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Dmytro Uhryn[1], Prof., DSc., **Oleksandr Dorenskyi**[2], Assoc. Prof., PhD tech. sci., **Oleksii Iliuk**[3], **Yuriy Ushenko**[1], Prof., DSc., **Shkidina Kateryna**[1]
[1]*Yuriy Fedkovych Chernivtsi National University, Chernivtsi, Ukraine,*
[2]*Central Ukrainian National Technical University, Kropyvnytskyi, Ukraine*
[3]*Temabit LLC, Kyiv, Ukraine*
e-mail: d.ugryn@chnu.edu.ua, dorenskyiop@kntu.kr.ua, olexiyilyukm@gmail.com, y.ushenko@chnu.edu.ua, shkidina.kateryna@chnu.edu.ua

Experimental Analysis of Deep Neural Networks for Automated Object Classification Using MRI Images

The article presents a system analysis and comparative study of the efficiency of modern deep neural networks for the task of automated brain tumor classification based on MRI images. Three architectures were used in the study ResNet50, DenseNet121, and EfficientNet-B0, which belong to the most widely adopted models in computer vision. The experimental part is based on a medical dataset that was preprocessed using standard augmentation and normalization methods. Quantitative results showed that ResNet50 achieved an accuracy of 92%, DenseNet121 reached 74%, and EfficientNet-B0 demonstrated the highest performance with an accuracy of 97%. Additional qualitative metrics supported these findings: the F1-score for EfficientNet-B0 reached 0.96, indicating a strong balance between precision and recall, while ResNet50 achieved an F1-score of 0.91, and DenseNet121 scored 0.73. Visualization of classification results showed that all models correctly identified the tumor class, but their confidence levels varied from 0.74 in DenseNet121 to 0.97 in EfficientNet-B0. The qualitative analysis confirmed the suitability of EfficientNet-B0 for cases where fast and accurate inference is prioritized under limited computational resources. Despite higher computational costs, ResNet50 can be effective in tasks that require robustness and maximum precision. The obtained results highlight the significant potential of deep learning models in medical diagnostics and the development of intelligent decision-support systems in neuroradiology.

AI, machine learning, convolutional neural networks, transfer learning, deep learning, image classification, medical diagnostics

Problem Statement. The field of computer science is rapidly evolving, driven by the swift advancement of information technologies. Among the many sectors into which IT is integrated, the healthcare sector, including medical diagnostics, undoubtedly stands out. Timely and accurate diagnosis of brain tumors is one of the key factors influencing treatment effectiveness and reducing mortality rates. As is well known, digital MRI images are analysed by medical professionals. This process involves a human factor, which can lead to errors, such as inaccuracies in tumour type identification. This issue can largely be addressed by IT solutions. Deep learning provides an opportunity to automate the classification of formations (tumours). However, there is a problem: the effectiveness of models depends on the quality of data preparation and the chosen neural network architecture. On the other hand, there are additional challenges: the data preprocessing process, which involves improving image quality, balancing the classes, and using augmentation techniques to stabilise the model; the limited amount of training data, and the uneven distribution of tumour types (which can complicate maintaining high accuracy, especially for rare tumour categories). Therefore, the choice of deep learning architecture requires balancing classification accuracy with computational efficiency. Additionally, model interpretability (the "black box" problem) must also be considered, which is particularly important in healthcare, where clinicians need to trust and explain the model's predictions.

From practice and numerous publications, including [2-5], a well-supported conclusion emerges: the focus of AI application in global healthcare is the process of diagnosing brain conditions using MRI images. Recent publications reveal a clear trend toward the use of deep learning, particularly CNN, which demonstrate high efficiency in tasks of multiclass tumor classification and segmentation. According to the systematic review by Kazerooni et al. (2021), CNN models, when combined with preprocessing and data augmentation, can achieve accuracy rates exceeding 95% in recognizing major types of brain tumors [1]. Similar findings are reported by Pei, Vidyaratne, and Iftekharuddin (2022), who emphasize that the most effective architectures for medical applications are ResNet, DenseNet, and EfficientNet, as they provide an optimal balance between accuracy and computational complexity [2, 3].

