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Class Weighting Approach For Handling Imbalanced Data On Forest Fire Classification Using EfficientNet-B1

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Abstract

Wildfires threaten ecosystems and human safety, necessitating effective monitoring techniques. Detecting forest fires based on images of forest conditions could be a breakthrough. But, the model built from imbalanced data leads to low accuracy. This research addresses the challenge of class imbalance in multiclass classification for forest fire detection using the EfficientNet-B1 model. This research explores the implementation of class weighting to enhance model performance, particularly focusing on minority classes, namely: Fire and Smoke. A dataset of 7,331 training images was categorized into four classes. The results showed that employing the class weighting method achieved an accuracy of 90%. The training duration of 14 minutes and 45 seconds outperforms the data augmentation method in terms of time efficiency. This study contributes to the development of more effective methods for forest fire monitoring and provides insights for future research in machine learning applications in environmental contexts.

Keywords: Classification, Image Classification, Imbalanced Data, Efficientnet-B1, Forest Fire Detection

Abstrak

Kebakaran hutan menimbulkan ancaman besar terhadap ekosistem dan keselamatan manusia sehingga memerlukan teknik pemantauan yang efektif. Mendeteksi kebakaran hutan berdasarkan gambaran kondisi hutan bisa menjadi sebuah terobosan. Namun, model yang dibangun dari data yang tidak seimbang menyebabkan akurasi yang rendah. Penelitian ini bertujuan mengatasi ketidakseimbangan kelas dalam klasifikasi citra multi-kelas untuk deteksi kebakaran hutan menggunakan model EfficientNet-B1. Penerapan metode *Class Weighting* bertujuan meningkatkan kinerja model pada data tidak seimbang ini, terutama berfokus pada kelas minoritas yaitu kelas “Api” dan kelas “Asap”. Ekperimen ini menggunakan dataset terdiri 7,331 gambar untuk data pelatihan, yang dikategorikan ke dalam empat kelas. Hasil penelitian menunjukkan bahwa metode *Class Weighting* mencapai akurasi 90%. Sedangkan durasi pelatihan hanya memerlukan waktu 14 menit dan 45 detik, ini mengungguli metode augmentasi data dalam hal efisiensi waktu. Hasil penelitian ini berkontribusi pada pengembangan metode yang lebih efektif untuk pemantauan kebakaran hutan dan memberikan wawasan untuk penelitian di masa depan dalam aplikasi pembelajaran mesin dalam konteks lingkungan.

Kata Kunci: Klasifikasi, Klasifikasi Gambar, Data Tidak Seimbang, Efficientnet-B1, Kebakaran Hutan

1. INTRODUCTION

In recent years, climate change and human-induced factors have significantly impacted the environment. These events include heatwaves, droughts, dust storms, floods, hurricanes, and wildfires (Barmpoutis et al., 2020). Wildfires onseverely affect local and global ecosystems, resulting in significant damage to infrastructure, injuries, and loss of human life. Wildfires can be sparked by various human activities, including campfires, burning debris, unattended flames, smoking, the careless disposal of lit cigarettes, and natural causes like lightning (Chaturvedi et al., 2022). As a result, detecting fires and precisely monitoring type, size, and impact of disturbances across large areas are becoming increasingly crucial (Tanase et al., 2018). Today, the technology for detecting forest fires has advanced significantly through satellites, drones, and advanced sensors. The use of deep learning methods is one such advancement towards detecting forest fires (Madhuri et al., 2024). Image-based monitoring technology offers a promising solution for automating the identification of fires and smoke through digital image processing. Multiclass image classification is essential for distinguishing between various objects and conditions related to wildfires. Therefore, developing accurate and efficient classification models can significantly contribute to disaster mitigation efforts.

Deep neural network models, such as EfficientNet-B1, have demonstrated outstanding performance in various image classification tasks (Frederich et al., 2024; Islam et al., 2024). EfficientNet is an innovation in network architecture that optimizes the scale of the model to achieve a balance between accuracy and computational efficiency (Raza et al., 2023). By utilizing intelligent scaling techniques, EfficientNet-B1 can better identify patterns in imagery compared to another model architecture, as it employs Compound Scaling, which scales all three dimensions depth, width, and image resolution simultaneously while maintaining this balance across the network (Papoutsis et al., 2023). This is especially important in forest fire monitoring, where the speed and accuracy of detection can be the difference between successful prevention or widespread damage. However, despite the great potential of these models, the challenges faced in multiclass classification often relate to class imbalance in the training data. Therefore, approaches are needed to ensure that all classes, including underrepresented classes, are well-learned by the model (Dogra et al., 2022; Rodríguez et al., 2020; Tanveer et al., 2021).

