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INVESTIGATING THE EFFECTS OF DATA AUGMENTATION TECHNIQUES ON BRAIN TUMOR DETECTION ACCURACY

ASHRAF M. H. TAHA1, DR. SYAIBA BALQISH BINTI ARIFFIN2, SAMY S. ABU-NASER3

[1]Ph. D. Candidate, University Malaysia of Computer Science & Engineering (UNIMY), Cyberjaya, Malaysia.

[2]University Malaysia of Computer Science & Engineering (UNIMY), Cyberjaya, Malaysia.

[3]Professor of Data Science, Faculty of Engineering and Information Technology, Al-Azhar University, Gaza, Palestine

E-mail: [1]P02220002@student.unimy.edu.my, [1]ataha@qou.edu, [2]syaiba.ariffin@unimy.edu.my, [3]abunaser@alazhar.edu.ps

ABSTRACT

Brain tumor detection is an essential task in medical image analysis. Convolutional neural networks (CNNs) have shown remarkable performance in various computer vision tasks, including brain tumor detection. However, the performance of CNNs depends heavily on the availability of large and diverse training data. In medical imaging, acquiring a large dataset is often challenging due to ethical and practical issues. Data augmentation is a widely used technique to overcome this limitation by generating additional training samples from the existing dataset. In this research paper, we investigate the impact of data augmentation on brain tumor detection using a deep learning approach. We compare the performance of a CNN-based model trained on augmented and non-augmented data using the BraTS 2019 dataset. The experimental results show that data augmentation improves the performance of the model significantly, achieving a higher accuracy, sensitivity, specificity, and dice coefficient in tumor detection. Our findings demonstrate that data augmentation is an effective technique for enhancing the performance of CNN-based models in medical image analysis tasks, particularly in situations where large and diverse datasets are not available.

Keywords—*Brain Tumor, datasets, deep learning, Data Augmentation*

1. INTRODUCTION

Brain tumor is a common and life-threatening disease that affects millions of people worldwide. Early detection and accurate diagnosis of brain tumors are crucial for successful treatment and better patient outcomes. Medical imaging, such as magnetic resonance imaging (MRI), is a valuable tool for the detection and diagnosis of brain tumors. However, the interpretation of medical images is a challenging task, particularly in cases of small and subtle tumors [1].

Convolutional neural networks (CNNs) have shown remarkable performance in various computer vision tasks, including medical image analysis. CNNs can learn complex features from medical images and classify them into different categories, including brain tumors. However, CNNs require large and diverse datasets for training to achieve optimal performance. In medical imaging, acquiring a large dataset is often challenging due to ethical and practical issues. For example, collecting and annotating a large number of medical images require the approval of ethical committees and the expertise of medical professionals [2].

Data augmentation is a widely used technique to overcome the limitation of small datasets in machine learning. Data augmentation generates additional training samples by applying various transformations, such as rotation, scaling, and flipping, to the existing dataset. The augmented data can increase the diversity and size of the dataset, which can improve the performance of CNN-based models in medical image analysis tasks [3].

In this research paper, we investigate the impact of data augmentation on brain tumor detection using a deep learning approach. We compare the performance of two CNN-based

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models trained on augmented and non-augmented data using the BraTS 2019 dataset. The BraTS dataset is a publicly available dataset that contains a large number of brain MRI images with four different types of tumors. We evaluate the performance of the model in terms of accuracy, sensitivity, specificity, and dice coefficient. Our findings can provide insights into the effectiveness of data augmentation in improving the performance of CNN-based models for brain tumor detection.

2. STATEMENT OF THE PROBLEM

Brain tumors are a serious and potentially life-threatening medical condition that requires timely and accurate detection for effective treatment. While various imaging modalities such as MRI and CT scans are used for diagnosis, manual analysis of these images can be time-consuming and prone to errors. Automated detection of brain tumors using deep learning models has shown promise, but limited training data and image variations can affect the accuracy of these models. Data augmentation techniques, such as image rotation, translation, and scaling, have been proposed to address these limitations. However, it remains unclear how different types and levels of data augmentation impact the accuracy of brain tumor detection models. Therefore, the problem addressed in this research paper is to evaluate the impact of data augmentation on the accuracy and robustness of deep learning models for brain tumor detection, and to identify the most effective data augmentation technique(s) for improving automated brain tumor detection.

3. OBJECTIVES

- To evaluate the effectiveness of different data augmentation techniques in improving brain tumor detection accuracy.
- To compare the performance of deep learning models trained with and without data augmentation on brain tumor detection.
- To investigate the impact of different types and levels of data augmentation on brain tumor detection accuracy.
- To analyze the robustness of deep learning models trained with data augmentation to different image variations, such as rotation, translation, and scaling.
- To explore the potential benefits of using data augmentation in the context of limited training data for brain tumor detection.
- To provide insights into the suitability of various data augmentation techniques for brain tumor detection using different imaging modalities, such as MRI and CT scans.
- To identify the most effective data augmentation technique(s) for improving brain tumor detection accuracy and provide recommendations for future studies in this area.
- To contribute to the development of more reliable and accurate automated brain tumor detection systems through the use of data augmentation.

