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HYBRID LEARNING STRATEGY COMBINING MODEL-LEVEL TRANSFER LEARNING AND DATA-LEVEL AUGMENTATION FOR BRAIN CANCER CLASSIFICATION

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Abstract—*Due to the complexity of images, size, and balance of data, brain cancer diagnosis is still one of the most challenging problems to solve. It is shown that traditional classification methods based on 'first principles' do not produce ideal results, often due to different brain tumours. This research uses a hybrid model that leverages transfer learning with data augmentation and AI refinement to categorise three brain tumours: glioma, meningioma, and others. This research aims to improve the classification performance of brain cancer detection using this model. The methodology uses a framework created with a specific dataset, mixed data enhancement, and InceptionV3 model refinement to improve performance. With a validation accuracy of 0.95, the F1 scores for glioma, meningioma, and other brain tumours were 0.98, 0.95, and 0.92, respectively. This hybrid model achieves accuracy without complexity in design while addressing data scarcity and balance issues. The primary focus of this research was to create an effective and robust model for classifying brain cancers that is easy to use in low-resource clinical environments. The results demonstrate how deep learning can improve diagnostic precision and provide a scalable method for detecting brain cancer in the early stages of medical imaging.*

Keywords: *brain cancer classification, data augmentation, InceptionV3, Mixup, transfer learning*

Intisari—*Kompleksitas gambar dan ukuran diagnosis kanker otak masih menjadi salah satu masalah yang paling sulit untuk dipecahkan. Hal ini menunjukkan bahwa metode klasifikasi tradisional tidak memberikan hasil yang ideal, seringkali disebabkan oleh tumor otak yang berbeda. Penelitian ini menggunakan model hibrida yang memanfaatkan pembelajaran transfer dengan augmentasi data dan penyempurnaan kecerdasan buatan untuk mengkategorikan tiga tumor otak: glioma, meningioma, dan lainnya. Penelitian ini bertujuan untuk meningkatkan kinerja klasifikasi deteksi kanker otak menggunakan model pembelajaran hybrid. Metodologi penelitian ini menggunakan kerangka kerja yang dibuat dengan dataset tertentu, augmentasi data campuran, dan penyempurnaan model InceptionV3 untuk meningkatkan kinerja. Dengan akurasi validasi sebesar 0,95, skor F1 untuk glioma, meningioma, dan tumor otak lainnya masing-masing adalah 0,98, 0,95, dan 0,92. Model hibrida ini mencapai akurasi tanpa kompleksitas dalam desain sekaligus mengatasi masalah keterbatasan data. Fokus utama dari penelitian ini adalah untuk menghasilkan model yang efektif dan kuat dalam mengklasifikasi kanker otak yang mudah digunakan di lingkungan klinis dengan sumber daya yang terbatas. Hasil penelitian menunjukkan bagaimana deep learning dapat meningkatkan akurasi diagnostik dan menyediakan metode yang terukur untuk mendeteksi kanker otak pada tahap awal pencitraan medis.*

Kata Kunci: *klasifikasi kanker otak, augmentasi data, InceptionV3, Mixup, pembelajaran transfer.*

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INTRODUCTION

Deep learning has made a huge difference in the diagnosis and classification of brain cancer, both in terms of accuracy and efficiency with prior testing capabilities [1]. Convolutional Neural Networks (CNN) and other architectures are part of the developments in early and accurate tumor detection and classification using MRI images and Optical Coherence Tomography (OCT) images [2], [3], and can also reduce the manual examination process in diagnosis by simplifying the diagnosis process [4]. Models such as NeuroNet, which integrates CNN and spatial attention processes, have improved the overall classification of brain tumors, particularly gliomas and meningiomas, while improving feature representation and reducing manual processes [5]. The VGG-16 model has been shown to be stable and resilient to overfitting, providing a model that can be applied to real-world clinical cases, especially on heterogeneous data sets [6].

