African Journal of Advanced Pure and Applied Sciences (AJAPAS)

Online ISSN: 2957-644X

Volume 3, Issue 3, 2024, Page No: 603-613

Website: *https://aaasjournals.com/index.php/ajapas/index*

معامل التأثير العربي 2023: (1.55) SJIFactor 2023: 5.689 ISI 2022-2023: 0.557

Special issue: First Libyan Conference on Technology and Innovation (LCTI-2024), Benghazi, Libya

Brain Tumor Classification Using EfficientNet-B1: A Deep Learning Approach

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تصنيف أورام الدماغ باستخدام EfficientNetB1: نهج التعلم العميق

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Received: March 01, 2024	Accepted: May 05, 2024	Published: May 30, 2024

Abstract

Tumors in the brain are the most common cause of death, and detection at an early stage is very important for treatment and better patient outcomes. Lacking a clear primary cause still makes the correct diagnosis of brain tumors very important to lower the high death rate of these tumors. This study focuses on the classification of three common types of brain tumors: meningioma, pituitary, and glioma. Applying deep learning capabilities of pre-trained convolutional neural networks (CNNs) will help in feature extraction and classification of brain tumors. This work employs EfficientNet-B1 as an advanced pre-trained CNN to achieve brain tumor classification accuracy of 100%. Our findings show that deep learning algorithms could be the tool that ensures the accuracy of brain tumor diagnosis to allow early intervention and decrease mortality.

Keywords: Brain tumour,EfficientNet-B1,MRI Images,CNN,Transfer learning.

الملخص

تعد اورام الدماغ السبب الأكثر شيوعًا في الوفيات، والكشف عنها في مراحل مبكرة أمر مهم جدًا للعلاج وتحسين نتائج المرضى. عدم وجود سبب رئيسي واضح للمرض يجعل التشخيص الصحيح للأورام الدماغية أمرًا مهمًا لتقليل معدل الوفيات العالي. يركز هذا البحث على تصنيف ثلاثة أنواع شائعة من الأورام الدماغية: الورم اللويحي، وورم النخامية، والجليوما. تساعد قدرات التعلم العميق للشبكات العصبية التلافيفية المسبقة التدريب (CNNs) على استخراج السمات وتصنيف الأورام الدماغية. في هذه الورقة تم استخدام الشبكة التلافيفية المسبقة التدريب المتقدمة EfficientNet-B1 لتحقيق دقة عالية لتصنيف الأورام الدماغية بنسبة 100٪. حيث تظهر نتائجنا أن خوارزميات التعلم العميق يمكن أن تكون الأداة التي تضمن دقة تشخيص الأورام الدماغية للسماح بالكشف المبكر للمرض وتقليل معدل الوفيات.

الكلمات المفتاحية: أورام الدماغ، التعلم العميق، الصور الأشعاعية، الشبكات العصبية التلافيفية.

Introduction

Brain tumors are currently the leading cause of cancer-induced mortality, globally, with over 200 000 new cases diagnosed per year [1]. Precise and timely brain tumors diagnosis is an important factor for further treatment and to increase survival rate in patients. Magnetic Resonance Imaging (MRI) is vital diagnostic tool that has got wide acceptance for brain tumor detection and classification because of its non-invasive nature and high spatial resolution. Nonetheless, the tedious manual interpretation of MRI images by radiologists can be affected by subjectivity and errors.

In the past years, it has been discovered that methods that use deep learning applications are quite effective in the brain tumor classification field, where the choice is to use MRI scans for this classification. Thin Convolutional Neural Networks (CNNs) show high effectiveness in this case because they learn hierarchic patterns of image elements characteristics. On the other hand, the CNNs performance is strongly connected to the architecture choice and the training can be computationally demanding.

EfficientNet, a family of CNN architectures proposed by Tan and Le [2], is capable of getting the best possible result on different image recognition tasks such as ImageNet dataset. EfficientNet implements the compound scaling method in its architecture that simultaneously optimizes depth, width, and resolution of the network to improve the accuracy but also maintain efficiency. More specifically, the EfficientNet-B1 model is shown to bring a good balance of accuracy with low computing load, and hence is a good option for apps with limited resource.

In this paper we are investigating the implementation of EfficientNet-B1 using MRI scans for classification of brain tumors. We propose the new model based on the strengths of EfficientNet-B1 for the classification of brain tumors into subgroups, such as gliomas, meningiomas and pituitary tumors. Our approach is assessed with a large MRI images dataset, which proves the efficiency of EfficientNet-B1 to get high accuracies and robustness in brain tumor classification.

Literature Review

Among the various methods for brain tumor classification is the proposed method by Ranjbarzadeh et al. (2021) [3] which uses an ensemble of deep features and machine learning classifiers. The study found that the deep feature combination helped to significantly increase performance with SVM showing the remarkable performance mainly for large datasets. As Kang et al (2021) [4] also did, they evaluated their method alongside the classical methods while having a tumor classification accuracy of 97.3%. These results indicate that the use of ensembles of deep features along with machine learning algorithms can be very useful for the analysis of brain tumors

Raza et al. (2022) [5] proposed a hybrid deep learning-based approach that is able to classify brain tumors with a remarkable accuracy of 99.25% using a dataset including 25,000 brain MR images. It may seem that there is no concrete information given, but the study's conclusion emphasizes the ability of a hybrid deep learning model to carry out correct and efficient brain tumor classifications.

An analogical situation was also found where Chattopadhyay and Maitra (2022)[6] implemented a transfer-learned model to have a high accuracy for classifying brain tumors. The model reached the level of accuracy of 95.75% for the same machine dataset and reached the level of 96.89% for the unseen MRI dataset. This can be treated as evidence of deep learning approach reliability and generalization in the classification of brain tumors.

