbalance mitigation(Alberto et al., n.d.), providing empirical insights into whether simpler sampling methods can yield competitive performance compared to more complex techniques. The objective of this study is to analyze the performance differences between these random sampling methods and to evaluate their classification accuracy. By leveraging state of the art CNN techniques, this research contributes to improving lung disease detection and supports more accurate and efficient medical diagnosis.

2. Method

The proposed methodology follows a structured workflow for developing an effective image based machine learning model. The initial stage begins with data collection to obtain a diverse and relevant set of images for the intended application. To reduce bias and ensure data representation, random sampling is applied to divide the dataset into balanced subsets. Next, preprocessing techniques such as noise reduction, normalization, and data augmentation are applied to enhance image quality and improve the model's generalization capability. The implementation architecture is then designed using Convolutional Neural Networks (CNNs) to extract hierarchical features from the preprocessed images. Model testing is conducted to validate its performance on unseen data. Finally, comprehensive evaluation is performed using metrics such as accuracy, precision, recall, and F1-score to assess the model's robustness and readiness for real world deployment.

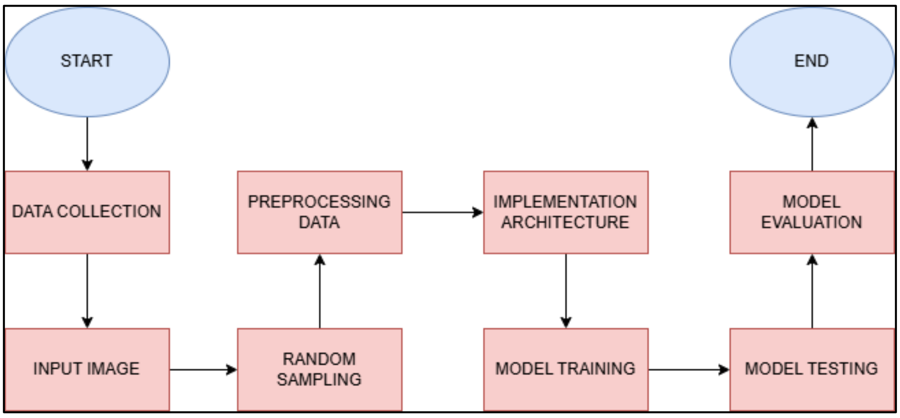

Figure 1. Research Methodology Diagram

a) Data Collection

The data were collected from public sources on Mendeley Data, consisting of a total of 11,702 chest X-ray images in JPG format. These include normal cases

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(3,270 images), viral pneumonia (1,656 images), bacterial pneumonia (3,001 images), and COVID-19 (1,281 images) from contributors such as Unais Sait, Gokul Lal KV, Sunny Prakash Prajapati, Rahul Bhaumik, Tarun Kumar, Sanjana Shivakumar, and Kriti Bhalla (Sait et al., 2021), as well as tuberculosis data (2,494 images) from contributors Saira Kiran and Dr. Ishrat Jabeen (Kiran & Jabeen, 2024).

b) Random Sampling

Random sampling is used to balance the imbalanced data through two techniques: oversampling and undersampling(Saputro & Rosiyadi, 2022). Oversampling increases the number of samples in the minority class by randomly duplicating them, while undersampling reduces the number of samples in the majority class by randomly selecting a subset. This results in a more balanced dataset(He et al., 2018).

c) Preprocessing

To standardize the lung disease image data, preprocessing steps include image resizing using compound scaling 260×260 pixels for EfficientNet-B2 and 224×224 pixels for MobileNetV3-Large. This study used 30 epochs, a batch size of 32, a learning rate of 0.0001, and the Adam optimizer. Two data splitting scenarios were applied 70% training and 30% testing, and 80% training and 20% testing.

Additionally, image augmentation was performed to enhance the model's generalization ability and prevent overfitting. Random sampling was also applied to explore optimal training conditions, especially in addressing class imbalance in the dataset. The augmentation process expands the dataset by generating new image variations without changing their labels, contributing to improved model performance in classification tasks.

d) EfficientNet-B2

This model uses compound scaling to balance depth, width, and resolution simultaneously. It also adopts the Swish activation function, which outperforms ReLU in supporting the learning process. EfficientNet is a CNN architecture optimized for a balance between depth, width, and resolution to achieve efficient and accurate image classification(Tan & Le, 2019).