The increasing prominence of explainable deep learning has also led to the advent of methods such as class activation mapping, improving transparency in medical imaging applications [7]. Hybrid deep learning systems, such as the Multi-Head Self-Attention Dilated CNNs, have enhanced tumor detection and risk management accuracy [8]. Deep ensemble methods have been applied effectively in Optical Coherence Tomography (OCT) image analysis and are beneficial for real-time applications [9]. While these transformations continue, challenges remain, including long training time and the need for a large and diverse dataset. Specific models, such as VGG-16, cannot practically be implemented due to time and material constraints, as they are too demanding of resources [6], [10].

Combining deep learning with other machine learning methods (hybrid modelling and transfer learning) possesses ramifications for gains in accuracy and efficiency in diagnosis regarding possible advancements of superior diagnostic systems aiding medical professionals, particularly neurologists, in diagnosing brain cancer faster and earlier [8], [10]. Various research studies have developed hybrid models for the classification of brain tumours, such as Lamba et al. (2021) hybrid strategy based on an in-depth learning approach and supervised learning for the classification of glioblastoma and meningioma using MRI data [11] and Agarwal et al. (2021) modified deep CNNs for the classification of malignant tumours [11], and Agarwal et al. (2021) modified deep CNNs for the classification of malignant tumours [12]. An equally proper technique has been the transfer learning efforts from pre-trained models such as DenseNet, ResNetV2, and InceptionResNetV2, improving classification accuracy [13].

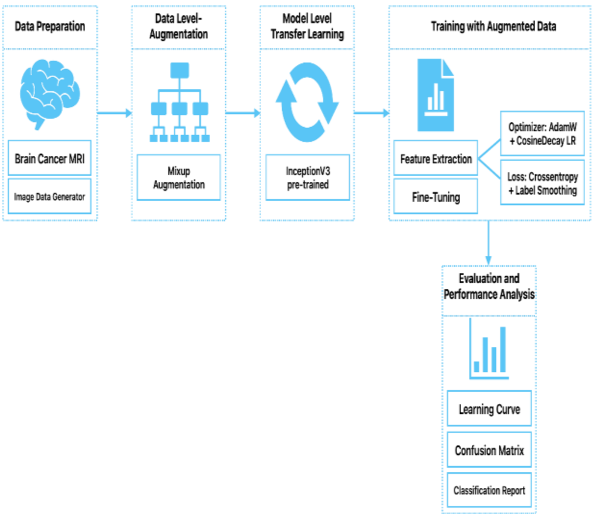
Hybrid models and data augmentation strategies have contributed similarly to brain tumor classification. In a paper, Shaikh and Shaikh (2021) proposed a hybrid model with transfer learning, ensemble learning, and data augmentation, and they demonstrated strong robustness with hyperparameter tuning and data augmentation [14]. More examples of data augmentation and models such as U-Net for segmentation of tumours were provided [15], [16]. Hybrid models also produced compelling classification performance, so models combining VGG-16 with ResNet-50 demonstrated strong accuracy [17]. DenseNet121 with InceptionV2 and combined with auto encoders showed a valid upgrade to the current baseline method of classification by reducing dimension and noise [18], [19]. Transfer learning techniques using models with Inception-v3 and EfficientNetV2B3 showed promise with glioma and meningioma tumour classification [20], [21]. Data augmentation methods such as rotation, various flips, and colour jittering have also been shown to improve the generalisation of these classification models through additional unique image samples [22], [23]. Finally, CNN-SVM approaches and hybrid models that included vision transformers (ViT) have well-documented strong classification performance that shows they could one day be incorporated into clinically required models [24], [25].

This study seeks to tackle the challenges in brain tumour classification with medical images by recommending a hybrid method which blends two primary machine learning methods, transfer learning at the model level and data augmentation at the data level. MRI images using brain cancer classification can often prove challenging due to the issues with small datasets and class imbalance. These challenges cause overfitting and affect the generalization capability of the model. This study attempts to utilize transfer learning using pretrained models and data augmentation to increase the diversity of a training dataset, to allow for improved accuracy and efficiency at detecting the types of brain cancer, gliomas, meningiomas, and other brain tumours. Utilizing both of these strategies will generate more accurate classification models in the context of a particular application, often in situations of limited resources on behalf of operators, as is the case concerning medical image-based diagnosis in brain cancer systems.