One approach that can address the problem of class imbalance is the application of class weights (Benkendorf et al., 2023). By assigning higher weights to underrepresented classes, the model can be trained to pay more attention to patterns within those classes. By assigning higher weights to underrepresented classes, the model can be trained to pay more attention to patterns within those classes. This not only improves accuracy for the minority class but also helps prevent the model from being biased towards the majority class (De Angeli et al., 2022). Many studies have demonstrated that class weights can enhance model performance in multiclass classification, particularly when the dataset is imbalanced (Fan et al., 2022; Zhao et al., 2020). In the context of forest fires, where images from the fire class may be much fewer than other classes, the application of class weights becomes especially relevant. Thus, this study aims to explore the implementation of class weights in multiclass image classification for forest fires and smoke.

In this study, we will analyze the effect of applying class weights on the performance of the EfficientNet-B1 model in detecting and classifying forest fire and smoke images. We will also compare the results obtained from the model using class weights with the model that uses data augmentation to address the imbalanced data issue. The evaluation method will include various metrics, such as accuracy, precision, recall, and F1-score, to provide a comprehensive picture of the model's performance. In addition, experiments will be conducted on a dataset of forest fire and smoke images collected from various sources to ensure diversity and representativeness. Through this analysis, we hope to provide deeper insights into how class weights can improve classification performance in this context. The results of this study are expected to contribute to developing a more effective fire monitoring system.

The results of this study will provide a stronger foundation for developing more accurate and efficient forest fire monitoring applications. In addition, this study is expected to researchers and practitioners in applying class weight techniques to other image classification tasks. With the increasing need for effective early detection systems, it is important to explore various approaches that can improve model accuracy and efficiency (Cremen & Galasso, 2020). This study can also open up opportunities for further research on the use of machine learning techniques in the environment and disaster mitigation context. We hope relevant to forest fires and can also be applied in other image classification contexts that face similar challenges. Thus, this study can contribute to global efforts in addressing the problem of forest fires and their impacts on the environment.

2. METHODS

This research uses a method framework named CRISP-DM (Cross Industry Standard Process for Data Mining). The CRISP-DM methodology provides a structured and widely accepted framework for data mining projects, comprising six key phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment (Wirth & Hipp, n.d.). It is known for offering a well-organized yet adaptable approach to conducting data-driven projects (Elkabalawy et al., 2024). Adopting the CRISP-DM methodology for this image classification of a forest fire dataset ensures that the solution developed will be robust and efficient. By following this structured framework, each phase of the project, from understanding the problem to model deployment, will be systematically addressed to provide the best results and solutions for the forest fire multiclass classification problem. The steps of our research can be seen in Figure 1.

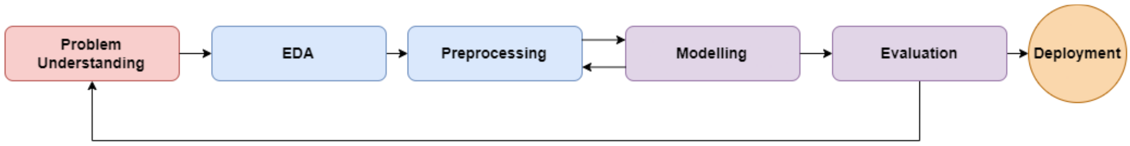

Figure 1 Research Workflow Chart

2.1 Dataset

The dataset utilized in this research was sourced from the Big Data Competition 2024 organized by the Statistics Department of Syiah Kuala University, where the data can be accessed at the Kaggle website (Bahtiar, 2024). The dataset is divided into two subsets: training and testing. The data training contains 7,331 images in .jpg format, while the data testing contains 543 images. The 7,331 images in the training set are categorized into four classes, with an uneven distribution across the categories: 3,083 images in the "None" class, 1,230 in the "Fire" class, 303 in the "Smoke" class, and 2,715 in the "Fire and Smoke" class.