Mahmud et al. (2023) [7] applied a seven-layer deep CNN models for brain tumor classification in MR images and the top performing CNN model attained 97.12% accuracy average score. This result demonstrates that CNN models are promising in classifying MRIs into brain tumors with great precision. Similarly, the studies of Gómez-Guzmán et al. (2023) [8] and Kurdi et al. (2023) [9] were directed at the application of convolutional neural networks for the detection of brain tumors based on magnetic resonance imaging, once again demonstrating the high efficiency of deep learning procedures in this field.

Saeedi et al. (2023) [10] suggested a Multilayer Perceptron ensemble model with weighted average as the core mechanism of deep learning for the detection of brain tumors using MRI images. This framework resulted in better accuracy, precision and F1-score than any individual system and is considered the most victorious. Alongside, Anand, et al. (2023) [11] developed a new deep learning method transfer learning and obtain outstanding accuracy results for classification of brain tumors. On the other hand, with the use of a proposed convolutional neural network (CNN) architecture by Talukder et al (2023) [12], the tumor distinction in MR brain images became more proficient having an accuracy of 93.3% and an AUC of 98.43%. These statistical observations total show the feasibility of these models in correctly identifying brain cancers from MRI scans.

Mohanty et al. (2024) [13] has been introduced a new BTC-SAGAN-CHA-MRI model that has demonstrated better performance than others mods BTC-KNN-SVM-MRI, BTC-CNN-DEMFOA-MRI, BTC-Hie DNN-MRI. The presented method was with 18.29%, 14.09%, and 7.34% higher accuracy and 67.92%, 54.04%, and 59.08% reduced computation time, so its success in improving both precision as well as computation time.

Besides, the QTbMPA (Mohanty et al., 2024) is another classifier with this feature-selection design that combines the highest-rated features and uses them to classify tumors via a serial-based approach. Concrete this point points to feature importance and fusion which in turn promote the performance of the classifier model.

S et al. (2024) [14] proposed an attention based cosmopolitan analog network optimized with the color harmony algorithm for brain tumor classification. Unlike in an ordinary class where findings were presented, the usage of self-attention as well as generative adversarial networks hints at the introduction of innovative techniques to enhance classification accuracy and reliability.

Furthermore, Nogay and Adeli (2024) [15] and Ullah et al. (2024) [16] came out with their own models for brain tumor classification using deep learning tools. Nogay and Adeli (2024) succeeded to attain high accuracy of 99.80 %; sensitivity rate of 99.83 %; and specificity of 17% by being used for testing a modified version of the dataset on Figshare. However, Ullah et al. (2024) presented a hybrid deep learning model, which was assisted by Bayesian optimization and an algorithm, inspired by the nature of marine predators, which enriched the field even more.

EfficientNet Family

The computer vision area have been the subject for significant progress marked by the rise of powerful deep learning architectures. Among these structures, the family members of EfficientNet, which was introduced by Tan and Le [2], attracted the greatest attention, as they demonstrated a very high performance and computational efficiency.

The EfficientNet family of models is based on a new architecture of convolutional neural networks (CNN) for visual recognition tasks and is acknowledged as a game-changer in this area. EfficiencNet primary mission is to offer higher accuracy level and keep computational efficiency. The scalable model designs are produced using a novel particular compound scaling approach which allows for an even scaling of the network depth, width, and also resolution. Thus, the new approach gives the output in the form of a balanced and efficient network [2].

The family includes eight models, beginning with EfficientNet-B0, which has lower complexity but equal accuracy, and ending with EfficientNet-B7, which is the most precise and has higher complexity. In these architectures, the neural networks are proved to be the best in performance among different datasets like ImageNet [17], CIFAR-100 [18], and COCO [19]. They achieved higher accuracy and efficiency than the previous models such as ResNet [20] and MobileNet [21] on benchmark datasets.

EfficientNets models comprehend the accuracy issue and at the same time save tremendously on computer resources which is the main advantage offered by the compound scaling optimization technique [2]. In addition, the expansion of the compound scaling approach allows for the development of a variety of models with different sizes and complexity levels. Thus, the user can select the best one for his particular needs. As its name suggests, EfficientNet has well demonstrated transfer learning where top-performing pre-trained ones achieve great results upon fine-tuning on downstream applications over the subjects such as medical image analysis [22] and remote sensing.

Through investigation of EfficientNet-B1 architecture, main characteristics, and its behavior in the transfer learning settings - the EfficientNet family model, is the central theme of this paper.

EfficientNet-B1 Architecture and Key Design Features

EfficientNet-B1 is a model of the EfficientNet series, with the main goal to avoid compromising both accuracy and computational cost. Figure 1 (EfficientNet-B1 Model Architecture) portrays the basic skeleton of our EfficientNet-B1 model.