The key contribution of this study is a more efficient and more accurate classifier of brain cancer using two learning approaches: transfer learning and data augmentation. This combination of learning techniques enhances classification accuracy and aligns with a strategy for overcoming issues with a lack of data and slight variation in medical datasets. In addition, Mixup techniques in data augmentation and fine-tuning in InceptionV3 models continue to enhance model performance without developing complicated model architectures, which can mean even more computational work. Therefore, this research has practical contributions to implementing image-based medical diagnostics and enables the effective use of deep learning technologies in clinical settings with limited resources.

MATERIALS AND METHODS

The processes proposed are shown in Figure 1. The research suggests a hybrid approach combining two predominant methodologies in machine learning (ML) to improve brain cancer classification models' capability: model-level transfer learning, data-level sample augmentation, and simultaneously, aims to improve accuracy when classifying brain cancer types in medical images.

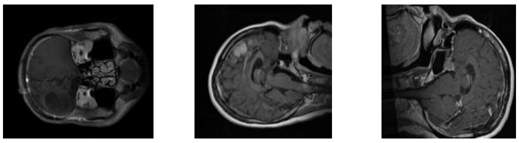


Source: (Research Result, 2025)

Figure 1. Proposed Method

1. Data Preparation

The preliminary stage in this research cycle is the input of data that consists of collected brain images. Here, the images are MRI medical images that depict various types of brain cancer (i.e., glioma, meningioma, and other brain tumors). This data will be used for brain tumor classification using deep learning.



brain_glioma brain_menin brain_tumor

Source: (Brain Cancer MRI Dataset [26], 2025)

Figure 2: Sample DataSet

The MRI medical image data portrayed in Figure 2, which will describe the dataset, has a set of images from Kaggle, comprising 300 images with 100 images per class, and uses an approach for preprocessing the pictures included in the dataset that utilizes ImageDataGenerator in Keras. ImageDataGenerator is a highly beneficial way to apply data augmentation automatically. It will modify images so that the model can learn more from variations in the data. In this case, it also rescales the images by dividing the pixel values by 255 to fall between 0 and 1, which is useful when training the model. The training set is broken down into two sets, specifically a training (80%) and a validation set (20%).

2. Data Level-Augmentation

One of the data augmentation techniques we use is called Mixup. Mixup is an augmentation method that creates new training samples via linear interpolation between two random images and their corresponding labels. This means we take two images, x and x', and calculate the image mixture, such that the weighting is controlled by a value λ drawn from a Beta distribution. This construction means the new image is a weighted combination of two input images and their labels. This method provides more variance to the training data, giving the model a better generalization variance.

3. Model-Level Transfer Learning

The model is built on InceptionV3, a convolutional neural network trained on millions of images and known for classification tasks. The script removes the top classification layers of InceptionV3, leaving only the convolutional base for feature extraction purposes. This means the model can still take advantage of the learned weights from the ImageNet dataset, but layers at the top of the model will be modified for the specific task of brain cancer classification. To build the whole model, more layers are added: First, a GlobalAveragePooling2D layer will produce a one-dimensional vector as output using the high-dimensional output from the convolutional layers. Then, a dropout layer will randomly turn off some fraction of the neurons during training, which can help prevent overfitting so that the model can learn

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more generalizable features. The last layer is a dense layer with a softmax activation function, which gives a probability distribution across the classes (brain cancer types) so that the model can predict every image. The AdamW optimizer is selected for optimization, which performs like a standard Adam optimizer with weight decay regularization to help avoid overfitting. The loss function being used is CategoricalCrossentropy, which allows it to be used for a multi-class classification problem.

4. Training with Augmented Data

The model is trained using data produced by the mixup generator. The mixup generator creates a mixed-up image at each batch. This results in the model being trained on mixed-up photos, enriching the training data and improving model generalization.

The model will be trained for 50 epochs. To prevent overfitting, EarlyStopping is used, and ModelCheckpoint ensures that training halts when the model starts overfitting or when the best model is achieved. "verbose=1" will print detailed information to the console during each epoch.