Figure 2 Sample of Each Class

To facilitate model evaluation, 20% of the training data was set aside as a validation set. The class distribution within the validation set includes 619 images for the "None" class, 224 for "Fire", 67 for "Smoke", and 556 for "Fire and Smoke." This split ensures that the model is evaluated using a representative portion of the dataset across all classes.

2.2 Problem Understanding

The increasing frequency of extreme wildfires, characterized by their large scale, prolonged duration, high intensity, and severe consequences, has substantially negative effects on human health and well-being, ecosystems, the climate, and the global economy. In recent years, these extreme wildfire events have been particularly destructive (Tyndall, 2023). For instance, the 2015 wildfires in Indonesia resulted in an estimated economic loss of approximately USD 16 billion, equivalent to 2% of the nation's gross domestic product (GDP).

This research aims to achieve efficient and high-performing image multiclass classification. However, the dataset used in this study presents a significant challenge in reaching this goal, and that is, imbalanced data. This problem arises from an uneven distribution of target classes in the dataset, causing the model to favor the majority class while neglecting the minority classes (Bader et al., 2024a). In our case, the "fire" and "smoke" classes are the minority classes, with a significant disparity in their distribution compared to the other classes.

2.3 Data Preprocessing

Figure 3 illustrates the data preprocessing workflow using the class weighting approach. This method is based on applying class weights, which penalize the algorithm more heavily for incorrect predictions by assigning higher penalties for misclassifying the minority class (Bader et al., 2024a).

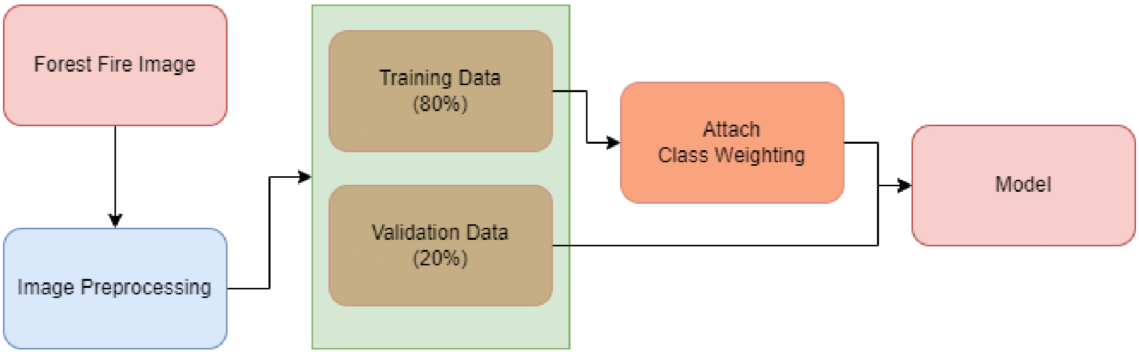

Figure 3 Class Weight Approach

Figure 4 presents the data preprocessing workflow using the data augmentation approach, which will be used to compare the performance of our primary approach, class weighting. Data augmentation methods mitigate challenges related to small datasets by artificially expanding their size and variety, ultimately improving model accuracy and generalization (Gracia Moisés et al., 2023a).

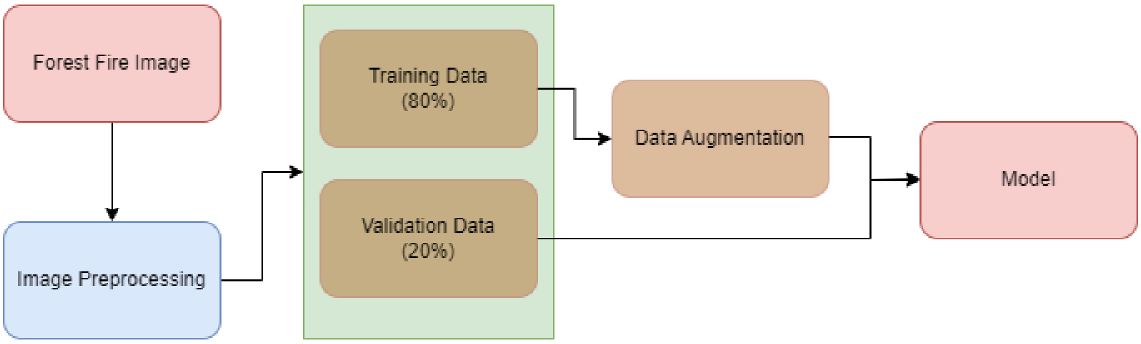

Figure 4 Data Augmentation Approach

Table 1 presents the detailed parameters and values used in the image processing steps illustrated in both approaches flow diagrams, as shown in Figures 3 and 4.