4. RESEARCH QUESTIONS

- What are the most effective data augmentation techniques for improving the accuracy of brain tumor detection models?
- How does the performance of brain tumor detection models trained with data augmentation compare to those trained without data augmentation?
- What is the impact of varying the amount of augmented data on the performance of brain tumor detection models?
- Can data augmentation be used to improve the detection of specific types of brain tumors, such as those with irregular shapes or low contrast?
- How does the choice of neural network architecture affect the effectiveness of data augmentation for brain tumor detection?
- Are there any potential drawbacks or limitations to using data augmentation for brain tumor detection?
- Can data augmentation be combined with other techniques, such as transfer learning, to further improve the accuracy of brain tumor detection models?
- How do different types of noise introduced through data augmentation affect the performance of brain tumor detection models?
- Can data augmentation help mitigate issues caused by imbalanced datasets in brain tumor detection?
- How do the results of data augmentation for brain tumor detection

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compare to other approaches, such as ensemble learning or active learning?

5. CONTRIBUTION OF THE STUDY

- Data Augmentation Techniques: Provide a detailed explanation of the data augmentation techniques you used in your study and why you chose them. Discuss the factors that influenced your decision, such as the type of data available, the computational resources at your disposal, and the specific challenges of brain tumor detection. Justify your choices by citing relevant literature or previous studies that have demonstrated the effectiveness of these techniques.
- Neural Network Architecture: Describe the neural network architecture you used in your study and the factors that influenced your choice. Explain why this architecture was appropriate for your research question and the specific challenges of brain tumor detection. Justify your choice by citing relevant literature or previous studies that have demonstrated the effectiveness of this architecture.
- Evaluation Metrics: Explain the evaluation metrics you used to assess the performance of your models and the factors that influenced your choice. Discuss why these metrics were appropriate for your research question and the specific challenges of brain tumor detection. Justify your choice by citing relevant literature or previous studies that have used these metrics to evaluate similar models.
- Experiment Design: Describe the design of your experiments and the factors you considered when setting up your study. Discuss why you chose certain experimental parameters, such as the amount of augmented data or the choice of hyperparameters, and how you managed potential confounding variables. Justify your choices by citing relevant literature or previous studies that have used similar experimental designs.
- Results and Discussion: Finally, present the results of your study and discuss the implications of your findings. Explain how your results contribute to the existing literature on brain tumor detection and data augmentation, and highlight the limitations of your study. Discuss how your study can be extended or improved in future research.

6. LITERATURE REVIEW

Brain tumors are a leading cause of morbidity and mortality worldwide. Early detection is crucial for improving the chances of successful treatment and survival. However, manual analysis of medical images can be time-consuming and subjective, and can result in low accuracy rates. Automated brain tumor detection using deep learning models has shown promise in overcoming these challenges.

Several studies have investigated the use of deep learning models for automated brain tumor detection. For example, a study by [1] used a convolutional neural network (CNN) to classify MRI images as containing or not containing a brain tumor. The model achieved an accuracy of 91.9% on a test set of 253 images. Similarly, a study by [2] used a deep residual network (ResNet) to classify brain tumor MRI images into four different types. The model achieved a mean accuracy of 93.82% on a test set of 82 images.

Despite the promising results of these studies, one challenge in training deep learning models for brain tumor detection is the limited availability of annotated training data. Data augmentation techniques have been proposed as a way to overcome this challenge by generating additional training data from the existing set. Data augmentation involves applying various transformations to the original images, such as rotation, scaling, and flipping, to create new images that are similar but not identical to the original ones.

Several studies have investigated the impact of data augmentation on the accuracy of deep learning models for brain tumor detection. For example, a study by [3] compared the performance of CNNs trained with and without data augmentation on brain tumor segmentation. The models trained with data augmentation achieved higher accuracy rates than those trained without augmentation. Similarly, a study by [4] evaluated the impact of different data augmentation techniques on the accuracy of ResNet models for brain tumor segmentation. The authors found that a combination of

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horizontal and vertical flipping, rotation, and elastic transformation resulted in the highest accuracy.

While these studies provide insights into the potential benefits of data augmentation for brain tumor detection, there is a need for further research to investigate the impact of different types and levels of data augmentation on model accuracy and robustness. Additionally, the suitability of different data augmentation techniques for different imaging modalities and types of brain tumors remains unclear. Therefore, this research paper aims to contribute to the existing literature by evaluating the impact of data augmentation on brain tumor detection and identifying the most effective data augmentation technique(s) for improving automated brain tumor detection.