Call backs:

a. Early stopping prevents overfitting by monitoring validation accuracy and stopping training if there is no improvement for several epochs.
b. Based on validation accuracy, ModelCheckpoint stores the best-performing model.
c. TensorBoard displays metrics, including loss and accuracy over time, and visualizes real-time training progress.

The model will be fine-tuned after this training phase. The InceptionV3 model, once frozen, will be unfrozen during this phase. While earlier layers stay frozen, only the last few will be fine-tuned..

5. Evaluation and Performance Analysis

After a model has been trained, it is time to evaluate the model using the validation set. During the evaluation stage, there are two essential metrics that we want to find to give us a better understanding of the model's performance on new/unseen data: validation loss and validation accuracy. These two metrics will also provide insight into the model's ability to generalize to new examples that the model has never seen during training. The learning curves for accuracy and loss are also plotted to visualize the model's performance over time. This helps us see and understand if the model is learning or overfitting.

The model's performance for each class is shown in the classification report, which includes metrics such as accuracy, precision, recall, F1 score, and support. The metrics for recall, precision, accuracy, and F1 score are obtained using equations (1) to (4):

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$Accuracy = \frac{\text{TP + TN}}{\text{TP +TN+FP+FN}} \tag{3}$$

$$F1 - Score = \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \tag{4}$$

A confusion matrix evaluates model accuracy by comparing each class's predictions and actual labels. It illustrates how many predictions were correctly or incorrectly labeled for each class. The confusion matrix offers some insight into which classes are often confused with one another. If there are some classes that we may want to focus on improving, the confusion matrix can show these classes. We will depict the confusion matrix with a heatmap so it is easy to see the model's successes through its misclassifications.

RESULTS AND DISCUSSION

Testing the InceptionV3 Model indicates that this training method is best suited for brain cancer image classification. The images for the training are gathered from a dataset of 240 images, and for validation, 60 images were collected from a total of three classes: brain_glioma, brain_menin, and brain_tumor.

The feature extraction is completed in the model by passing the InceptionV3 architecture trained with ImageNet. Because of the consortium of filtering of multiple sizes and complex design as an architecture, InceptionV3 architecture provides excellent feature extraction of images as it can learn a comprehensive range of image features in various image pairs of numerous permissible variations and can distinguish the most significant image features. The extracted features from this stage contain helpful information about the texture, pattern, and shape characteristics of the image of a brain tumor. The InceptionV3 model, as a consequence of transfer learning, can draw upon the ImageNet weights, which extract low-level features (patterns and lines) that brain cancer data will make further

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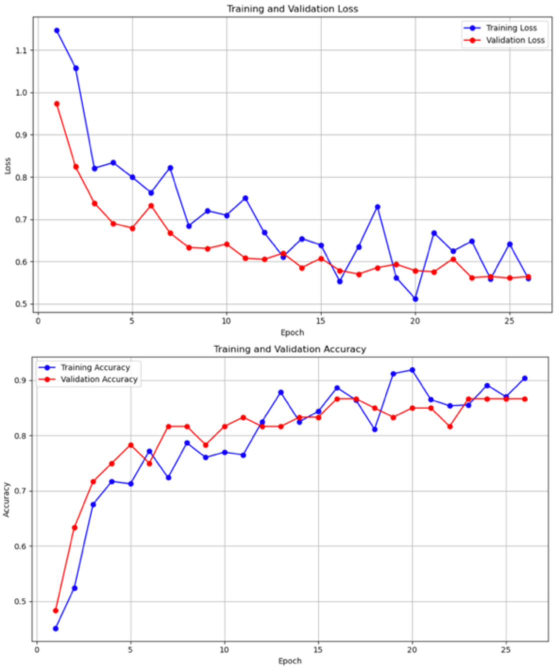
use of. The model provides features that provide the input for image classification activities (i.e., classifying brain tumors into three classifications or categories). Fine-tuning of the features allows switching on specific networks to modify the obtained features with more complex features extracted from the brain cancer database.