Practical studies also confirm the effectiveness of CNN in diagnostic applications. For example, Zhou et al. (2020) employed a multilevel CNN for the classification of three tumor types, however meningioma, glioma, and pituitary adenoma is a achieving an accuracy above 96% [4]. Shboul et al. (2021) demonstrated that even moderately deep models can successfully classify gliomas, offering a valuable support tool for radiologists [5].

Analysis of Recent Research and Publications. The digital transformation of processes in the healthcare sector is actively underway. This is evidenced by the results of numerous studies, including [11]. At the same time, cutting-edge information technologies are being actively integrated into medicine. At the same time, the results of the analysis of publications [2-5] demonstrate the relevance of using effective artificial intelligence technologies for the classification of brain objects (formations) based on digital MRI images. The scientific trends in this area involve the application of machine learning for tumor identification and segmentation [2, 3].

A key development in this field is the creation and analysis of large open datasets, with the international BraTS project being a prime example. In recent editions of this challenge, the focus has shifted from just segmentation to also include synthetic data generation and cross-institutional result comparison. This has significantly improved the reproducibility and reliability of models. These initiatives highlight the strong potential of open datasets for training and evaluating algorithms in medical diagnostics.

However, several reviews (Ranjbarzadeh, 2023) point out important challenges, such as the lack of labelled data, the high computational resources needed for training, and the absence of standardised evaluation protocols. Additionally, Wen (2021) stresses that when deploying AI algorithms in clinical practice, they must meet strict validation standards, as even minor diagnostic errors can have serious consequences for patients.

According to the findings of the study [1], ResNet, DenseNet, and EfficientNet show high effectiveness in the medical field. As mentioned earlier, these models offer high accuracy while maintaining good computational efficiency. However, for wider clinical use, further research is needed to improve how models generalise, utilise multicentre datasets, and integrate AI technologies into practical, user-friendly diagnostic systems.

Problem Definition. The aim of this study is to conduct an experimental analysis of the effectiveness of deep neural networks (ResNet, DenseNet, and EfficientNet) for the automated classification of brain tumour formations using MRI images. To achieve this goal, the following tasks must be addressed: 1) perform a comparative analysis of deep neural network architectures for brain tumour classification based on MRI images; 2) optimise deep learning models for deployment in environments with limited computational resources; 3) establish criteria for the medical application of deep learning models in brain tumour diagnostics; 4) carry out both quantitative and qualitative analysis of the effectiveness of deep neural networks in terms of inference speed and accuracy under computational constraints.

Main Results. Method for preparing brain tumor data based on MRI images.

Step 1. Identification and selection of characteristics. We will employ feature extraction methods for the automatic identification of characteristics, eliminating the need for manual feature engineering.

The study uses pre-trained CNN (DenseNet121, ResNet50, and EfficientNet-B0) in transfer learning mode.

1. ResNet (Residual Networks). The key idea behind ResNet is to use residual connections that overcome the problem of gradient vanishing in very deep networks. Formally, instead of training a direct mapping

$$H(x) \approx F(x), \tag{1}$$

ResNet trains the residual function:

$$H(x) = F(x) + x, \tag{2}$$

where x – entrance to the block, $F(x)$ – nonlinear transformation (convolution, normalization, ReLU), $H(x)$ – block output.

Thus, the model learns to construct only "deviations" from identity, which simplifies optimization. This allows training networks with hundreds or even thousands of layers without degrading accuracy.

2. DenseNet introduces dense connections (dense blocks), in which the output of each layer is used as input for all subsequent layers. Mathematically, it can be represented as:

$$x_l = H_l([x_0, x_{1,\dots,}x_{l-1}]), \tag{3}$$

where x_l – output l layer; $x_0, x_{1,\dots,}x_{l-1}$ – concatenation of all previous outputs; $H_l(\cdot)$ – composition of folding, normalization, and activation.

This mechanism:

- ensures reuse of features;
- reduces the number of parameters (because there is no need to duplicate filters);
- improves gradient propagation in deep networks.

3. EfficientNet-B0 optimizes architecture using compound scaling, which simultaneously takes into account three parameters: depth, width, and resolution of the input image.

Scaling formulas are characterized by:

$$d = \alpha^{\phi},\ \omega = \beta^{\phi},\ r = \gamma^{\phi}, \tag{4}$$

where d – depth (number of layers); ω – width (number of channels); r – resolution of input images; ϕ scaling factor, α, β, γ – parameters that determine proportions.