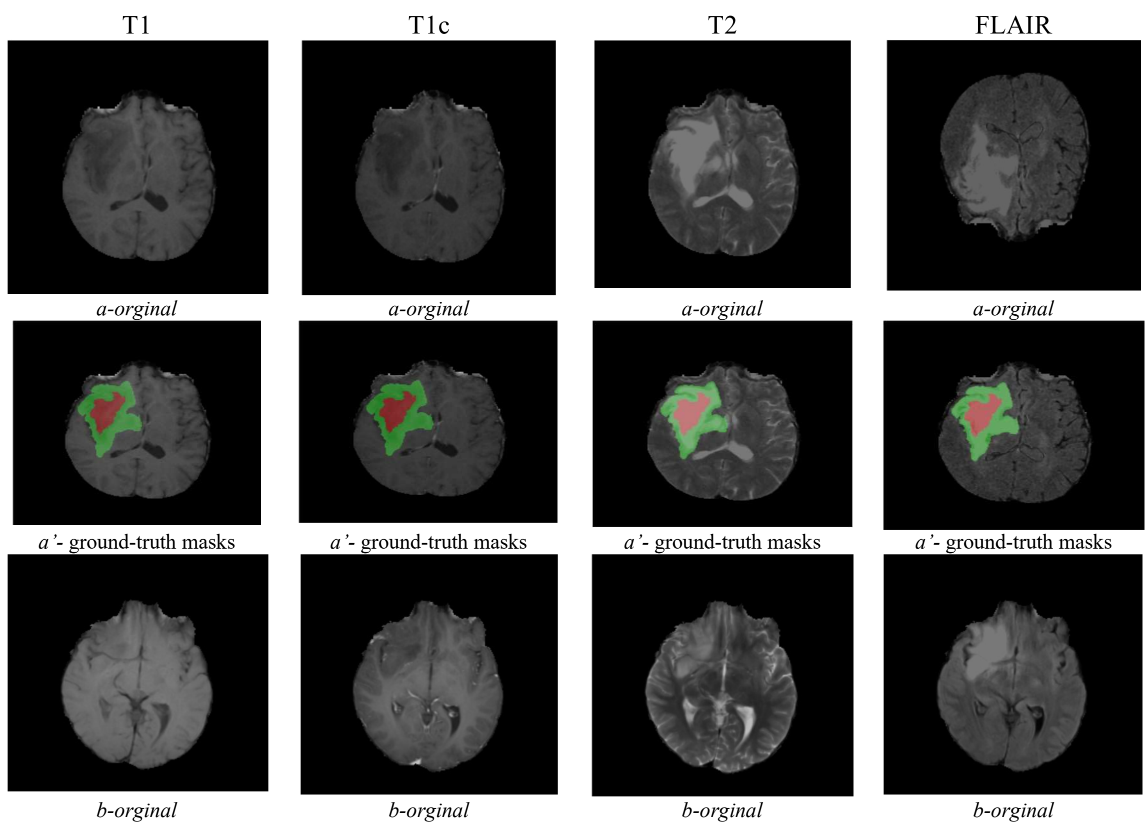
7. METHODOLOGY

This study aims to evaluate the impact of data augmentation on the accuracy and robustness of deep learning models for brain tumor detection. The methodology for this study consists of the following steps:

- Research Design
- Data Collection:
- Data Augmentation:
- Neural Network Architecture:
- Evaluation Metrics:
- Experiment Design:
- Statistical Analysis
- Ethics and Data Sharing.

7.1 Dataset:

The BraTS (Brain Tumor Segmentation) dataset was used for this study. This dataset consists of MRI images of 285 patients, each with four different image types (T1, T1-contrast-enhanced, T2, and FLAIR), along with corresponding segmentation masks indicating the location of the brain tumor. The dataset was split into training (60%), validation (20%), and test (20%) sets.