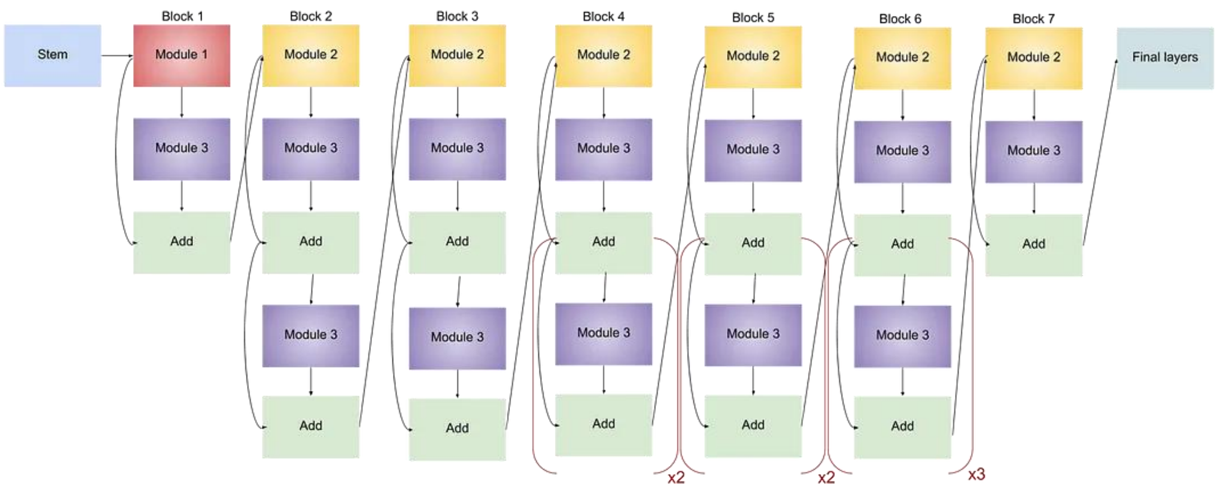

Figure 1: Architecture for EfficientNet-B1

It incorporates the fundamental design principles established in the EfficientNet architecture:

A. MBConv Blocks
The EfficientNet-B1 is equipped with a convolution block version known as MBConv, they are a modified version of the blocks used in the Convolution inverted residual blocks in MobileNetV2 [21]. MBConv blocks include several operations applied in succession: depthwise convolutions, pointwise convolutions, and squeeze-excitation [SE] blocks [23]. These blocks, through capturing spatial information and reducing the algorithm complexity as well, proved to be really effective [2].

B. Compound Scaling
The compound scaling used in the creation of EfficientNet-B1 is one of the most eminent features. Scale parameterization generally computes the same level of depth, width, and resolution of the filter based on the given scaling parameters. This strategy gives an opportunity for the creation of family of models which feature different dimensions of size and amount of complexity. This way it will be easier for practitioners to pick the most helpful model for their specific needs [2].

C. Swish Activation Function
EfficientNet-B1 substitutes the Swish activation function for ReLU which is a better-known tool in activation activation. Swish is a converged, non-monotonous function which is one of the well-known techniques that has increased the accuracy of deep learning models. It helps vanishing gradient problem disappears and also promotes information moving through the network [2].

D. Pretty, sightly, and high quality.
In the case of EfficientNet-B1, these elements are equally and careful balanced to create the most efficient system. The depth is the number of the network layers, the width stands for the number of channels in each of the layers, whereas the resolution corresponds to the dimension of the input image. Technique for compound scaling makes sure that these dimensions are scaled in a systematic way and principal manner with the purpose to lessen network complexity while increase accuracy/efficiency at the same time [2].

E. Squeeze-and-Excitation (SE) Blocks
In addition to dense connections in the MobileNetV2 architecture, EfficientNet-B1 features SE blocks [23] responsible for stronger modeling of the relationships between channels instead of relying on implicit assumptions about them. SE blocks typically involve a squeeze step, where global information across all channels is collected, and an excitation step, which provides channel-specific parameter vector based on information derived from the moments of the channel feature responses. e.g. adding of SE block provides rich features detecting and less features suppressing functionality of network [2].

F. Inverted Residual Blocks
The inverted residual blocks that appear in the MobileNetV2 [21] are one of the main building blocks of EfficientNet-B1. These blocks are different from the residual blocks by using pointwise convolutions to expand the number of filters and then applying depthwise convolutions. The reduction in computational expense here is achieved because the number of parameters and computations are reduced. EfficientNet-B1 is designed to obtain this balance with the help of inverted residual blocks [2].

EfficientNet-B1 with Transfer Learning
Transfer learning as a strong technique is considered for the former reason where pre-trained models can be reused for new tasks after supplying only small amount of training data. Transfer learning performance in EfficientNet-B1 has apparently revealed top class performance in domains like natural language processing, computer vision, etc.

In terms of its utilization in medical image analysis, notably, it was shown to be efficient and effective for tasks such as skin lesion classification [22], retinal disease detection [24], brain tumor segmentation [25], etc. Through the fine-tune of the EfficientNet-B1 pre-trained models using medical data, the researchers obtained outstanding results for the same time requirement and the quantity of data mined.

Also, just as it has been proven to be the best choice in remote sensing missions like land cover classification,object detection [26] and change detection[27], EfficientNet-B1 has shown up as the best network. Given EfficientNet-B1’s capability to pinpoint tiny details and features of high resolution imagery from space, this model is widely accepted in the remote sensing realm.

The success of EfficientNet models can be the result of their specifically configured architecture and the fact the technique of compound scaling has been proven to be feasible. Through its ability to utilize the learned, transportable features from the large-scale image dataset, ImageNet [17], the proposed model can adapt to new tasks with very little fine-tuning needed.

Materials and Methods

The Dataset:

This study leveraged a dataset sourced from Kaggle, which stands as a testament to its transparency and potential for broad applicability due to its public accessibility via the Kaggle platform under the title "Brain Tumor MRI Dataset." With a total of 3285 instances designated for training and 389 for testing, the dataset encompasses a wide spectrum of MRI scans. Notably, the training set comprises 926 instances of glioma tumors, 1077 instances of meningioma tumors, 901 instances of pituitary tumors, and 501 instances depicting no discernible tumors on the MRI scans. Conversely, the testing set contains 100 instances of pituitary tumors, 115 instances of glioma tumors, 74 instances of meningioma tumors, and 105 instances without any detectable tumors. The dataset is structured into four distinct classes: glioma_tumor, meningioma_tumor, pituitary_tumor, and no_tumor. Figure 2 shown a selection of images from the dataset.