Thus, the model is scaled in a balanced manner, rather than in only one direction (e.g., depth only), which allows for high accuracy with a minimum number of parameters.

Neural networks perform automatic feature selection by optimizing filter weights W in the learning process. The convolution operation is formalized as:

$$y_{i,j,k} = \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{c=1}^{C} W_{m,n,c,k} \cdot x_{i+m,j+n,c}, \tag{5}$$

where x – input image, W – convolution kernel, $y_{i,j,k}$ – activation at position (i, j) in the k output channel.

During training weights W are configured to focus on the most informative characteristics of the image (e.g., tumor contours or textural features).

Step 2. Balancing classes. A class imbalance problem was detected in the dataset. To compensate for the imbalance, a class weighting method was applied in the loss function. Each class i assigned weight ω_i, inversely proportional to the number of samples N_i in this class:

$$\omega_i = \frac{N_{total}}{C \cdot N_i}, \quad (6)$$

where N_{total} total number of samples in the dataset, C – number of classes. Thus, smaller classes receive greater weight, which increases the penalty for misclassification of these classes.

These weights are then integrated into the CrossEntropyLoss function in PyTorch.:

$$L = -\sum_{i=1}^{C} \omega_i y_i log(\hat{y}_i), \quad (7)$$

where y_i – true class label (one–hot), and $\hat{y}_i$ – predicted probability for class i. Thanks to this approach, the model learns to account for class imbalance, which improves accuracy on underrepresented categories.

Step 3. Data cleansing and preparation.

Damaged or duplicate images can mislead the neural network and reduce the model's ability to generalize. To address this issue, damaged files and duplicates were identified and removed during the data preparation stage. Duplicates were identified by calculating MD5 hashes:

$$MD5(I_i) = MD5(I_j) \Rightarrow I_i = I_j \quad (8)$$

where I_i, I_j – two images, and the MD5(·) hash function. Removing duplicates and damaged samples makes the loss function more representative for training:

$$L = \frac{1}{N}\sum_{i=1}^{N} l(\hat{y}_i, y_i), \quad (9)$$

where $l(\cdot)$ – local loss function CrossEntropy, and $\hat{y}_i$ – model prediction for an image I_i.

To standardize the size, all images are converted to a standard format of 224×224 pixels, which ensures compatibility with pre-trained models and correct operation of convolutional layers:

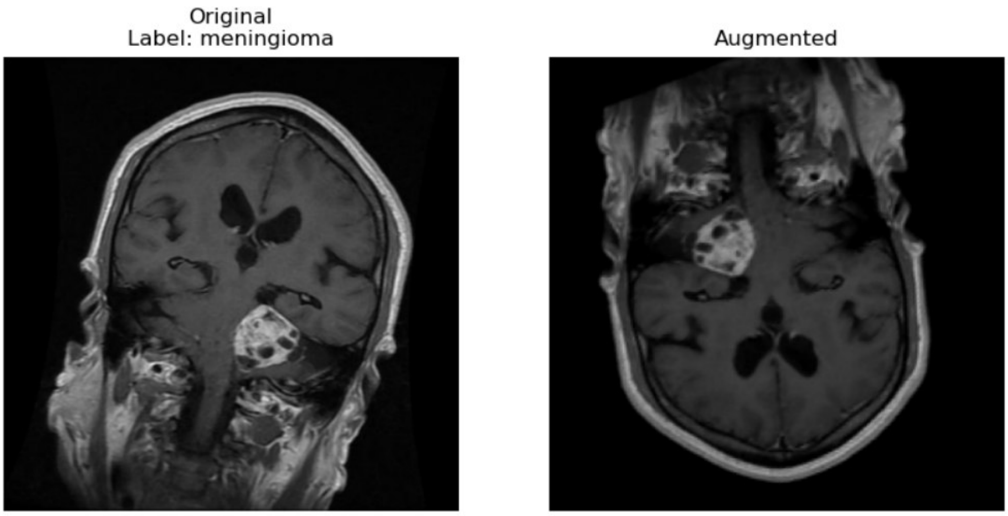

Figure 1 – Visualization of images before and after augmentation

Source: developed by the authors

The graphs (Fig. 2) show the results of training the DenseNet121 model for 105 epochs, reflecting the dynamics of Loss and Accuracy on the training and validation samples. The model demonstrated a stable training process with no signs of overfitting: accuracy on the validation set reached about 86%, losses gradually decreased, and the differences between the Train and Val metrics can be explained by the use of augmentations (in particular, the addition of noise to the training data). This indicates the model's ability to generalize information well and work effectively with new images.