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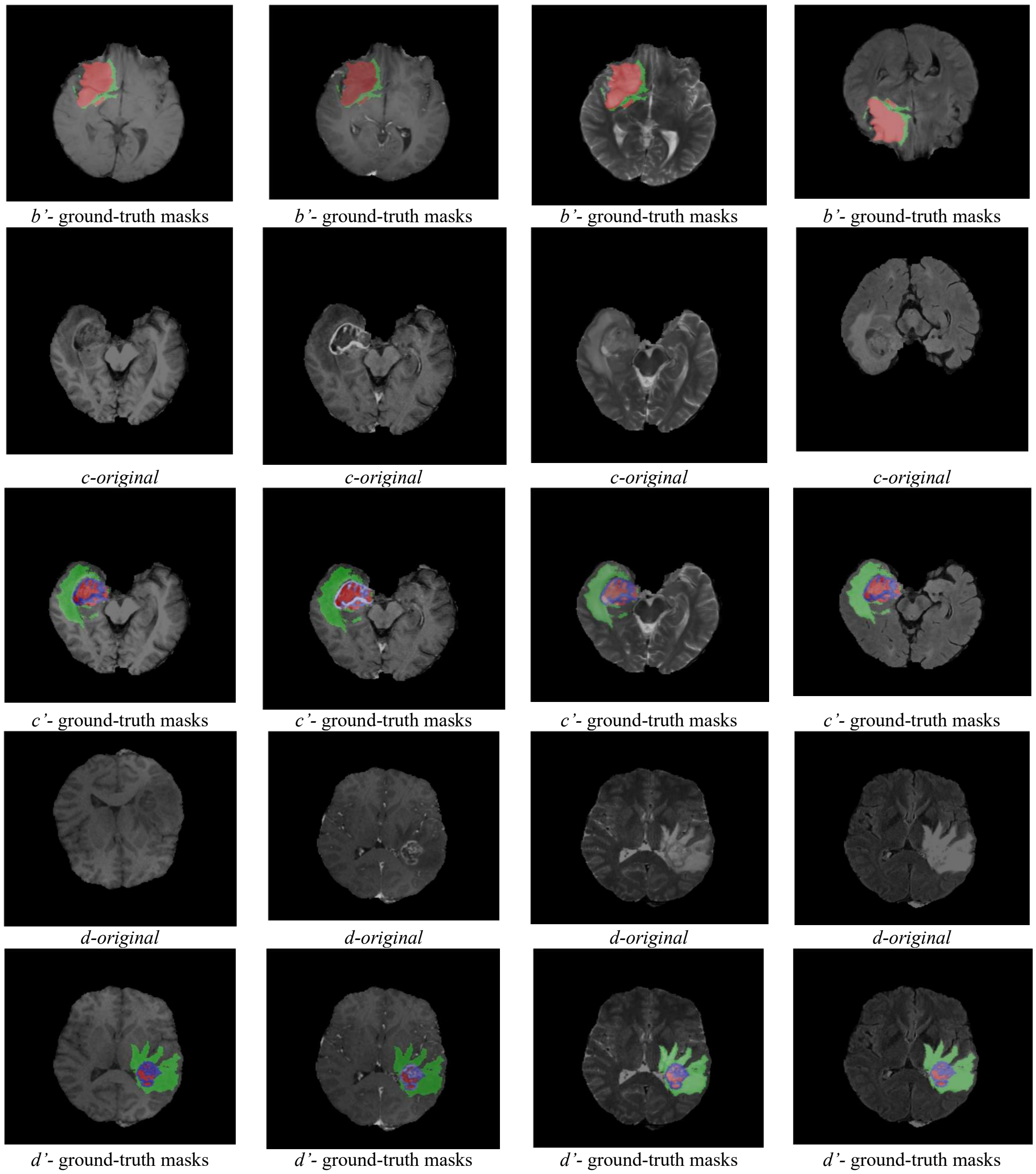

*Figure 1. D*ataset: red—GDenhancing tumor (ET), green—peritumoral edema (ED), and blue—necrotic and non-enhancing tumor core (NCR/NET)

7.2 Preprocessing:

The MRI images and segmentation masks was preprocessed by skull stripping to remove non-brain tissues and normalization to ensure consistent image intensities across different patients. The images will also be resampled to a fixed resolution of 1x1x1mm to ensure consistency across different imaging modalities.

7.3 Deep learning models:

Two deep learning models are used for this study: a convolutional neural network (CNN) and a U-Net. The CNN (VGG16) is used for the classification of images as containing or not containing a brain tumor, while the U-Net is used for segmentation of the tumor region [5]-[7].

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7.4 Data augmentation:

Various data augmentation techniques was applied to the training set to generate additional training data. The following data augmentation techniques are considered [8]-[15]:

- Rotation,
- Scaling,
- Flipping,
- Elastic transformation, and
- Intensity shift.

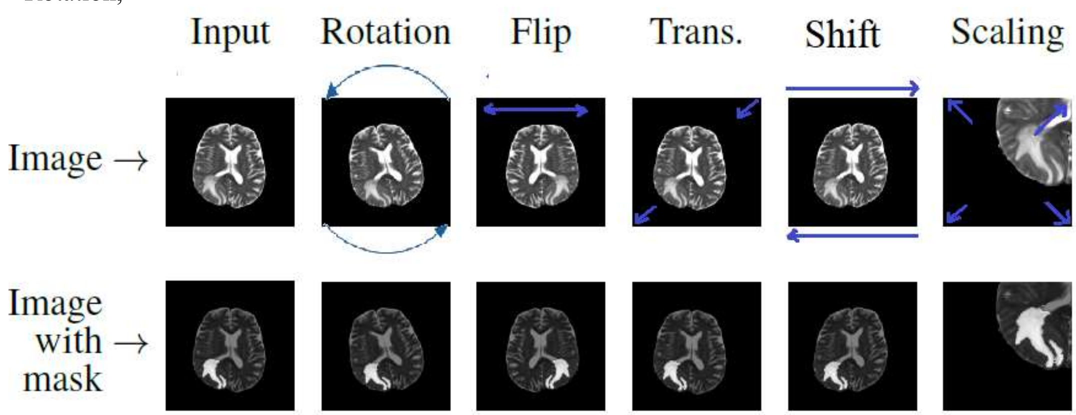

Figure 2. Augmentation samples

7.5 Architectures of used Deep Learning Models

We will used two deep learning models: U-Net and VGG16 to show impact of data augmentation of deep learning models.