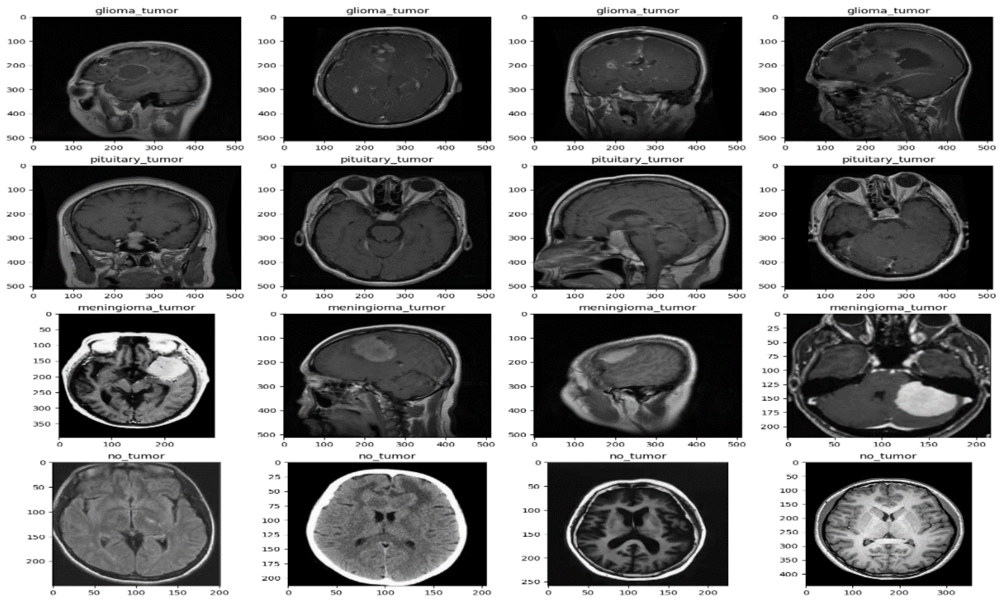

Figure 2: A selection of images from the dataset.

Method

Our method starts with the pre-processing of brain MRI scans by cutting out the useless darkness area surrounding the images. This effect is reached by leaving only the area of interest in the crop of images. Next, images are converted into grayscale and blurred using the 2D Gaussian filter for noise reduction purposes. A binary thresholding is applied to segment the images, and then there are steps of erosion and dilation to achieve a cleaner foreground object.

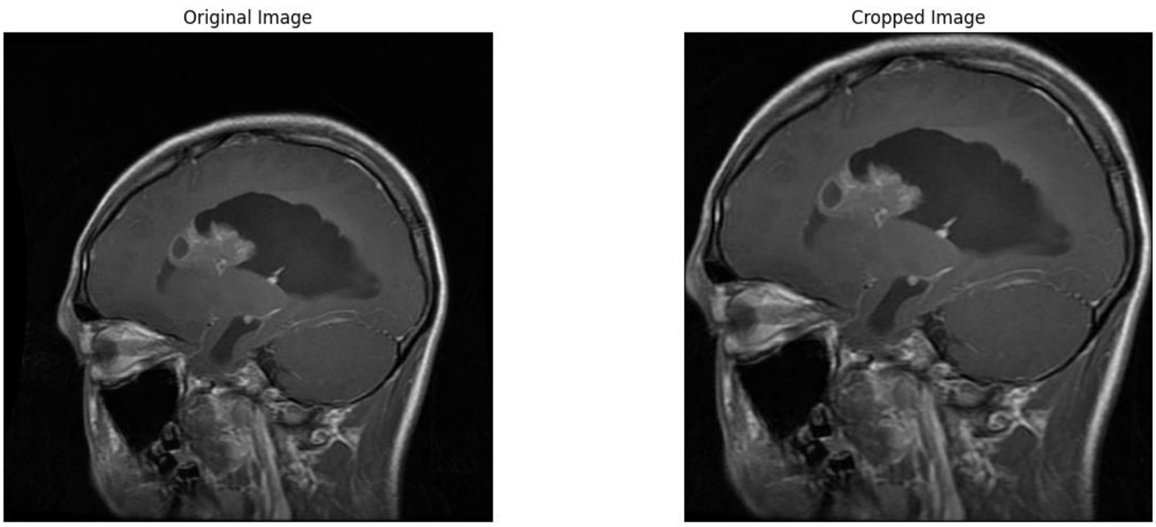

Figure 3: Pre-processed image example.

Contour detection comes afterwards, helping to outline the brain area in every picture. The circuit is made by copying the thresholded image and retaining only the external contours of the circuit. The contour approximation mode facilitates simplified representation of the contour and only the end points of the contour are left.

The largest contour is selected, that is, the one of maximum area, and its extreme points (left, right, top, and bottom) are used to obtain the cropping region. An image is produced, which is selected, and if the visualization is required the resulting image is shown. This preprocessor pipeline is done to all 3,285 images in both the training and test database and they are saved in different folders for further processing.

To enrich the training process of our deep neural network, we employ image augmentation techniques to artificially create training images by means of various processing methods, e.g. randomly rotating, shifting, shear, and flipping. By means of this method, the model is becoming more capable of generalizing which is achieved through exposing the model to various types of the images that in turn help to decrease overfitting.