EfficientNet-B2 utilizes only 9.2 million parameters, fewer than similar variants like B3. Its architecture consists of an initial stem layer, seven main blocks with MBConv modules, residual connections, and a final layer for classification.

e) MobileNetV3-Large

MobileNetV3-Large is a deep learning architecture designed for high efficiency in image recognition, particularly on resource constrained devices. This model integrates several innovations such as the h-swish activation, inverted residual bottleneck blocks (IRLB), and neural architecture search (NAS). The IRLB structure includes 1×1 convolution, 3×3 depthwise convolution, and 1×1 pointwise convolution designed for computational efficiency and training stability.

MobileNetV3-Large retains critical information through pooling and nonlinear bottleneck stages before classification, making it well suited for large scale applications with limited hardware resources(Goodfellow et al., 2016). Moreover, the MobileNet architecture leverages depthwise separable convolutions to enhance computational efficiency(Goodfellow et al., 2016), making it ideal for deployment on devices such as smartphones and embedded systems.

f) Model Training

After designing the models and setting the hyperparameters for EfficientNet-B2 and MobileNetV3-Large, the training process was conducted over 30 epochs using Google Colab Pro. The number of samples was adjusted according to the testing schemes defined.

g) Model Testing

The models were tested using 3,511 images under the 70:30 scenario and 2,341 images under the 80:20 scenario for the original data, 3,249 images under the 70:30 scenario and 2,436 images under the 80:20 scenario for the oversampled data, and 1,282 images under the 70:30 scenario and 961 images under the 80:20 scenario for the undersampled data. The prediction results were then compared with the ground truth labels and evaluated using confusion matrices.

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h) *Model Evaluation*

After training, the models were evaluated using test data to assess their efficiency and accuracy. Evaluation was conducted using confusion matrices to calculate metrics such as accuracy, precision, recall, and F1-score. This study tested two architectures EfficientNet-B2 and MobileNetV3-Large with three sampling techniques (oversampling, original data, and undersampling) to analyze the impact of class imbalance and determine the best configuration. Confusion matrices were used to compute various evaluation metrics such as accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correct predictions over the total test data, especially relevant when class distribution is balanced, as defined in Equation (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Precision focuses on how accurately the model classifies positive predictions, as defined in Equation (2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall measures the model's ability to identify all correctly classified positive instances, as defined in Equation (3).

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

F1-score is the harmonic mean between precision and recall, as defined in Equation (4).

$$F1 - Score = 2\,x\,\frac{Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

3. Result and Discussion

This section will explain the training and evaluation results of the CNN architecture and describe the comparative results based on the scenarios used.

Model Training

Tables 1. Training Results with Data Oversampling

No	Training Scenario	Time	Accuracy Results		
			Training Data	Testing Data	Validation Data
1	EfficientNet-B2 With Data Over Sampling Data Split 70% training and 30% testing	15.490 Seconds	99,61%	93,65%	94,33%
2	EfficientNet-B2 With Data Over Sampling Data Split 80% training and 20% testing	17.567 Seconds	98,66%	92,48%	92,61%
3	MobileNet V3 Large With Data Over Sampling Data Split 70% training and 30% testing	16.519 Seconds	97,47%	90,52%	91,12%
4	MobileNet V3 Large With Data Over Sampling Data Split 80% training and 20% testing	18.232 Seconds	98,36%	93,18%	93,71%

Based on the results in Tables 1, the best scenario is achieved using the EfficientNet-B2 model with over sampling and a data split of 70% for training and 30% for testing. This is supported by a very high training accuracy of 99.61%, the highest testing accuracy of 93.65%, and the highest validation accuracy of 94.33%. In addition, the relatively fast training time of 15.490 seconds further confirms that this scenario is the most optimal overall.