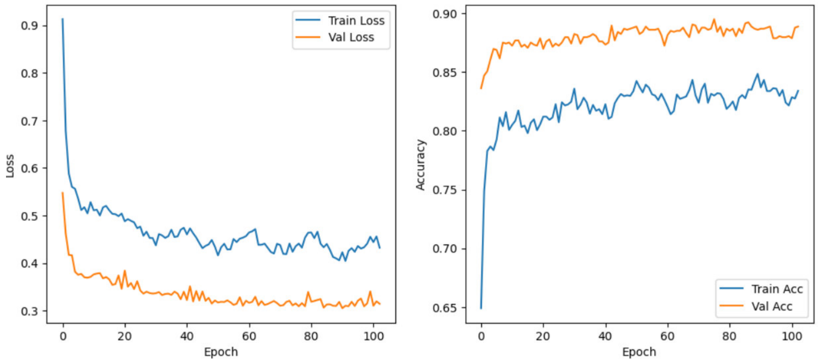

Figure 2 – The DenseNet121 training process

Source: developed by the authors

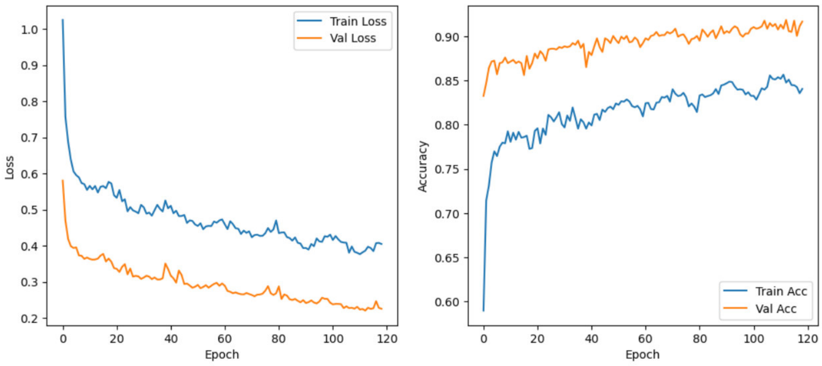

Figure 3 – The ResNet50 training process

Source: developed by the authors

The graph below (Fig. 3) shows the results of training the ResNet50 model over 120 epochs. The model demonstrated high efficiency, maintaining a balance between training and validation metrics, with no signs of overfitting, and achieved over 91% accuracy on the validation sample. Figure 4 shows the training curve of the EfficientNet-B0 model over 89 epochs. Due to the lack of improvement over the last 15 epochs, the early stopping mechanism was activated.

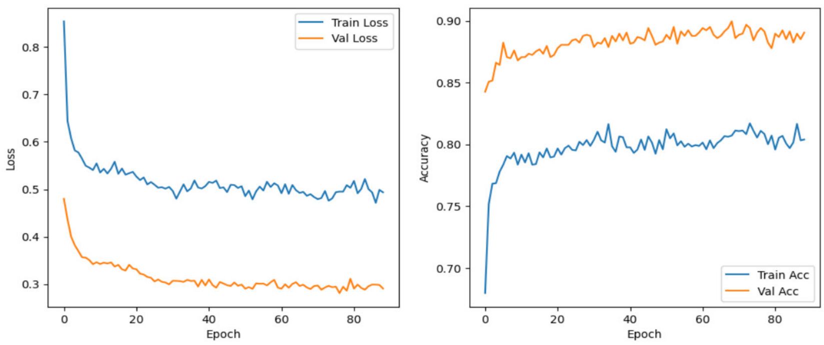

Figure 4 – The EfficientNet-B0 training process

Source: developed by the authors

As a result, the ResNet model showed the most stable and balanced results, but all three architectures proved to be suitable for solving the task of brain tumor classification. In the task of classifying brain tumors using MRI images, the ResNet50 model showed the best results. It achieved 90% accuracy, the highest F1-metrics values, and AUC-ROC = 0.9863. ResNet50 classified the pituitary and no tumor classes particularly well, providing high precision and recall rates.