Source: (Research Result, 2025)
Figure 3: Training and Validation

Figure 1 illustrates the training and validation history for the model. In epoch 1, the training accuracy began at 0.4512, and the validation accuracy was only 0.4833, demonstrating that the model could not learn properly. However, in epoch 2, the model improved to a validation accuracy of approximately 0.6333, which hinted that the model had to recognize patterns in the data set. In epoch 3, validation accuracy increased to 0.7167 and training accuracy to 0.6753, demonstrating that the model was constructing a more informed understanding of the data features. As the training steps continued, in epoch 6, despite the training accuracy improving to 0.7621, the validation accuracy was still stuck at around 0.75. This indicated that overfitting was occurring, which demonstrated that the model could better recognize the training data, without being able to handle data that had not been seen before. Due to the modeling being fitted, early stopping was applied, and the training was stopped at epoch 45, which was deemed the best epoch to take. This came from the validation accuracy of 0.95. The train had now constructed the essential patterns from the brain cancer data and produced excellent results in image classification.

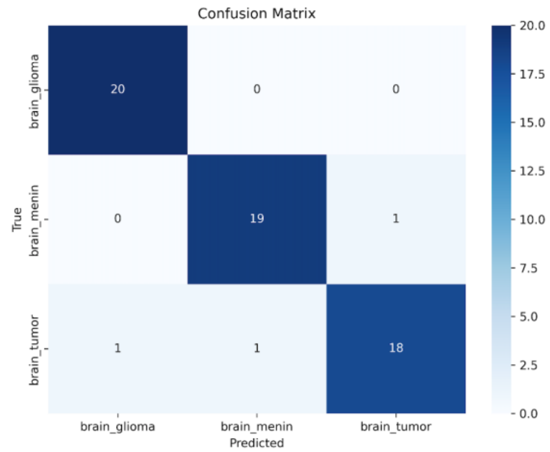
In the fine-tuning stage, the learning rate was reduced so the model could learn more on the specific data. This worked as, after fine tuning, the model performed the best at Epoch 45 with a validation accuracy of 0.95. Precision, recall, and F1-score for each class were excellent, with F1-score of 0.98 for brain_glioma, 0.95 for brain_menin, and 0.92 for brain_tumour. So the model can detect all courses with very high accuracy and sensitivity, even if the dataset is not large. Overall training with Mixup, fine tuning, and early stopping efficiently fine-tuned the InceptionV3 model for brain cancer classification.

Table 1. Classification Report

Class	Precision	Recall	F1-Score	Support
brain_glioma	0.95	1.00	0.98	20
brain_menin	0.95	0.95	0.95	20
brain_tumor	0.95	0.90	0.92	20
Accuracy			0.95	60
Macro Avg	0.95	0.95	0.95	60
Weighted Avg	0.95	0.95	0.95	60

Source: (Research Results, 2025)

Table 1 is the classification report. Regarding the validation data, the model did very well, with an accuracy of 0.95, classifying the images into three classes. Other metrics like precision, recall, and F1-score also showed excellent results, F1-score for brain_glioma was 0.98, brain_menin 0.95, and brain_tumour 0.92. This means the model is good at classifying images with minimal misclassification regarding false positives and negatives. The high precision and recall for all three classes means the model can classify the images well without much error in grouping the photos to the right class.



Source: (Research Result, 2025)
Figure 4. Confusion Matrix

Accredited Rank 2 (Sinta 2) based on the Decree of the Dirjen Penguatan RisBang Kemenristekdikti No.225/E/KPT/2022, December 07, 2022. Published by LPPM Universitas Nusa Mandiri

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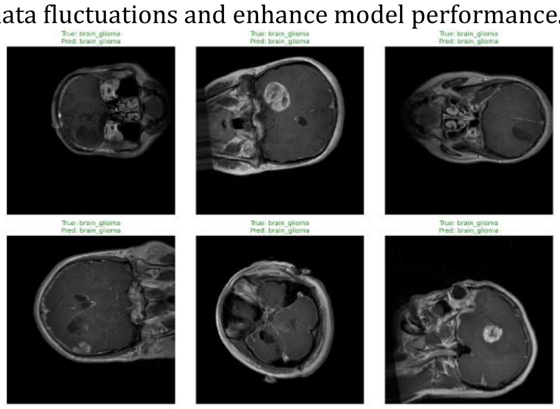
This conclusion is supported by the confusion matrix result in Figure 4, which shows that the model correctly classifies the images with minimal misclassification between the meningioma and other kinds of brain tumors. Additionally, the developed model uses the Mixup technique for data augmentation, which blends labels and images during training to increase the model's resilience to data fluctuations and enhance model performance.