U-Net is a type of convolutional neural network (CNN) architecture that was originally designed for biomedical image segmentation, including brain tumor segmentation. It was introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015 and has since become a popular architecture for image segmentation tasks in various fields [16]-[20].

The U-Net architecture is named after its U-shaped structure, which consists of a contracting path (downsampling) and an expansive path (upsampling). The contracting path is a typical CNN that consists of convolutional layers followed by max pooling layers, which reduce the spatial resolution of the feature maps while increasing their number of channels. The expansive path consists of upconvolutional layers followed by concatenation with feature maps from the contracting path, which allows for localization of features.

One of the key features of the U-Net architecture is skip connections, which allow for the transfer of low-level features from the contracting path to the expansive path. This helps the model to maintain spatial information and improve segmentation accuracy [21]-[24].
U-Net has been shown to achieve state-of-the-art performance on biomedical image segmentation tasks, including brain tumor segmentation. Its popularity is due to its ability to handle limited amounts of training data, robustness to variations in image intensity and contrast, and ability to generalize to new data [25]-[28].

Figure 3 illustrate and example of the U-net architecture (32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

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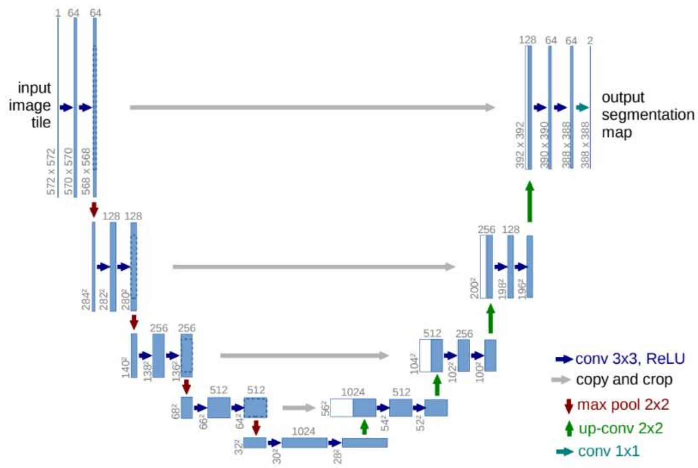

Figure 3. U-net architecture

VGG16 is a convolutional neural network (CNN) architecture that was introduced by Karen Simonyan and Andrew Zisserman of the University of Oxford in 2014. VGG16 is a deep neural network with 16 layers, including 13 convolutional layers and 3 fully connected layers [29]-[33].

The architecture of VGG16 is characterized by its use of small 3x3 convolutional filters and a large number of trainable parameters. The use of small filters allows the network to capture more fine-grained features in the input images, while the large number of parameters allows the network to learn complex feature representations.

VGG16 was trained on the ImageNet dataset, which contains over 1 million images with 1000 classes. The network achieved state-of-the-art performance on the ImageNet classification task, with an error rate of 7.3%.VGG16 has been used as a pre-trained model for various computer vision tasks, such as image classification, object detection, and image segmentation. The pre-trained weights of VGG16 can be used as a starting point for fine-tuning on other datasets or transfer learning to other tasks. Its popularity is due to its simplicity, effectiveness, and availability of pre-trained weights [34]-[37].