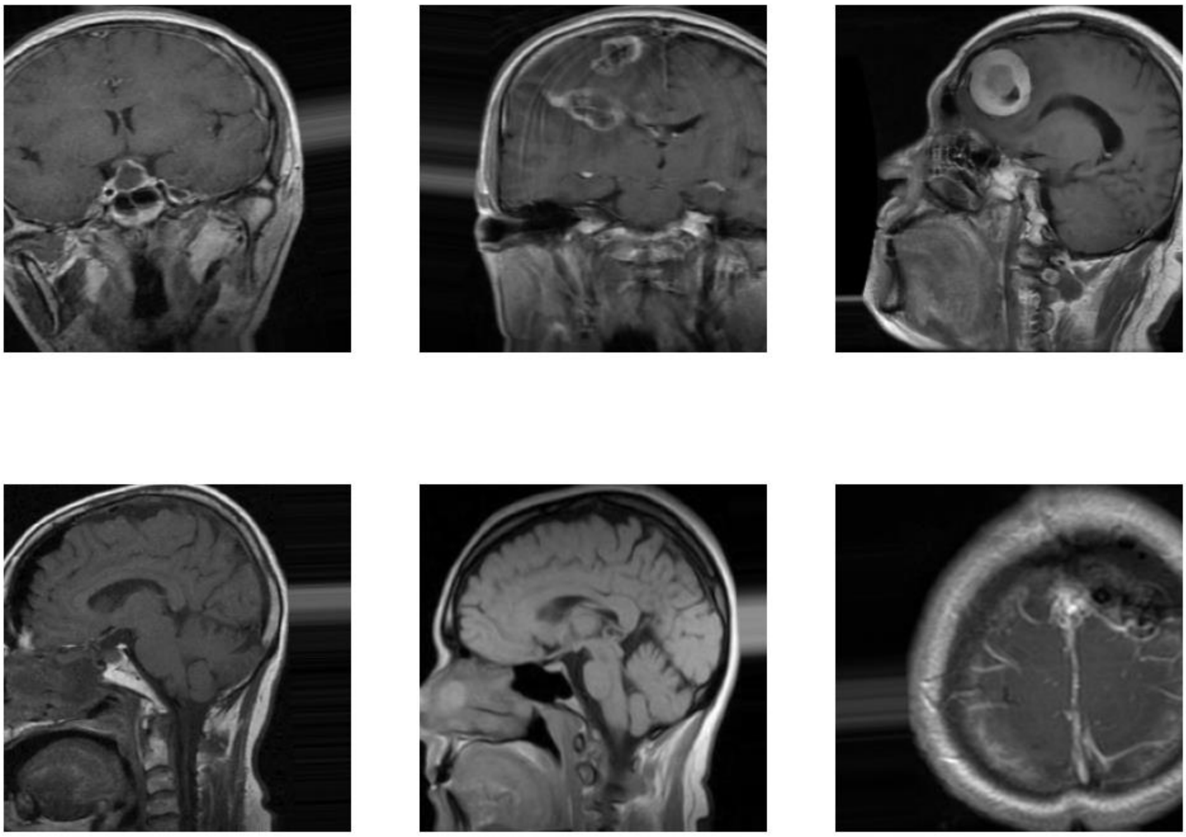

Figure 4: Examples of image augmentation techniques.

To enrich the training process of our deep neural network, we employ some techniques to artificially create training images by means of various processing methods, e.g. randomly rotating, shifting, shear, and flipping. By means of this method, the model is becoming more capable of generalizing which is achieved through exposing the model to various types of the images that in turn help to decrease overfitting.

To smoothen the process of training, we have a data labeller which can automatically label of any datasets stored in each class folder. Data cleanup is therefore the initial step towards network training.

For the training, we state augmentation parameters' values such as rotation range, height shift range and horizontal shift. Secondly, the data is divided into training and validation sets, where 80% is dedicated to training and the rest 20% serves for validation. Thus, all the images are trained purposefully and a goal size of 240x240 pixels for their resizing. The mode of ancillary variables is set to categorical, since it is a problem of multi-class classification.

As for the testing phase, we do not apply any modification to the original generator which does not utilize augmentation because only raw data are available in real scenarios. We put shuffle flag to False to save the order of test data unchanged, so we don't have to modify the model's performance during the evaluation.

We presume a pre-trained EfficientNet-B1 initial model, utilizing ImageNet weights (roughly 14 million labeled high-resolution images from 20000 classes). Through this we can convert the knowledge from the pre-training process into the one that is useful to our training model.

To initiate the transfer learning, we use the `include_top` parameter set to `False` which is defined at the EfficientNet-B1 model we exclude the top layers. The replacement of the concept of the final dense layer with custom layers has been made possible through this step and this allowed us to use the EfficientNet as a feature extractor.

The input shape is declared for (240, 240). Later on, there is a stage where we add custom layers (Global Average Pooling 2D layer, Dropout Layer, and Dense layer with Softmax Activation Function) to the EfficientNet-B1 model that was established earlier to suit multi-class classification tasks. Consequently, the model has a total of about 6.5 million parameters.

The model is compiled using the Adam optimizer, the categorical cross-entropy loss function, and accuracy as the evaluation function. Besides, to avoid overfitting and enhance convergence, we apply a checkpoint paradigm, alongside ReduceLROnPlateau and EarlyStopping regularization methods, with the patience level of 5 epochs.

The model is trained for 30 epochs with the training data loaded into a history variable that gets used later in the model. The model is validated on using the validation data.

Results

The proposed model was evaluated on a brain MRI dataset, where the task was to classify the tumor into four classes: pituitary, glioma, meningioma, and no-tumor. Figure 5 illustrates the training and validation performance of the model.

