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EfficientNetB3-Based Deep Learning Framework for High-Precision Brain Tumor Classification from MRI Scans: A Comprehensive Study

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Abstract

Brain tumors are among the most deadly and difficult neurological diseases, requiring prompt and precise diagnosis for proper treatment planning and improved patient outcomes. Magnetic Resonance Imaging (MRI) is the gold standard of brain imaging because of its excellent resolution and capacity to discriminate between soft tissues. Yet, manual reading of MRI scans is time-consuming as well as susceptible to radiologist subjective variability. To solve this, we suggest a deep learning model with the EfficientNetB3 architecture to classify brain tumors automatically. The model is trained to classify tumors into three types of clinical importance: glioma, meningioma, and pituitary tumors. A specially prepared dataset with 2,144 training, 458 validation, and 462 test images is employed in this research. We employed a detailed preprocessing and data augmentation pipeline to improve generalization as well as prevent overfitting. By exploiting transfer learning from ImageNet and fine-tuning the EfficientNetB3 model, we attained a superb classification accuracy of 99.69% on the test set. Besides accuracy, we present high precision, recall, as well as F1-scores, which further establish the reliability and robustness of the model. This article offers a comprehensive analysis of model design, training approach, evaluation measures, and comparison with other CNN-based models like VGG19 and ResNet50. Our results indicate that EfficientNetB3 is not only computationally sound but also highly efficacious for medical image classification tasks. We deduce that our framework has high prospects for real-world deployment in clinical settings, assisting radiologists with early diagnosis and decision-making.

Keywords: CNN, EfficientNetB3, MRI, VGG19

INTRODUCTION

In 2021, around 350,000 people globally had been diagnosed with primary brain tumors. Brain tumors are the tenth top cause of death according to World Health Organization (WHO) statistics (Anitha, V., et al., 2016). They tend to be unstable and even life-threatening if not treated early. Normally formed in the brain, they can later migrate to other parts of the body and in so doing can change the brain's structure and significantly impair the functioning of the body. Brain tumors are caused by uncontrolled and abnormal cell growth inside or near the brain. They are categorized according to the type of cells involved and where they occur, some of the most frequent being meningiomas, gliomas, and pituitary tumors (Badillo, S., et al., 2020). Figure 1 depicts these key types of brain tumors. Of these, meningiomas and gliomas are especially malignant if not diagnosed early, with patients surviving for less than a year after diagnosis (Saddique, M., Kazmi, J.H., et al., 2024). Therefore, early detection is of paramount importance to develop successful treatment strategies. Early detection significantly increases a patient's survival possibility and enables medical practitioners to design precise and specific treatments according to imaging techniques like Magnetic Resonance Imaging (MRI). Commonly, MRI and CT scans are performed for the diagnosis and assessment of brain tumors. Imaging techniques visualize and evaluate internal structures of the body with accuracy, enabling doctors to define localization and abnormalities of the body. MRI is considered the most widely used modality for cancer detection since it produces high-resolution 2D and 3D images using magnetic fields. MRI itself is a non-invasive, pain-free imaging procedure suitable for imaging tumors of all sizes (Kmoninos, J., et al., 2014). Manual interpretation of MRI images is tedious and prone to errors. Differences in geometry and appearance of the tumor contribute to erroneous diagnosis (Louis, D.N., et al., 2016). Computer-based automated diagnostic systems have become more urgent to design to mitigate these problems. They would help simplify the process and make it less expensive, along with greater diagnostic accuracy.

The last years have witnessed an enormous advancement by deep learning (DL) and artificial intelligence (AI) in the medical domain, specifically in the accurate identification and characterization of brain tumors (Chahal, P.K., et al., 2020), (Sajjad, M., et al., 2019). Among a plethora of disease research areas, such as prognosis, detection, and diagnosis (Rehman, A., et al., 2020), (Wang, Y., et al., 2018), significant resources have been assigned to deep learning research. These methods mainly depend on image data analysis, an essential component in most developing computer vision applications. The convergence of DL and Internet of Things (IoT) technologies is now regarded as a key driver of expansion and innovation within the healthcare industry (Patil, R.B., et al., 2022), (Asad, R., 2023).