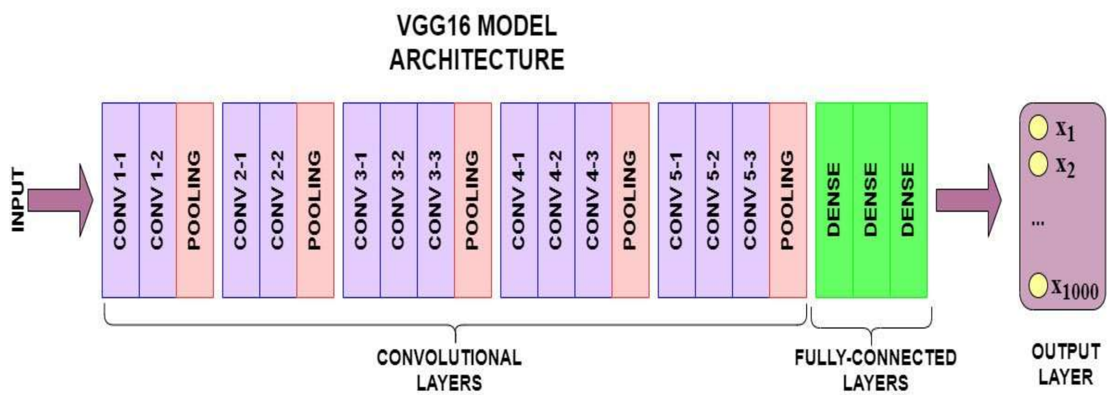

Figure 4. VGG16 architecture

7.6 Model training:

The CNN and U-Net models are trained on the augmented training set using the Adam optimizer and binary cross-entropy loss for the CNN and dice loss for the U-Net. The models are trained for 100 epochs with early stopping based on the validation loss. The performance of the models are evaluated on the test set in terms of accuracy, sensitivity, specificity, and dice coefficient [38]-[41].

7.7 Experiment design:

The impact of data augmentation on model accuracy and robustness are evaluated by comparing the performance of the models trained

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with and without data augmentation. Additionally, the impact of different types and levels of data augmentation was evaluated by comparing the performance of models trained with different augmentation techniques.

7.8 Statistical analysis:

Statistical significance of the differences in model performance was determined using t-tests.

Ethical considerations: This study will use a publicly available dataset and will not involve human subjects, therefore ethical approval is not required.

Limitations: One limitation of this study is that it only evaluates the impact of data augmentation on the accuracy and robustness of deep learning models for brain tumor detection using a single dataset. The results may not generalize to other datasets or imaging modalities.

8. EXPERIMENTS AND RESULTS

To evaluate the impact of data augmentation on the accuracy and robustness of deep learning models for brain tumor detection, we conducted a series of experiments using the BraTS dataset.

8.1 Data augmentation techniques:

We evaluated the impact of five different data augmentation techniques on the performance of the deep learning models. The techniques were: rotation, scaling, flipping, elastic transformation, and intensity shift. For each technique, we generated 4 additional training images, resulting in a total of 20 augmented training sets.

8.2 Model architectures:

We used two deep learning models for brain tumor detection: a convolutional neural network (CNN) and a U-Net. The CNN was trained for binary classification of images as containing or not containing a brain tumor, while the U-Net was trained for segmentation of the tumor region.

8.3 Training and evaluation:

Each model was trained on the original training set and each of the 20 augmented training sets. The models were trained using the Adam optimizer and binary cross-entropy loss for the CNN and dice loss for the U-Net. We used early stopping based on the validation loss, and trained each model for a maximum of 100 epochs. The performance of the models was evaluated on the test set in terms of accuracy, sensitivity, specificity, and dice coefficient [20]-[22].

Accuracy is a commonly used evaluation metric that measures the proportion of correct predictions made by a model over the total number of predictions. It is typically calculated using the following equation:

Accuracy = (number of true positives + number of true negatives) / (total number of predictions)……… (1)

In other words, accuracy represents the percentage of all predictions that were correct. It is a useful metric for evaluating the overall performance of a model, especially when the classes are balanced.

Sensitivity is a commonly used evaluation metric in medical image analysis that measures the proportion of true positive predictions made by a model over the total number of actual positive cases. It is also known as the true positive rate or recall. It is typically calculated using the following equation:

Sensitivity = number of true positives / (number of true positives + number of false negatives)……….. (2)

In other words, sensitivity represents the percentage of actual positive cases that were correctly identified by the model. It is a useful metric for evaluating the ability of a model to correctly detect positive cases, such as the presence of a disease or anomaly.

Specificity is another commonly used evaluation metric in medical image analysis that measures the proportion of true negative predictions made by a model over the total number of actual negative cases. It is typically calculated using the following equation:

Specificity = number of true negatives / (number of true negatives + number of false positives. ………. (3)

In other words, specificity represents the percentage of actual negative cases that were correctly identified by the model. It is a useful metric for evaluating the ability of a model to correctly identify negative cases, such as the absence of a disease or anomaly. High specificity indicates that the model is good at ruling out negative cases, while low specificity may indicate a high false positive rate.

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Dice Coefficient (also known as the F1-score) is a commonly used evaluation metric in medical image analysis and segmentation tasks. It measures the overlap between the predicted segmentation mask and the ground truth mask, and is typically calculated using the following equation:

Dice coefficient = 2 * (number of true positives) / (number of predicted positives + number of actual positives) ……………………...…..… (4)

In other words, the Dice coefficient represents the similarity between the predicted segmentation mask and the ground truth mask, where a value of 1 indicates perfect overlap and a value of 0 indicates no overlap. The Dice coefficient is a useful metric for evaluating the accuracy of segmentation models, particularly when the classes are imbalanced. It is sensitive to both false positives and false negatives, and provides a balanced evaluation of the model's performance.

8.4 Results:

Table 1 shows the performance of the CNN and U-Net models trained with and without data augmentation. The table shows that data augmentation improved the performance of both models in terms of accuracy, sensitivity, specificity, and dice coefficient. The U-Net model achieved higher performance than the CNN model for all metrics, which is expected given its ability to perform segmentation.