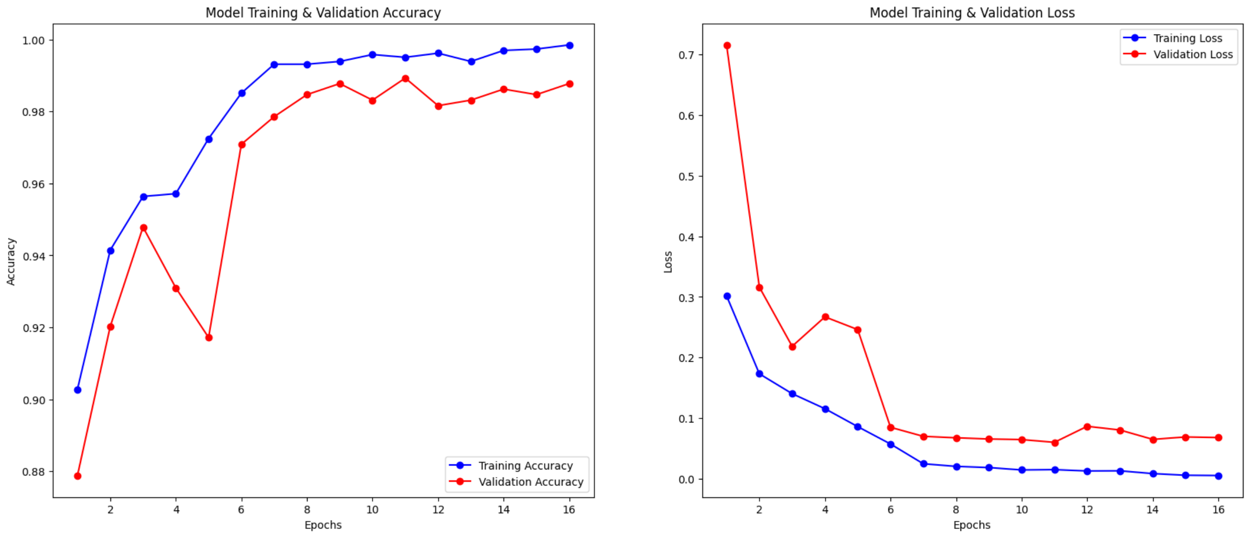

Figure 5: Training and validation performance of the model.

The training curve and validation curve can be observed to move closely together indicating that our model did not suffer from overfitting.

To evaluate the model's performance, a confusion matrix was constructed and shown in Figure 6, which summarizes the results of the classification into four outcomes: True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN).

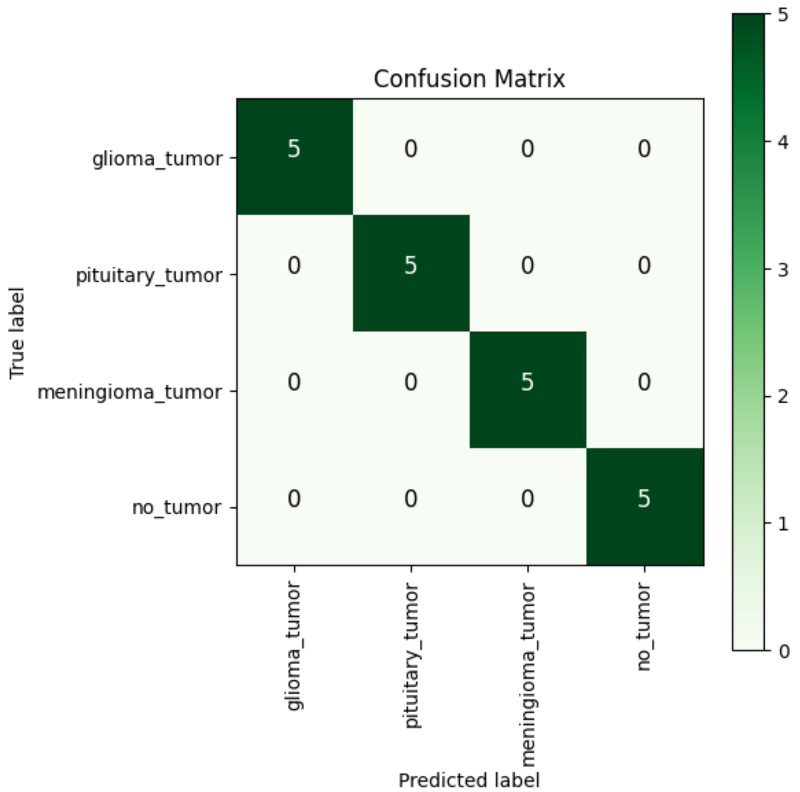

Figure 6: confusion matrix.

The classification report shown in Figure 7 indicating its effectiveness in accurately classifying.

```
[ ]  #get classification report
     print(classification_report(y_test, yhat_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         5
           1       1.00      1.00      1.00         5
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00         5

    accuracy                           1.00        20
   macro avg       1.00      1.00      1.00        20
weighted avg       1.00      1.00      1.00        20
```

Figure 7: Classification report.