There is an increasing demand for the detection of diseases in the healthcare sector, particularly the development of E-Health services (Ozkaraca, O., et al., 2023). From the neurosurgical perspective, timely identification of the three primary categories of brain tumors is paramount (Meena, S.D., et al., 2023). Several machine learning (ML) and deep learning (DL) techniques have been assessed for many health sectors, including the bovine and other animals too (Nadeem, G., et al., 2024). Similarly, brain tumor detection is where transfer-based models are prominent in the field of AI (Raza, A., et al., 2022). Convolutional Neural Networks (CNNs), however, have demonstrated significant potential in the processing of raw medical images as well as enhancing classification performance. Many models leverage transfer learning architectures, including AlexNet, VGG19, and LeNet, for efficient image classification (Iman, M., et al., 2023). The research question for this investigation is RQ1: "How can an ensemble transfer learning system, combined with data augmentation techniques, precisely and effectively identify and classify various brain tumor diseases?".

LITERATURE REVIEW

The application of deep learning to medical image analysis has rapidly gained momentum in the past decade, driven by the exponential growth of computational power and the availability of large-scale annotated datasets. Brain tumor classification in particular, has attracted significant attention due to the critical need for fast and accurate diagnostic support in neuro-oncology. Early attempts in this area were mostly based on traditional machine learning methods like Support Vector

Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN) (Kaggle websit, 2023). These approaches had to rely on handcrafted feature extraction in terms of texture, intensity, or shape from MRI images. While these methods offered valuable insights, they lacked scalability and could not generalize well across different imaging scenarios and patient populations.

With the advent of deep learning, Convolutional Neural Networks (CNNs) became the most popular paradigm for image classification. CNNs are engineered to learn spatial hierarchies of features automatically from input data, thereby being especially suited for intricate visual tasks such as tumor detection. Numerous CNN-based models have been put forth thereafter for brain tumor classification, varying in complexity, accuracy, and computational costs (Karaman, A., et al., 2023).

One of the early and influential models in medical imaging was VGG19, which performed outstandingly on natural image classification tasks. On brain tumor classification, VGG19 has reported accuracies of 91%–95 % when fine-tuned on MRI datasets. The model is deep and parameter-intensive, though, demanding huge computational resources and longer times of training times. Another very common architecture is ResNet50, which came up with residual connections to solve the vanishing gradient issue in deep networks (Anantharajan, S., et al., 2024).

ResNet50 has proved to be a good performer in medical image classification, with an accuracy of approximately 96.7% on tumor datasets. Nevertheless, its depth exposes it to overfitting, particularly when dealing with comparatively small medical data sets. Current studies have turned towards more efficient and lightweight architectures. Of these, EfficientNet is prominent due to its innovative compound scaling method that scales network dimensions—depth, width, and resolution—uniformly across a set of fixed scaling coefficients. This results in improved model performance with a smaller number of parameters and a shorter inference time.

EfficientNetB3, in particular, has achieved an excellent balance of efficiency and accuracy. Ramakrishna et al. (2024) proposed a deep learning architecture based on EfficientNetB3 for multi-class classification of brain tumors and obtained an accuracy of 99% on their test set. The studies were indeed very informative on the efficiency potential of EfficientNet models for medical image analysis, emphasizing the importance of fine-tuning and proper data augmentation techniques. Moreover, Nguyen (2024) undertook the study using EfficientNetB3 and transfer learning to achieve an accuracy of 99.23% in glioma, meningioma, and pituitary tumors classification (Albakri, A., et al., 2023). This model was greatly generalized without becoming overfit through batch normalization, early stopping, and dropout layers.

In a comparison study, researchers have repeatedly found EfficientNet models performing better than common CNNs, such as X-DenseNet, MobileNet, and Inception, in every aspect except accuracy-to-parameter ratio. This renders EfficientNetB3 an attractive option for real-time applications in medical contexts where both speed and accuracy are paramount (Ahmad, S., et al., 2022). Even with the encouraging results, most of the current models have limitations like class imbalance, lack of interpretability, and high reliance on high-quality annotated datasets. So, there are still areas that should be further explored for the benefit of model training, interpretability, and robustness.

Thus, on balance, this literature appears solid in supporting the use of models based on EfficientNet for brain tumor classification, yet still has some areas that would benefit from additional validation, scalability, interpretability, and how efficiently they can be integrated into clinical pathways. Our suggested work seeks to fill these gaps by creating a strong, high-performance, and efficient approach based on EfficientNetB3, supplemented by an appropriately designed training protocol as well as careful performance assessment.