Table 1 Image Preprocessing Details

Parameter	Value
Resize	(224,224)
Normalize	mean=[0.485, 0.456, 0.406],

Table 2 presents the detailed parameters and values of the augmentations applied to the minority classes, "fire" and "smoke," during the image transformation process in steps shown in Figure 4. The transformations included random rotations, translations, scaling, and shearing using RandomAffine, along with perspective distortions with RandomPerspective, to create new variations of the images artificially.

Table 2 Data Augmentation Details

Parameter	Value
RandomRotation	20
RandomPerspective	distortion_scale=0.2, p=0.5
RandomAffine	degrees=0, translate=(0.1, 0.1)

2.4 Data Augmentation

In the problem of forest fire image classification, data augmentation is a crucial technique used to address the challenge of limited and imbalanced datasets. Given the variability in environmental conditions such as lighting, smoke, and fire intensity, obtaining a sufficiently large and diverse dataset is often difficult. Data augmentation helps by artificially increasing the size of the training dataset through transformations like rotations, flips, brightness adjustments, and noise additions. These variations make the model more robust to different real-world scenarios, improving its ability to classify images, especially in challenging conditions correctly (Chlap et al., 2021).

2.5 Class Weight

Class weight is a process used to address the problem of class imbalance in image segmentation and classification tasks, where certain classes, such as those of interest, have significantly fewer examples than others. This imbalance can lead to models, especially Convolutional Neural Networks (CNNs), becoming biased towards the majority class, resulting in poor performance for the minority class. For instance, medical applications like tumor segmentation aim to make the model more sensitive to the lesion class, ensuring that critical regions, such as tumors, are accurately detected.(Ben Naceur et al., 2019).

In our forest fire classification task, where we aim to categorize images into "None," "Fire," "Smoke," and "Fire and Smoke" categories, we face a similar challenge. The "Smoke" and "Fire" classes are underrepresented compared to the "None" and "Fire and Smoke" classes, leading to an imbalance that could cause the model to underperform in detecting fire and smoke conditions, which are crucial for wildfire management. By using a class-weighting strategy, such as the one based on the Weighted Cross-Entropy function, we can assign higher weights to the minority classes (e.g., "Smoke" and "Fire"), helping the model to focus more on these underrepresented categories during training. This approach could improve the model's sensitivity toward detecting fire and smoke, much like how it effectively improved the segmentation of Glioblastoma tumors in medical applications, ensuring better detection of critical regions (Ben Naceur et al., 2019).

The balanced class weight method that we used can be explained by Equation (1) (Bakirarar & Elhan, 2023). In this formula, N represents the total number of samples in the dataset, $Class$ is the total number of unique classes, and $Sample_{class}$ is the number of samples in the respective class. By dividing the dataset size by the product of the total classes and the sample count for a given class, this method assigns higher weights to minority classes and lower weights to majority classes. This approach ensures that the training process does not disproportionately favor the majority class, improving the model's ability to generalize and recognize patterns across all classes effectively, including underrepresented ones.

$$W = \frac{N}{(class * sample)} \quad (1)$$

2.6 Modelling

Convolutional Neural Networks (CNNs) are a powerful deep learning model designed explicitly for visual data processing, such as images. Widely used for image recognition and classification tasks, CNNs excel in automatically learning spatial hierarchies of features from input data. In the study conducted by Nayak et al. (2022) a CNN-based architecture called dense EfficientNet was employed to classify 3,260 T1-weighted contrast-enhanced brain magnetic resonance images into four categories: glioma, meningioma, pituitary, and no tumor (Nayak et al., 2022). The EfficientNet architecture utilizes Inverted Residual Blocks (MBConv), similar to MobileNetV2's core building blocks. Unlike traditional CNNs, which require manual adjustments across three dimensions: depth, width, and resolution, EfficientNet employs a compound scaling approach to scale these parameters together.