Conclusions. The article presents a system analysis and an experimental study of the effectiveness of three deep learning architectures - ResNet50, DenseNet121, and EfficientNet-B0 - for the task of brain tumor classification based on MRI images:

1. Proved to be the most accurate and robust model: achieved the highest accuracy (90–91%), demonstrated the best F1-score and AUC-ROC values (0.9863), showed the highest resistance to noise and image artifacts. In addition, Grad-CAM visualizations revealed that ResNet50 most precisely highlights relevant image regions, which enhances interpretability and true in the results.
2. EfficientNet-B0 achieved slightly lower accuracy but demonstrated balanced recall across all classes and significantly lower computational requirements. This result indicates that EfficientNet-B0 is optimal for situations where hardware limitations and inference speed are critically important factors.
3. As shown in the Main Results, the experimental study of DenseNet121 revealed that recall scores for the glioma and meningioma classes are lower, however, the model performs effectively in classifying the absence of tumors and primary cases. This result holds practical value. However, this architecture showed the highest sensitivity to noise and less informative Grad-CAM visualizations, reducing its practical diagnostic value.
4. From a system analysis perspective, recall should be considered the primary criterion for medical applications, as missing a pathology is critically undesirable. According to this metric, ResNet50 and EfficientNet-B0 demonstrated the most balanced and practically significant performance.

Thus, the conducted research confirms the high efficiency of deep neural networks in brain tumor classification. ResNet50 can be considered the most promising model for clinical practice, while EfficientNet-B0 is recommended for deployment in environments with limited computational resources.

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Д. І. Угрин[1], проф., д-р техн. наук, **О. П. Доренський**[2], доц., канд. техн. наук,
О. Д. Іл'юк[3], **Ю. О. Ушенко**[1], проф., д-р фіз.-мат. наук, **К. С. Шкідіна**[1]
[1]*Чернівецький національний університет імені Юрія Федьковича, м. Чернівці, Україна*
[2]*Центральноукраїнський національний технічний університет, м. Кропивницький, Україна*
[3]*ТОВ «Темабіт», м. Київ, Україна*

Експериментальний аналіз ефективності глибоких нейронних мереж для автоматизованої класифікації об'єктів за зображеннями МРТ

У праці представлено результати системного аналізу та порівняльного дослідження ефективності сучасних глибоких нейронних мереж ResNet50, DenseNet121 та EfficientNet-B0 для задачі автоматизованої класифікації пухлин головного мозку за цифровими зображеннями МРТ. Експериментальна частина ґрунтується на медичному наборі даних, попередньо підданому стандартним методам аугментації та нормалізації. Кількісні результати показали, що ResNet50 досягла точності 92%, DenseNet121 – 74%, а EfficientNet-B0 продемонструвала найвищий результат із точністю 97%. Додаткові якісні метрики підтвердили отримані висновки: показник F1-міри для EfficientNet-B0 склав 0,96, що свідчить про баланс між точністю та повнотою, тоді як ResNet50 забезпечила F1-міру на рівні 0,91, а DenseNet121 – 0,73. Візуалізація результатів класифікації продемонструвала, що всі моделі правильно визначають клас пухлини, проте рівень впевненості відрізняється: від 0,74 у DenseNet121 до 0,97 у EfficientNet-B0. Якісний аналіз підтвердив доцільність застосування EfficientNet-B0 у випадках, де пріоритетом є швидка та точна інференція за обмежених обчислювальних ресурсів. ResNet50, попри вищі обчислювальні витрати, може бути ефективною для задач, де потрібна стійкість і максимальна точність. Отримані результати свідчать про значний потенціал використання глибоких моделей у медичній діагностиці та створенні інтелектуальних систем підтримки прийняття рішень у нейрорадіології.

ШІ, машинне навчання, згорткові нейронні мережі, переносне навчання, глибоке навчання, класифікація зображень, медична діагностика

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