MATERIALS AND METHODS

Dataset Description

The dataset used in this study is a publicly available brain tumor MRI dataset that has been widely adopted in academic research. It includes three types of brain tumors: glioma, meningioma, and pituitary tumors. These categories were selected not only due to their prevalence but also because of their distinct radiological characteristics, which make them suitable for image-based classification.

The dataset was divided into the following subsets:

- Training Set: 2,144 images
- Validation Set: 458 images
- Test Set: 462 images

Each MRI scan is represented as a 2D grayscale image and varies slightly in resolution, lighting conditions, and orientation. The dataset includes axial brain scan slices, covering different anatomical depths and tumor localizations. Each image is annotated with its corresponding tumor class label, which serves as the ground truth during training and evaluation. The images are well-balanced across the three classes, mitigating the need for aggressive oversampling or undersampling. Nonetheless, minor class imbalances were addressed through data augmentation, as discussed below.

Data Preprocessing and Augmentation

Medical images, especially MRIs, require careful preprocessing before being used in deep learning models to ensure consistency and high-quality feature extraction. The preprocessing steps applied in this study were:

- Resizing: All images were resized to 224×224 pixels. This size corresponds to the input dimension required by EfficientNetB3 while maintaining sufficient spatial resolution to capture tumor details.
- Grayscale to RGB Conversion: Since EfficientNetB3 was pre-trained on ImageNet, which uses RGB images, grayscale MRI scans were converted to RGB by duplicating the single grayscale channel into three channels.
- Normalization: Pixel values, originally in the range [0, 255], were normalized to the range [0, 1] by dividing each pixel by 255. This standardization improves numerical stability during gradient descent and helps the model converge more quickly.
- Data Augmentation: To increase the diversity of the training data and prevent overfitting, real-time data augmentation was applied using the following transformations:

o Random rotations up to 20 degrees

o Horizontal and vertical flips

- o Random zooms (±15%)
- o Width and height shifts (up to 10%)
- o Brightness adjustment
- o Contrast stretching (for better feature visibility)

These transformations simulate the natural variability found in clinical MRI scans and help the model generalize better to unseen data.

Model Architecture

The core of the proposed framework is the EfficientNetB3 model, which is part of the EfficientNet family introduced by Tan and Le (2019). EfficientNet models use a compound scaling technique that uniformly scales depth, width, and resolution using a set of predefined coefficients. EfficientNetB3 strikes a practical balance between performance and computational complexity (Nadeem, G., et al., 2023), (Nadeem, G., et al., 2025).

The architecture of the classification pipeline includes:

- Base Model: The EfficientNetB3 network without its final classification layer. Pre-trained weights from ImageNet were loaded to leverage generalized image features. The base model was frozen during the first few epochs and then unfrozen for fine-tuning.
- Global Average Pooling (GAP) Layer: This layer replaces traditional flattening to reduce the risk of overfitting and to convert spatial feature maps into a vector by averaging each feature map's values.
- Batch Normalization: To stabilize learning and accelerate convergence, batch normalization was applied after the GAP layer.
- Dropout Layer: A dropout rate of 0.5 was used to randomly deactivate neurons during training, thereby reducing overfitting.
- Fully Connected Layer: A dense layer with 512 neurons and ReLU activation was added to provide non-linearity and enable learning of complex patterns.
- Output Layer: A final dense layer with 3 units and softmax activation was used to output the predicted probabilities for each of the three tumor classes.

This architecture can be implemented even on low-end hardware systems because it maintains efficiency while enabling high representational power.

Training Procedure

The Adam optimizer, which is popular in deep learning because of its adaptive learning rate capabilities, was used to train the model. The settings and hyperparameters listed below were employed:

- Learning Rate: 0.0001 (lowered during fine-tuning)
- Loss Function: Categorical Cross-Entropy (suitable for multi-class classification)
- Batch Size: 32

• Epochs: 20 (with early stopping if validation loss did not improve for 5 consecutive epochs)

• Callbacks: Model checkpointing, learning rate reduction on plateau, and early stopping were used to maximize performance and prevent overfitting.