Additionally, it replaces the conventional ReLU activation function with the Swish activation function, which combines linear and sigmoid components. The input image is resized to 224 × 224 to match the standard input dimensions of CNN models (Ab Wahab et al., 2021) The whole EfficientNet architecture can be seen on Figure 5.

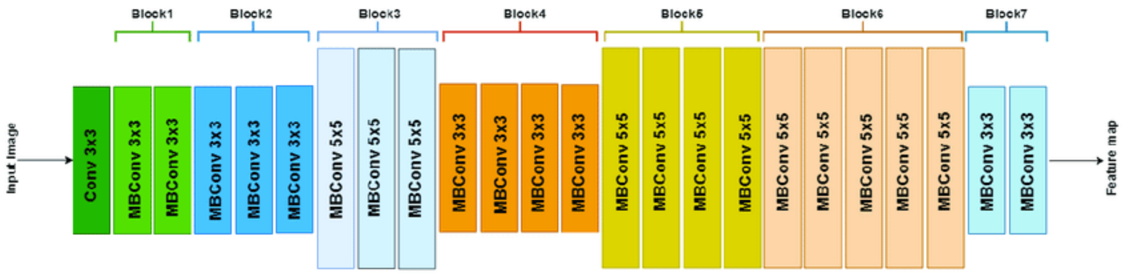

Figure 5 Architecture of EfficientNet-B1

2.7 Model Evaluation

Model evaluation is a critical process in machine learning that involves assessing the performance of a trained model using specific metrics to determine its effectiveness in making predictions. In multiclass classification, the accuracy metric is commonly used to quantify how well the model predicts the correct classes across various categories. Chen et al. (2021) highlight that maximizing training accuracy on a sufficient number of noisy samples can lead to an approximately optimal classifier even under class-conditional label noise. This finding underscores the importance of accuracy as a reliable metric for training and validation, as a noisy validation set can still provide valuable insights for model selection, including hyperparameter tuning and early stopping. By validating model performance using a noisy dataset, practitioners can achieve robust model evaluation, ensuring that the model is accurate and generalizable despite label noise (Chen et al., 2021).

This study used Accuracy (Acc) and F1-score (F1) as the primary metrics for evaluating the model. Accuracy measures the overall correctness of the model's predictions across the dataset. The F1-score, considering both precision and recall, provides a comprehensive assessment of the model's performance, especially in situations where the dataset contains uneven class distributions (Xiao et al., 2024).

Accuracy (Acc) is the ratio of correctly predicted instances to the total number of instances in the dataset. In the context of multiclass classification, accuracy evaluates the percentage of correctly classified images across all classes. The equation for accuracy is given by Equation (2).

$$Accuracy = \frac{Correct\ Predictions}{Total\ Number\ of\ Predictions} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

F1-Score (F1) combines both precision (the ability of the model to identify positive instances) and recall (the ability of the model to detect all relevant positive instances). The F1-score is defined as the harmonic mean of precision and recall, making it useful for assessing the performance of minority classes. The formulas for F1-score in Equation (3), precision in Equation (4), and recall in Equation (5).

$$F1 - Score = 2\frac{Precision\ \ Recall}{Precision +\ Recall} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

3. RESULTS AND DISCUSSION

This section systematically outlines the model training process using the EfficientNet-B1 architecture, which was optimized to achieve high accuracy with efficient computation. The training process involved fine-tuning all layers of the model architecture to maximize accuracy. A total of 20 epochs were conducted to gather sufficient information for evaluating and optimizing the model's performance. The evaluation used a validation dataset to assess the model’s ability to classify unseen images. This validation process was conducted at each epoch to monitor the model’s accuracy throughout the training phase.

3.1 Training Process

Figure 6 shows the accuracy and loss throughout each epoch of the training process using the class weight method. The training accuracy consistently improves with each epoch, showing continuous growth until epoch 10. Beyond this point, up to epoch 20, there is no further improvement, indicating that the model has likely reached its peak accuracy. The model begins to stabilize in terms of validation accuracy, reaching its highest accuracy within the range of 0.88 to 0.90, starting from epoch six and continuing through epoch 20, with only slight fluctuations observed during this period.