Tables 2. Training Results with Data Original

No	Training Scenario	Time	Accuracy Results		
			Training Data	Testing Data	Validation Data
1	EfficientNet-B2 With Data Original Data Split 70% training and 30% testing	11.100 seconds	89,17%	89,40%	90,25%
2	EfficientNet-B2 With Data Original Data Split 80% training and 20% testing	12.146 seconds	98,40%	92,48%	92,99%
3	MobileNet V3 Large With Data Original Data Split 70% training and 30% testing	10.483 seconds	93,38%	89,49%	88,88%
4	MobileNet V3 Large With Data Original Data Split 80% training and 20% testing	9.074 seconds	90,51%	87,17%	87,07%

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Based on the results in Tables 2, the best scenario is achieved using the EfficientNet-B2 model with original data and a data split of 80% for training and 20% for testing. This scenario demonstrates the most optimal performance with the highest training accuracy of 98.40%, testing accuracy of 92.48%, and validation accuracy of 92.99%. Although the training time is slightly longer at 12.146 seconds, this difference is still within a reasonable range and is justified by the significant improvement in accuracy. Therefore, this scenario is considered the best compared to others due to its superior accuracy.

Tables 3. Training Results with Data Under Sampling

No	Training Scenario	Time	Accuracy Results		
			Training Data	Testing Data	Validation Data
1	EfficientNet-B2 With Data Under Sampling Data Split 70% training and 30% testing	4.427 seconds	95,49%	89,23%	89,06%
2	EfficientNet-B2 With Data Under Sampling Data Split 80% training and 20% testing	6.220 seconds	97,88%	88,24%	87,81%
3	MobileNet V3 Large With Data Under Sampling Data Split 70% training and 30% testing	5.393 seconds	96,20%	88,22%	85,31%
4	MobileNet V3 Large With Data Under Sampling Data Split 80% training and 20% testing	5.193 seconds	89,31%	82,62%	83,74%

Based on the results in Tables 3, the best scenario is achieved using the EfficientNet-B2 model with a 70% training and 30% testing data split. This scenario shows the most optimal performance with a training accuracy of 95.49%, the highest testing accuracy of 89.23%, and a validation accuracy of 89.06%. Moreover, it also recorded the fastest training time at only 4.427 seconds, emphasizing its computational efficiency.

In this study, the comparison between EfficientNet-B2 and MobileNet V3 Large reveals that EfficientNet-B2 consistently provides better accuracy in both validation and testing datasets across all scenarios. The model performs more stably and effectively, especially when combined with oversampling and 70/30 data split, achieving the highest overall accuracies of 99.61% (training), 93.65% (testing), and 94.33% (validation). This indicates superior generalization capability to unseen data.

Overall, the oversampling scenario using EfficientNet-B2 with a 70/30 data split stands out as the best option in terms of accuracy, making it highly suitable for high reliability applications such as medical diagnostics or critical detection systems. Although the training time is slightly longer, the resulting accuracy gains are well worth the additional computational cost.

Nevertheless, for use cases with limited computational resources or where faster training time is a priority, other scenarios such as using original data with an 80/20 split, or under sampling with a 70/30 split data can be considered as viable alternatives. The 80/20 original data scenario offers a balance between high accuracy and training efficiency, while the under sampling scenario excels in speed, despite slightly lower accuracy. Therefore, selecting the best scenario ultimately depends on the specific priorities and requirements of each case study.

Model Testing

Tables 4. Testing and Evaluate Results with Data Over Sampling

No	Testing Scenario	Accuracy	Average		
			Precision	Recall	F1-Score
1	EfficientNet-B2 With Data Over Sampling Data Split 70% training and 30% testing	0,94	0,94	0,94	0,94
2	EfficientNet-B2 With Data Over Sampling Data Split 80% training and 20% testing	0,92	0,93	0,93	0,93
3	MobileNet V3 Large With Data Over Sampling Data Split 70% training and 30% testing	0,91	0,91	0,91	0,91
4	MobileNet V3 Large With Data Over Sampling Data Split 80% training and 20% testing	0,93	0,93	0,93	0,93

Based on the evaluation results in Tables 4, the best scenario is using the EfficientNet-B2 model with an oversampling approach and a data split of 70% for training and 30% for testing. This scenario consistently demonstrates the highest performance across all evaluation metrics, with accuracy, precision, recall, and F1-

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score each reaching 0.94. These values indicate that the model is not only able to classify the data accurately overall but also maintains a balanced capability in correctly identifying positive classes, detecting all positive cases, and sustaining a balance between precision and recall. Therefore, this scenario is considered the most optimal choice to achieve the best classification performance on the tested data.