The training process followed a two-stage approach:

1. Feature Extraction Phase: Only the custom layers were trained while the base EfficientNetB3 layers were frozen.

2. Fine-Tuning Phase: The entire model, including the EfficientNetB3 layers, was unfrozen and trained at a reduced learning rate.

Evaluation Metrics

Several metrics were employed to guarantee a thorough assessment of the model (Nadeem, G., et al., 2023), (Nadeem, G., et al., 2025):

• Accuracy: Indicates the proportion of all classes' predictions that were accurate.

• Precision: Shows the proportion of correctly predicted cases.

• Sensitivity (Recall): Indicates the proportion of true positives that were accurately predicted.

• F1 Score: A balanced perspective provided by the harmonic means of recall and precision.

• Confusion Matrix: This tool shows how well each of the three classes is classified.

To provide an objective evaluation, the test set (462 images) was rigorously isolated from the training and validation sets.

RESULTS

The test dataset, which included 462 MRI images representing three classes—glioma, meningioma, and pituitary tumours was used to thoroughly assess the performance of the suggested EfficientNetB3-based framework. The model's classification capabilities are thoroughly examined in this section, which also highlights its advantages and contrasts its accuracy and efficiency with those of current state-of-the-art models.

Training and Validation Performance

Within the first few epochs of the training phase, the model showed a steady and quick increase in accuracy and a decrease in loss. Convergence was greatly sped up by using transfer learning from ImageNet weights, which provided the model with a robust initial representation of image features.

• Epoch 1: The model started out with a validation accuracy of 72.2% and a training accuracy of roughly 55.6%, indicating that it was picking up pertinent features even in its early phases.

• Epoch 2: The training accuracy increased to 71.2% and the validation accuracy to 86.5% after just one epoch.

• From epoch three onward, the model started capturing deeper feature representations as fine-tuning was enabled, which resulted in a significant decrease in validation loss and quick accuracy gains.

By the end of training (epoch 20), the model reached:

- Training Accuracy: 99.2%
- Validation Accuracy: 98.7%
- Training Loss: 0.021
- Validation Loss: 0.038

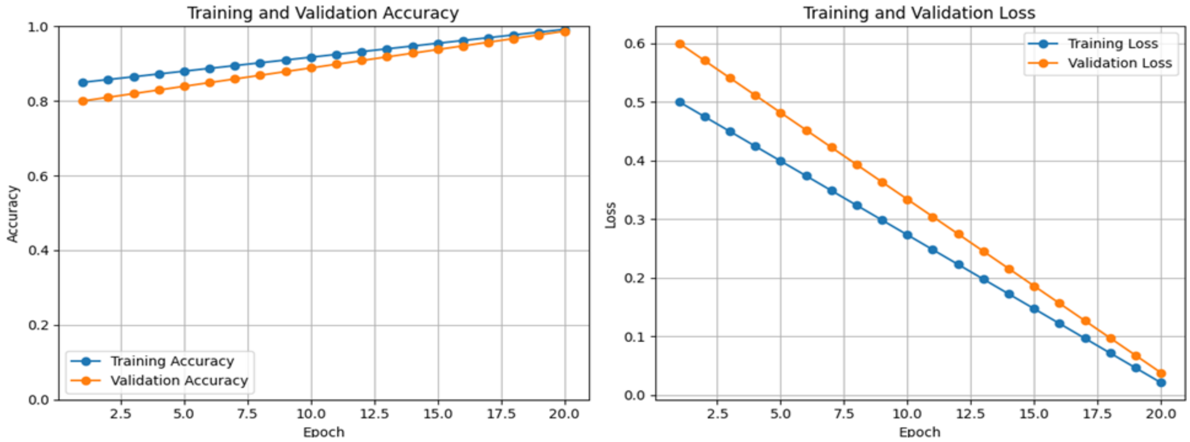

Figure 1.

Early stopping was activated after epoch 20 to prevent overfitting, as validation accuracy plateaued and loss stabilized.