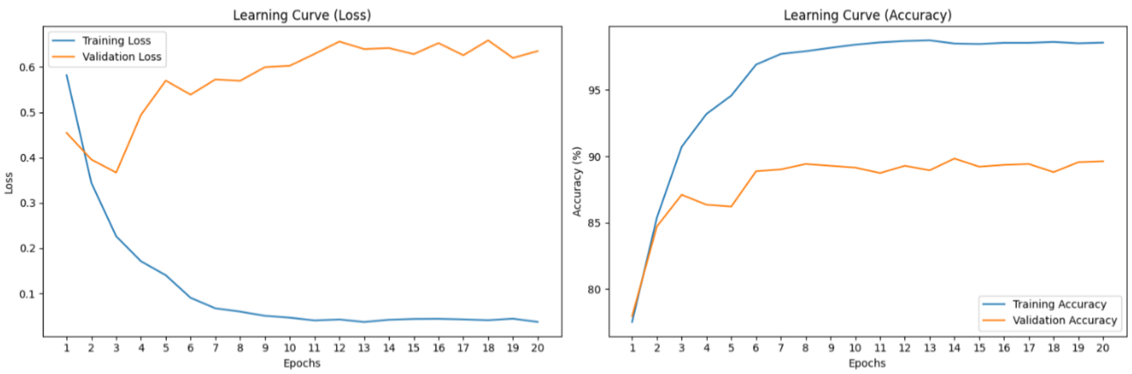

Figure 6 Loss and Accuracy of Model with Class Weight

Figure 7 shows the accuracy and loss throughout each epoch of the training process using the data augmentation method. The overall training accuracy does not differ significantly from the class weight method shown in Figure 6. However, there is a noticeable difference in the loss, with lower values ranging from 0.30 to 0.35 and smaller fluctuations. This suggests that the model, when using the augmentation method, is slightly better at addressing overfitting than the class weight method. However, the validation accuracy remains similar, consistently around 0.90.

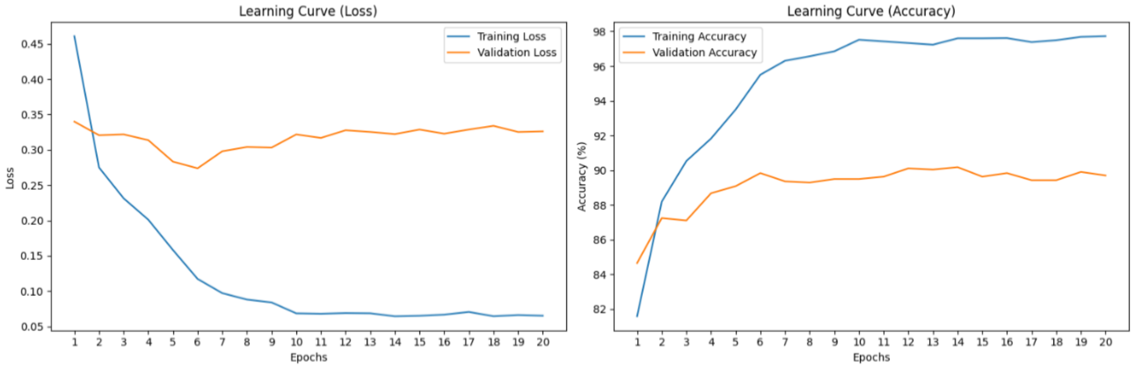

Figure 7 Loss and Accuracy of Model with Data Augmentation

However, aside fromboth methods' accuracy and loss results, the class weight method demonstrates significantly better resource and time efficiency during the training process compared to the data augmentation method. This is also quite reasonable, as the data augmentation method increases the data for the minority classes, requiring the model to train on a larger dataset. As shown in Table 3, both methods were trained using the same T4 x2 GPUs and the same model, EfficientNet-B1.