The model's prediction of Magnetic Resonance Image scans is depicted in Figure 8

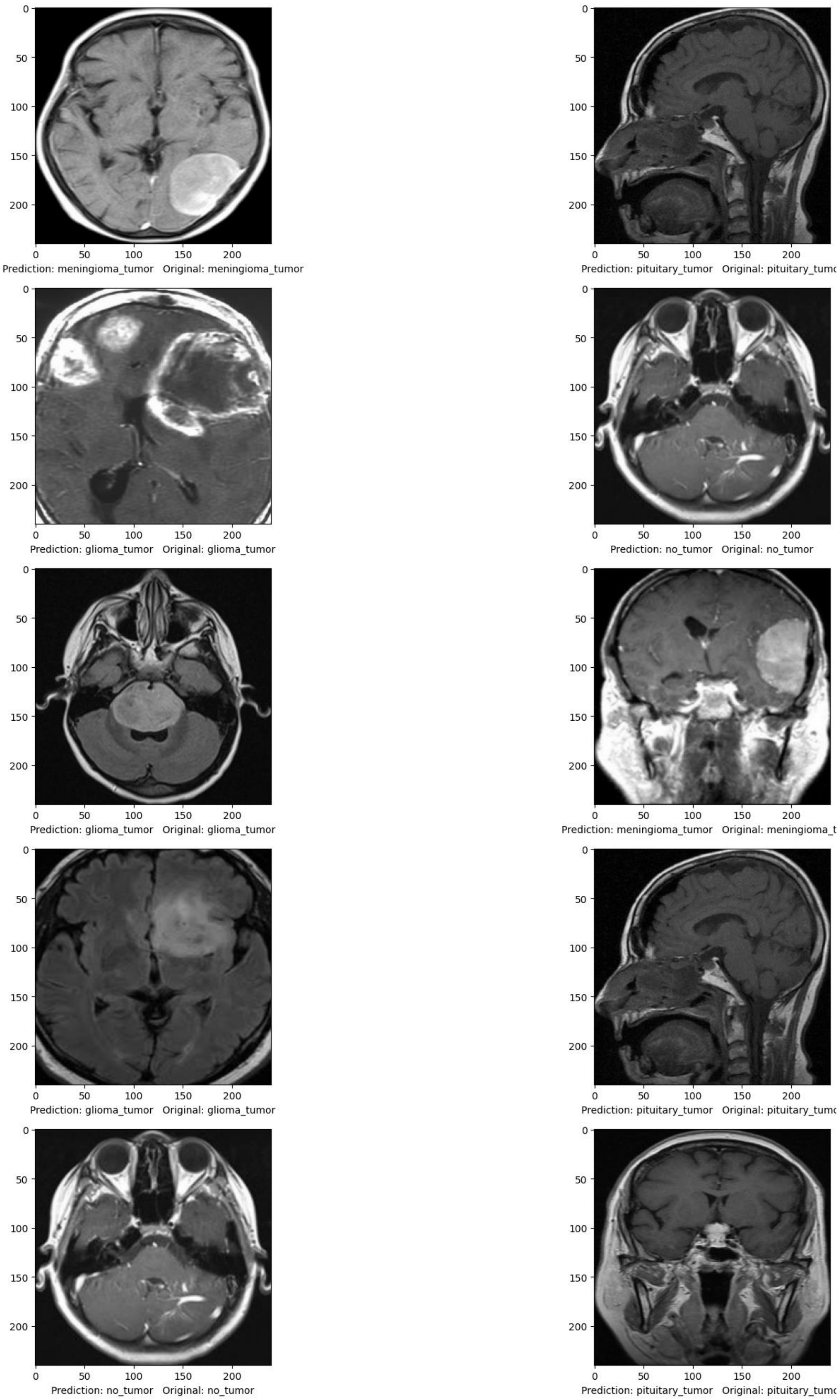

Figure 8: The model's prediction.

Conclusion

In the past decade, the medical imaging technologies have developed significantly, so they are a vital part of the diagnosis and treatment processes today. Neurosurgeons and Radiologists can apply it to the early detection of brain tumors, thus increasing the chances for the patient's recovery post-treatment. In this study, EfficientNet-B1 is recommended which is less complex and more accurate which is an already trained DL model. The aim of this study is to see how precisely the tumours could be classified into glioma, meningioma, pituitary tumours, or no tumour at all. This strategy used transfer learning and therefore had 100% accuracy in training and 100% accuracy in testing. Overall, the above set of results suggest that the model has performed excellent contour detection and brain area classification, and can be regarded as an accurate and reliable model for this purpose.

Reference

[1] Ostrom, Q. T., et al. (2020). CBTRUS statistical report: Primary brain and other central nervous system tumors diagnosed in the United States in 2013-2017. Neuro-Oncology, 22(12), 1751-1763.

[2] M. Tan and Q. V. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," arXiv:1905.11946 [cs], Sep. 2020, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1905.11946

[3] Ranjbarzadeh, R.., Kasgari, Abbas Bagherian., Ghoushchi, Saeid Jafarzadeh., Anari, Shokofeh., Naseri, Maryam., & Bendechache, Malika. (2021). Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Scientific Reports , 11 . http://doi.org/10.1038/s41598-021-90428-8

[4] Kang, Jaeyong., Ullah, Z.., & Gwak, Jeonghwan. (2021). MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers. Sensors (Basel, Switzerland) , 21 . http://doi.org/10.3390/s21062222

[5] Raza, Asaf., Ayub, Huma., Khan, J.., Ahmad, Ijaz., Salama, Ahmed S.., Daradkeh, Y.., Javeed, D.., Rehman, Ateeq Ur., & Hamam, Habib. (2022). A Hybrid Deep Learning-Based Approach for Brain Tumor Classification. Electronics . http://doi.org/10.3390/electronics11071146

[6] Chattopadhyay, Arkapravo., & Maitra, Mausumi. (2022). MRI-based Brain Tumor Image Detection Using CNN based Deep Learning Method. Neuroscience Informatics . http://doi.org/10.1016/j.neuri.2022.100060