Tables 5. Testing and Evaluate Results with Data Original

No	Testing Scenario	Accuracy	Average		
			Precision	Recall	F1-Score
1	EfficientNet-B2 With Data Original Data Split 70% training and 30% testing	0,89	0,88	0,88	0,88
2	EfficientNet-B2 With Data Original Data Split 80% training and 20% testing	0,92	0,91	0,91	0,91
3	MobileNet V3 Large With Data Original Data Split 70% training and 30% testing	0,89	0,88	0,89	0,89
4	MobileNet V3 Large With Data Original Data Split 80% training and 20% testing	0,87	0,85	0,86	0,86

Based on the evaluation results in Tables 5, the best scenario is achieved using the EfficientNet-B2 model with original data and a data split of 80% for training and 20% for testing. This scenario recorded the highest values across all evaluation metrics, with an accuracy of 0.92, precision of 0.91, recall of 0.91, and F1-score of 0.91. This indicates that the model is capable of delivering an optimal and balanced classification performance, both in terms of prediction accuracy and the ability to comprehensively detect the target class. Therefore, this scenario can be considered the superior choice among the other scenarios.

Tables 6. Testing and Evaluate Results with Data Under Sampling

No	Testing Scenario	Accuracy	Average		
			Precision	Recall	F1-Score
1	EfficientNet-B2 With Data Under Sampling Data Split 70% training and 30% testing	0,89	0,89	0,89	0,89
2	EfficientNet-B2 With Data Under Sampling Data Split	0,88	0,88	0,88	0,88

	80% training and 20% testing				
3	MobileNet V3 Large With Data Under Sampling Data Split 70% training and 30% testing	0,88	0,88	0,88	0,88
4	MobileNet V3 Large With Data Under Sampling Data Split 80% training and 20% testing	0,83	0,84	0,82	0,83

Based on the evaluation results in Tables 6, the best scenario is the use of the EfficientNet-B2 model with an under sampling approach and a 70% training and 30% testing data split. This scenario consistently delivers the highest evaluation results across all metrics, with accuracy, precision, recall, and F1-score each reaching 0.89. These values indicate that the model in this scenario has the most balanced and reliable classification performance compared to other scenarios, making it the most optimal choice for under sampling data usage.

Across all tested scenarios, the EfficientNet-B2 model demonstrates superior performance compared to MobileNet V3 Large. This is evident from the highest evaluation metric values achieved by EfficientNet-B2 in the oversampling scenario with a 70/30 data split, where accuracy, precision, recall, and F1-score each reach 0.94. In contrast, the best performance of MobileNet V3 Large was observed in the oversampling scenario with an 80/20 split, achieving metric values of 0.93. Although the performance gap is not large, EfficientNet-B2 consistently outperforms MobileNet V3 Large across original, oversampling, and undersampling data. Therefore, it can be concluded that in this study, EfficientNet-B2 provides better classification results compared to MobileNet V3 Large.

4. Conclusion

Based on the training and evaluation results, it can be concluded that the EfficientNet-B2 architecture consistently outperforms MobileNet V3 Large across all learning scenarios, including oversampling, original data, and undersampling. The overall best performance is achieved using EfficientNet-B2 with the oversampling method and a 70% training and 30% testing data split. In this

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scenario, the model reaches a training accuracy of 99.61%, testing accuracy of 93.65%, and validation accuracy of 94.33%. Additiplially, it achieves precision, recall, and F1-score values of 0.94 each. These results demonstrate not only high classification accuracy but also strong generalization capabilities on unseen data, making this configuration highly suitable for high reliability applications such as medical diagnosis and critical detection systems.

Alternatively, for use cases with limited computational resources or a need for faster training time, the original data scenario with an 80/20 split provides a good balance between training efficiency and performance, achieving an average evaluation score of 0.91. Furthermore, the undersampling scenario with a 70/30 split offers the fastest training time at only 4.427 seconds, while still maintaining stable evaluation metrics averaging 0.89. Therefore, while the oversampling scenario with EfficientNet-B2 remains the most optimal in terms of accuracy and overall performance, selecting the most appropriate scenario should consider the specific requirements and constraints of each use case.

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