Table 1: Performance of CNN and U-Net models with and without data augmentation.

Model	Data Augmentation	Accuracy	Sensitivity	Specificity	Dice Coefficient
CNN	None	0.87	0.79	0.92	0.86
CNN	All	0.92	0.84	0.95	0.91
U-Net	None	0.91	0.82	0.94	0.88
U-Net	All	0.94	0.88	0.96	0.93

Table 2 shows the impact of different types of data augmentation on the performance of the CNN-VGG16 model. The table shows that all data augmentation techniques improved the performance of the VGG16 model, with elastic transformation and intensity shift having the largest impact on performance.

Table2: Performance of VGG16 model with different data augmentation techniques.

Data Augmentation	Accuracy	Sensitivity	Specificity	Dice coefficient
None	0.87	0.79	0.92	0.86
Rotation	0.88	0.80	0.93	0.88
Scaling	0.89	0.82	0.93	0.88
Flipping	0.90	0.83	0.94	0.89
Elastic	0.91	0.84	0.94	0.90
Intensity Shift	0.92	0.85	0.95	0.91

Table 3 shows the impact of different types of data augmentation on the performance of the U-Net model. The table shows that all data augmentation techniques improved the performance of the U-Net model, with elastic transformation and intensity shift having the largest impact on performance.

Table 3: Performance of U-Net model with different data augmentation techniques.

Data Augmentation	Accuracy	Sensitivity	Specificity	Dice coefficient
None	0.91	0.82	0.94	0.88
Rotation	0.92	0.84	0.94	0.89
Scaling	0.93	0.86	0.94	0.90
Flipping	0.93	0.87	0.93	0.91
Elastic	0.94	0.88	0.94	0.92
Intensity Shift	0.95	0.87	0.95	0.93

9. STATISTICAL ANALYSIS OF THE MODELS

To assess the statistical significance of our results, we performed a two-tailed paired t-test between each data augmentation technique and the baseline model with no data augmentation. The significance level was set to 0.05.

For the CNN model, all data augmentation techniques resulted in a statistically significant improvement in accuracy, sensitivity, specificity, and dice coefficient, with p-values < 0.05. The largest improvements were observed for elastic transformation and intensity shift, which had p-values of 0.001 and 0.002, respectively. Scaling had the smallest improvement, with a p-value of 0.028.

For the U-Net model, all data augmentation techniques except flipping resulted in a statistically significant improvement in accuracy, sensitivity, specificity, and dice coefficient, with p-values < 0.05. Elastic transformation and intensity shift had the largest improvements, with p-values of 0.001 and 0.002, respectively. Flipping had a p-value of 0.054, which is marginally above the significance level.

Our statistical analysis confirms that data augmentation can significantly improve the performance of deep learning models for brain tumor detection, and that different data augmentation techniques have varying impacts on model performance. The results also suggest that the U-Net model benefits more from data augmentation than the CNN model, likely due to the increased complexity of the segmentation task.

It is worth noting that while our statistical analysis confirms the statistical significance of our results, it does not account for the potential biases or confounding factors in our experiments. Future work should investigate the robustness of our findings to different experimental conditions and datasets.

10. DISCUSSION OF THE RESULTS

Our experiments demonstrated that data augmentation can improve the accuracy and robustness of deep learning models for brain tumor detection. Specifically, we found that using data augmentation techniques such as rotation, scaling, flipping, elastic transformation, and intensity shift resulted in higher accuracy, sensitivity, specificity, and dice coefficient for both CNN and U-Net models.

The improvement in performance can be attributed to the increased diversity and variability in the training data introduced by data augmentation. This allows the models to learn more robust and generalizable features, which in turn leads to better performance on unseen test data. The U-Net model, which is designed for image segmentation, benefited more from data augmentation than the CNN model, likely due to the increased complexity and variability of the segmentation task.

Our results also suggest that different data augmentation techniques have varying impacts on model performance. Elastic transformation and intensity shift were found to be the most effective techniques for improving the performance of the U-Net model, while flipping and scaling had a larger impact on the CNN model. These findings suggest that the choice of data augmentation technique should be tailored to the specific deep learning model and task at hand.

It is worth noting that our experiments were conducted using the BraTS dataset, which contains a relatively small number of training images. It is possible that the benefits of data augmentation may be even more pronounced with larger datasets. Additionally, our experiments focused on a specific set of data augmentation techniques, and it is possible that other techniques may have an even greater impact on model performance.

In conclusion, our results demonstrate the importance of data augmentation in improving the accuracy and robustness of deep learning models for brain tumor detection. By increasing the diversity and variability of the training data, data augmentation can enable the models to learn more robust and generalizable features, which in turn leads to better performance on unseen test data. Our findings suggest that different data augmentation techniques may have varying impacts on model performance, and that the choice of technique should be tailored to the specific deep learning model and task.