Source: (Research Result, 2025)

Figure 5. Brain Cancer Prediction Optimization

Figure 5 depicts brain cancer prediction optimization. Overall, the InceptionV3 model trained using Mixup and fine-tuning approaches performed admirably, reaching 0.95 accuracy on the validation dataset. With a high F1 score and balanced precision-recall outcomes, the model has much potential for usage in medical applications, especially for diagnosing brain tumors from photos. The model's capacity to attain high levels of accuracy opens the door to its application in medical decision support systems, which can aid in the early Detection of brain cancer, delivering significant benefits in image-based medical diagnosis.

The following comparison table shows the results of this study using InceptionV3 models combined with Mixup and fine-tuned Mixup techniques for categorizing brain cancer, as opposed to two prior studies. The main differences between the methods used in this study and the models used in the earlier studies [10], [19] on metrics including accuracy, model architecture, data management, and possible therapeutic applications are shown in this table. Table 3 offers a thorough picture of the advantages and uniqueness of the approach used in this study by stressing the aspects ignored in the previous studies, especially concerning implementation efficacy, skill in handling data variability, and the possibility for use in the early Detection of brain cancer within the field of image-based medical diagnostics.

Table 2. Comparison Of Current And Previous Study

Aspect	This Study	[10]	[19]
Accuracy	95%	91.67%	93.80%
Model Architecture	Mixup and Fine-Tuning with InceptionV3	CNN-based deep learning model	EfficientNet with Autoencoder
Data Handling	Sophisticated methods—Mixup, fine-tuning, and early stopping	X	X
Performance Metrics	Across all three brain cancer types, high accuracy, precision, recall, and F1-score	Moderate accuracy and performance	High accuracy, but lower than InceptionV3
Effectiveness in Data Variations	Efficient at managing data fluctuations and lowering classification mistakes	X	X
Clinical Application Potential	In medical uses, there is a high possibility for early identification of brain tumors	X	X
Model Complexity	Easier design than hybrid models	Basic CNN model without extra refinement layers	More complex hybrid model requiring feature refinement and processing
Implementation Efficiency	Competitively and efficiently in execution	X	X
Suitability for Image-Based Diagnosis	Efficient and accurate make it very appropriate for medical picture classification.	Less suitable for complex medical image classification tasks	Suitable, but not as efficient as InceptionV3

Source: Research Results, 2025

CONCLUSION

This study aimed to tackle the difficulties in brain tumor classification using a hybrid strategy integrating transfer learning and data augmentation strategies. The findings showed that this method significantly increased the accuracy and efficiency of brain cancer categorization, particularly for glioma, meningioma, and other brain cancers. Impressive outcomes came from using InceptionV3 as a pre-trained model and methods including Mixup data augmentation and fine-tuning. With good precision, recall, and F1-scores—especially for glioma, where the F1-score hit 0.98—the model reached a validation accuracy of 0.95.

This study shows that using transfer learning with a model like InceptionV3, pre-trained on the large ImageNet dataset, and data augmentation strategies like Mixup helps us to solve problems connected with limited datasets and class imbalance, which often cause overfitting. Furthermore, improving the model with the specialized brain cancer dataset increased its performance. It allows it to apply the general characteristics obtained from ImageNet to classify brain tumors. The results provide strong evidence that, even with limited resources, deep learning methods, especially transfer learning using InceptionV3 with advanced augmentation techniques, can significantly enhance the diagnostic accuracy of brain cancer identification in medical imaging.

Future work should involve expert feedback to maintain the model's robustness in real-world applications. Moreover, incorporating expert opinions can help overcome data biases and improve the model's effectiveness in diverse clinical environments. As a result, this research makes excellent progress in medical image analysis and offers a practical and scalable method for brain cancer diagnosis through deep learning.

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