Table 3 Model Training Time with Two Different Approach

Methods	Training Time
Class Weight	14m 45s
Data Augmentation	33m 25s

3.2 Evaluation

Table 4 presents the model evaluation results using two different methods, measured by Precision, Recall, F1-Score, and Accuracy. The evaluation results are derived from the best model state based on the highest validation accuracy achieved during the training process, as shown in Figure 6 and Figure 7. The evaluation results show no significant differences between the two methods across various metrics and classes, achieving the same accuracy of 0.90. These findings show that the class weight method using the EfficientNet-B1 model on an imbalanced forest fire dataset can compete with the performance of the data augmentation approach for handling class imbalance while using around 56% less training time than the augmentation method, as shown previously in Table 3.

Table 4 EfficientNet-B1 Model Evaluation Result

	Precision		Recall		F1-Score	
	Class Weight	Data Augmentation	Class Weight	Data Augmentation	Class Weight	Data Augmentation
None	1.00	0.99	0.99	1.00	0.99	0.99
Fire	0.72	0.75	0.80	0.75	0.76	0.75
Smoke	0.72	0.81	0.76	0.72	0.74	0.76
Smoke and Fire	0.89	0.87	0.85	0.88	0.87	0.88
Accuracy					**0.90**	**0.90**

3.3 Performance Comparison with Other Models

To further assess the performance of EfficientNet-B1 in this study, we compared it to two other popular deep learning architectures, VGG-16 and ResNet50. Both models are widely used for image classification and are often benchmarked in various domains for their strong baseline performances. Each model was trained and evaluated on the same dataset under the same configuration and method of class weighting as applied in the EfficientNet-B1 training process to ensure a fair comparison. Table 5 and Table 6 show the classification reports for VGG-16 and ResNet50, respectively, allowing for a direct comparison with the results from EfficientNet-B1 in Table 4.

Table 5 VGG-16 Model Evaluation Result

	Precision	Recall	F1-Score
None	0.98	0.98	0.98
Fire	0.52	0.79	0.63
Smoke	0.58	0.78	0.66
Smoke and Fire	0.87	0.65	0.75
Accuracy			**0.82**

Table 5 shows that VGG-16 achieves an overall accuracy of 0.82, with relatively high precision and recall for the "None" class but lower performance in distinguishing between "Fire" and "Smoke" classes. The model struggles with balancing precision and recall for "Fire" and "Smoke and Fire" categories, which are critical for accurate identification.

Table 6 ResNet50 Model Evaluation Result

	Precision	Recall	F1-Score
None	1.00	0.99	0.99
Fire	0.70	0.74	0.72
Smoke	0.76	0.76	0.76
Smoke and Fire	0.87	0.85	0.86
Accuracy			**0.89**

Table 6 indicates that ResNet50 performs better than VGG-16, with an accuracy of 0.89. ResNet50 shows high precision and recall for the "None" and "Smoke" classes, but its F1-Score for "Fire" remains slightly lower than desired. Overall, ResNet50 results better than VGG-16, especially in the "Smoke and Fire" class, where it achieves an F1-Score of 0.86.

In contrast, EfficientNet-B1 at Table 4 achieves the highest accuracy at 0.90, with consistently high precision and recall across all classes, particularly excelling in distinguishing "Fire" and "Smoke" events, with F1-Scores of 0.76 and 0.74, respectively. The balanced performance across classes, coupled with the efficient training time, suggests that EfficientNet-B1 is the best-performing model for this dataset. EfficientNet-B1's superior performance may be attributed to its optimized architecture, which balances depth, width, and resolution, making it particularly suitable for complex multiclass classification tasks like the one in this study.

In conclusion, the comparison demonstrates that EfficientNet-B1 outperforms VGG-16 and ResNet50, proving the most effective model for achieving the highest accuracy in this case.

4. CONCLUSIONS

Implementing the class weight method in the EfficientNet-B1 model architecture successfully produced a successful classification model for the forest fire dataset, achieving a test accuracy of 90% within a training duration of just 14 minutes and 45 seconds. The evaluation results indicate the superiority of this class weight method in generating accurate outputs, effectively handling data imbalance during predictions, and maintaining high training efficiency.

Future research could further explore alternative model architectures, such as ResNext, MobileNet, and DenseNet, to achieve even higher accuracy scores while improving computational efficiency. Additionally, future research may investigate other class weight methods beyond the balanced weight approach employed in this research, such as the Inverse of Number of Samples (INS) and Inverse of Square Root of Number of Samples (ISNS).

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