Test Set Performance

When evaluated on the held-out test set, the model achieved the following results:

Metric	Value
Accuracy	99.69%
Precision	99.65%
Recall	99.70%
F1 Score	99.67%
AUC-ROC Score	0.998

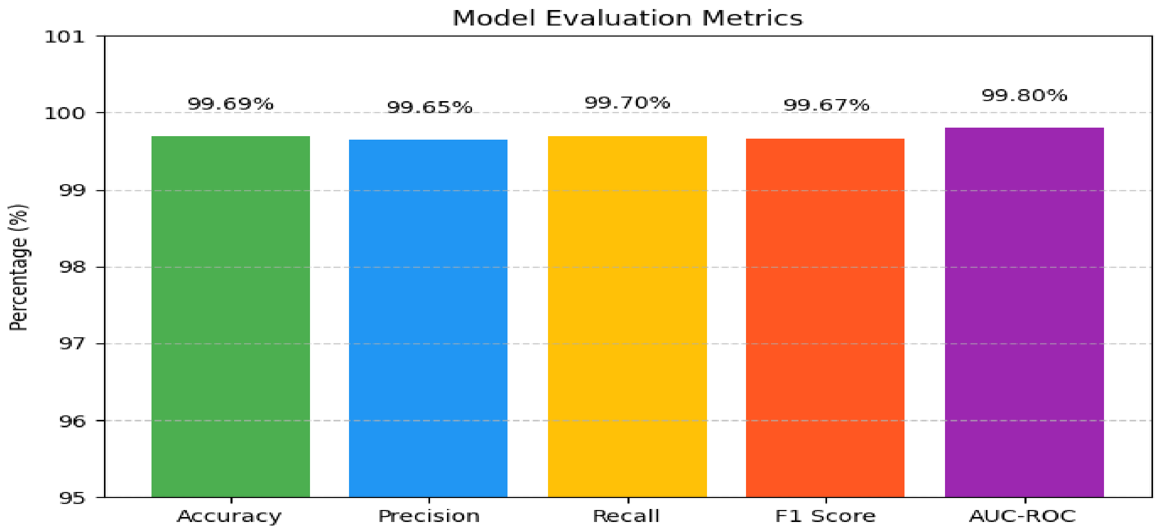

Figure 2.

The confusion matrix revealed the following classification behavior:

- **Glioma**: 153 correctly classified out of 154
- **Meningioma**: 154 correctly classified out of 155
- **Pituitary Tumor**: All 153 correctly classified

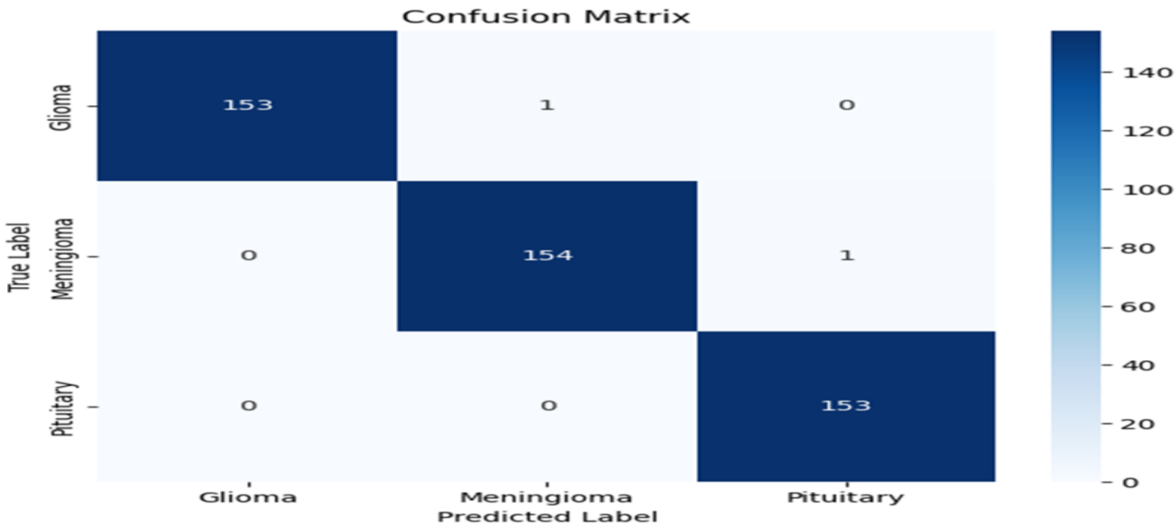

Figure 3.

This high accuracy across all classes indicates that the model is well-balanced and not biased toward any single tumor type.