[7] Mahmud, Md Ishtyaq., Mamun, M.., & Abdelgawad, A.. (2023). A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks. Algorithms , 16 , 176 . http://doi.org/10.3390/a16040176

[8] Gómez-Guzmán, Marco Antonio., Jiménez-Beristáin, Laura., García-Guerrero, E. E.., López-Bonilla, O.., Tamayo-Pérez, U. J.., Esqueda-Elizondo, J. J.., Palomino-Vizcaino, Kenia., & Inzunza-González, E.. (2023). Classifying Brain Tumors on Magnetic Resonance Imaging by Using Convolutional Neural Networks. Electronics . http://doi.org/10.3390/electronics12040955

[9] Kurdi, Sarah Zuhair., Ali, M. H.., Jaber, Mustafa Musa., Saba, T.., Rehman, A.., & Damaševičius, R.. (2023). Brain Tumor Classification Using Meta-Heuristic Optimized Convolutional Neural Networks. Journal of Personalized Medicine , 13 . http://doi.org/10.3390/jpm13020181

[10] Saeedi, Soheila., Rezayi, S.., Keshavarz, Hamidreza., & Kalhori, Sharareh R. Niakan. (2023). MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. BMC Medical Informatics and Decision Making , 23 . http://doi.org/10.1186/s12911-023-02114-6

[11] Anand, Vatsala., Gupta, Sheifali., Gupta, Deepali., Gulzar, Yonis., Xin, Qin., Juneja, Sapna., Shah, Asadullah., & Shaikh, A.. (2023). Weighted Average Ensemble Deep Learning Model for Stratification of Brain Tumor in MRI Images. Diagnostics , 13 . http://doi.org/10.3390/diagnostics13071320

[12] Talukder, Md. Alamin., Islam, Md. Manowarul., Uddin, Md. Ashraf., Akhter, Arnisha., Pramanik, Md. Alamgir Jalil., Aryal, Sunil., Almoyad, Muhammad Ali Abdulllah., Hasan, Khondokar Fida., & Moni, M.. (2023). An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning. Expert Syst. Appl. , 230 , 120534 . http://doi.org/10.48550/arXiv.2305.12844

[13] Mohanty, Bipin Ch.., Subudhi, P. K.., Dash, Ratnakar., & Mohanty, Bidyadhar. (2024). Feature-enhanced deep learning technique with soft attention for MRI-based brain tumor classification. International Journal of Information Technology . http://doi.org/10.1007/s41870-023-01701-0

[14] S, S.., A, S.., T, Kumaragurubaran., & S, Dhanasekaran. (2024). Self-attention-based generative adversarial network optimized with color harmony algorithm for brain tumor classification.. Electromagnetic biology and medicine , 1-15 . http://doi.org/10.1080/15368378.2024.2312363

[15] Nogay, H.., & Adeli, H.. (2024). Multiple Classification of Brain MRI Autism Spectrum Disorder by Age and Gender Using Deep Learning. Journal of Medical Systems , 48 . http://doi.org/10.1007/s10916-023-02032-0

[16] Ullah, Muhammad Sami., Khan, Muhammad Attique., Masood, Anum., Mzoughi, O.., Saidani, Oumaima., & Alturki, Nazik. (2024). Brain tumor classification from MRI scans: a framework of hybrid deep learning model with Bayesian optimization and quantum theory-based marine predator algorithm. Frontiers in Oncology , 14 . http://doi.org/10.3389/fonc.2024.1335740

[17] J. Deng, W. Dong, R. Socher, L.-J. Li, Kai Li, and Li Fei-Fei, "ImageNet: A large-scale hierarchical image database," in 2009 IEEE Conference on Computer Vision and Pattern Recognition, Jun. 2009, pp. 248–255. doi: 10.1109/CVPR.2009.5206848.

[18] A. Krizhevsky, "Learning Multiple Layers of Features from Tiny Images," (2009),p. 60.

[19] T.-Y. Lin et al., "Microsoft COCO: Common Objects in Context," arXiv:1405.0312 [cs], Feb. 2015, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1405.0312

[20] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," arXiv:1512.03385 [cs], Dec. 2015, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1512.03385

[21] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," arXiv:1801.04381 [cs], Mar. 2019, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1801.04381

[22] A. A. Adegun and S. Viriri, "Deep learning techniques for skin lesion analysis and melanoma cancer detection: a survey of state-of-the-art," Artificial Intelligence Review, vol. 54, no. 1, pp. 811–841, Jan. 2021, doi: 10.1007/s10462-020-09865-y.

[23] J. Hu, L. Shen, and G. Sun, "Squeeze-and-Excitation Networks," arXiv:1709.01507 [cs], May 2019, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1709.01507

[24] P. Porwal et al., "IDRiD: Diabetic Retinopathy – Segmentation and Grading Challenge," Medical Image Analysis, vol. 59, p. 101561, Jan. 2020, doi: 10.1016/j.media.2019.101561.

[25] S. Hussain, S. M. Anwar, and M. Majid, "Segmentation of glioma tumors in brain using deep convolutional neural network," Neurocomputing, vol. 282, pp. 248–261, Mar. 2018, doi: 10.1016/j.neucom.2017.12.032.

[26] G.-S. Xia et al., "DOTA: A Large-scale Dataset for Object Detection in Aerial Images," arXiv:1711.10398 [cs], Apr. 2018, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1711.10398

[27] R. C. Daudt, B. Le Saux, A. Boulch, and Y. Gousseau, "Urban Change Detection for Multispectral Earth Observation Using Convolutional Neural Networks," arXiv:1810.08468 [cs], Oct. 2018, Accessed: May 29, 2023. [Online]. Available: http://arxiv.org/abs/1810.08468