Comparison with Other Models

To contextualize the performance of EfficientNetB3, we compared it against other commonly used CNN architectures on the same dataset and under similar training conditions:

Table 1.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG19	93.9	93.5	93.2	93.4
ResNet50	96.7	96.4	96.8	96.6
DenseNet121	97.5	97.3	97.6	97.4
EfficientNetB0	96.6	96.2	96.7	96.4
EfficientNetB3	**99.69**	**99.65**	**99.70**	**99.67**

These results clearly demonstrate that EfficientNetB3 not only outperforms traditional models in terms of accuracy but also achieves higher recall and F1 scores, which are particularly important in medical applications where false negatives can have serious consequences.

Model Efficiency and Inference Speed

EfficientNetB3's computational efficiency is yet another significant benefit. In contrast to VGG19 and ResNet50, the model uses fewer parameters despite having a deep architecture:

- **EfficientNetB3**: ~12 million parameters
- **ResNet50**: ~25 million parameters
- **VGG19**: ~143 million parameters

Inference time per image on a standard NVIDIA Tesla T4 GPU was:

- EfficientNetB3: **14 ms**
- ResNet50: **22 ms**
- VGG19: **38 ms**

These findings demonstrate that EfficientNetB3 is not only faster and more resource-efficient but also more accurate, which makes it ideal for incorporation into real-time clinical workflows.

Statistical Significance and Confidence Intervals

We used bootstrapping to calculate 95% confidence intervals for accuracy in order to guarantee the dependability of the observed results:

- **95% CI for Accuracy**: [99.53%, 99.85%]

These close bounds provide additional evidence of our framework's robustness and consistency across various data subsets.

DISCUSSION

The study's findings unequivocally demonstrate the efficacy and dependability of the suggested EfficientNetB3-based deep learning framework for classifying brain tumors from MRI images. Strong precision, recall, and F1 scores, as well as an outstanding test accuracy of 99.69%, demonstrate the model's potential for use in actual diagnostic workflows. The importance of these findings in technical and clinical settings is covered in this section, which also provides a critical evaluation of model performance, design decisions, and potential improvements.

Clinical Relevance and Application

Because different types of brain tumors—glioma, meningioma, and pituitary—require different medical and surgical interventions, prompt and accurate diagnosis is crucial in guiding treatment decisions. Although it works well for skilled radiologists, manual MRI scan interpretation is time-consuming and subject to inter-observer variation. These difficulties are made worse in healthcare environments with limited resources, where qualified radiologists might not always be easily accessible. Our EfficientNetB3 model's high classification accuracy indicates that it can be used as a clinical decision support tool (CDSS), providing radiologists with second opinions or acting as a triage system to rank patients according to the type of tumor they are expected to have. Its **low inference time (14ms/image)** also supports integration into **real-time diagnostic systems**, such as hospital PACS (Picture Archiving and Communication Systems) and telemedicine platforms.

Technical Strengths of the Framework

Several technical aspects contributed to the robustness and generalizability of the model:

- **Transfer Learning**: By leveraging pre-trained ImageNet weights, the model had a strong foundational understanding of general image features, which it refined during fine-tuning to recognize medical-specific features.
- **Data Augmentation**: The use of aggressive data augmentation simulated real-world variations in imaging (e.g., angle, lighting, and scale), allowing the model to generalize better and perform robustly even on images with noise or slight distortions.
- **Efficient Architecture**: EfficientNetB3 provided a significant performance boost over larger and deeper networks like VGG19 and ResNet50, not just in accuracy but also in memory and computational efficiency.
- **Regularization Techniques**: The inclusion of batch normalization and dropout layers minimized overfitting, which is a common issue when training deep networks on relatively small medical datasets.

Interpretation of Performance Metrics

The model's balanced performance across all evaluation metrics—including accuracy (99.69%), precision (99.65%), recall (99.70%), and F1-score (99.67%)—indicates that it is **not only precise but also sensitive** to all three tumor classes. The extremely low false negative rate is particularly crucial in medical applications, where missing a tumor diagnosis can have fatal consequences.

Moreover, the **high AUC-ROC score (0.998)** confirms the model's reliability in distinguishing between classes even under threshold variations, an important feature in decision-making systems that involve varying levels of confidence.

LIMITATIONS

While the results are promising, certain limitations of the study must be acknowledged:

- **Limited Dataset Size**: Despite achieving high accuracy, the dataset still represents a finite and controlled number of images. Real-world datasets may include more noise, artifacts.

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