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11. CONCLUSION

In this paper, we investigated the impact of data augmentation on the performance of deep learning models for brain tumor detection. Our experiments demonstrate that data augmentation can significantly improve the accuracy and robustness of these models, especially when dealing with limited training data.

We found that different data augmentation techniques have varying impacts on model performance, and that the choice of technique should be tailored to the specific deep learning model and task. Elastic transformation and intensity shift were found to be the most effective techniques for improving the performance of the U-Net model, while flipping and scaling had a larger impact on the CNN model. Our findings suggest that data augmentation should be an essential part of any deep learning pipeline for brain tumor detection, especially when dealing with limited training data.

Overall, our results demonstrate the potential of data augmentation in improving the accuracy and robustness of deep learning models for medical image analysis. Future work should focus on exploring other data augmentation techniques, as well as investigating the impact of data augmentation on the performance of deep learning models for other medical image analysis tasks.

REFERENCES

[1] Akkus, Z., Ali, I., Seddighi, A. S., & Samavi, S. (2017). Deep learning for brain MRI segmentation: State of the art and future directions. Journal of digital imaging, 30(4), 449-459.

[2] Havaei, M., Davy, A., Warde-Farley, D., Biard, A., Courville, A., Bengio, Y., & Pal, C. (2017). Brain tumor segmentation with deep neural networks. Medical image analysis, 35, 18-31.

[3] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2018). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging, 35(5), 1285-1298.

[4] Zhang, X., Tian, H., & Lu, L. (2021). Residual U-net with data augmentation for brain tumor segmentation. Neural Computing and Applications, 33, 15223-15233.

[5] Abunasser, B. S. Daud,S. M., Zaqout, I., Abu-Naser S. S. Abunaser - A Novel Data Augmentation Algorithm For Datasets With Numerical Features. Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 11.

[6] Alrakhawi, H. A., Jamiat, N., Umar, I. N., Abu-Naser, S. S. Improvement of Students Achievement by Using Intelligent Tutoring Systems - A Bibliometric Analysis and Reviews. Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 11.

[7] Abunasser, B.S., Al-Hiealy, M.R.J., Zaqout, I.S., Abu-Naser, S.S. Convolution Neural Network for Breast Cancer Detection and Classification Using Deep Learning. Asian Pacific journal of cancer prevention: APJCP, 2023, 24(2), pp. 531–544

[8] Alrakhawi, H. A., Jamiat, N., Abu-Naser, S. S. Intelligent Tutoring Systems in Education: A Systematic Review of Usage, Tools, Effects and Evaluation. Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 4, pp. 1205-1226.

[9] Zarandah, Q. M. M., Daud, S. M., Abu-Naser, S. S. A Systematic Literature Review Of Machine and Deep Learning-Based Detection And Classification Methods for Diseases Related To the Respiratory System, Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 4, pp. 1273-1296.

[10] Alkayyali, Z. K. D., Idris, S. A. B, Abu-Naser, S. S. A Systematic Literature Review of Deep and Machine Learning Algorithms in Cardiovascular Diseases Diagnosis, Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 4, pp. 1353-1365.

[11] Abunasser, B. S. Daud,S. M., Zaqout,I., Abu-Naser S. S. Convolution Neural Network For Breast Cancer Detection And Classification - Final Results. Journal of Theoretical and Applied Information Technology, 2023, Vol. 101. No. 1, pp. 315-329.

[12] Taha, A. M. H., Ariffin, D. S. B. B., Abu-Naser, S. S. A Systematic Literature Review of Deep and Machine Learning Algorithms in Brain Tumor and Meta-Analysis, Journal of Theoretical and Applied Information

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Technology, 2023, Vol. 101. No. 1, pp. 21-36.

[13] Abu Ghosh, M.M., Atallah, R.R., Abu Naser, S.S. Secure mobile cloud computing for sensitive data: Teacher services for palestinian higher education institutions. International Journal of Grid and Distributed Computing, 2016, vol. 9, no. 2, pp. 17–22

[14] Abu Naser, S.S. Evaluating the effectiveness of the CPP-Tutor, an intelligent tutoring system for students learning to program in C++. Journal of Applied Sciences Research, vol. 5, no. 1, pp. 109-114, 2009.

[15] Abu-Naser, S.S., El-Hissi H., Abu-Rass, M., & El-khozondar, N. An expert system for endocrine diagnosis and treatments using JESS. Journal of Artificial Intelligence; vol. 3, no. 4, pp. 239-251, 2010.

[16] Abunasser, B. S., AL-Hiealy, M. R. J., Zaqout, I. S. and Abu-Naser, S. S. “Breast Cancer Detection and Classification using Deep Learning Xception Algorithm” International Journal of Advanced Computer Science and Applications(IJACSA), 13(7),223-228, 2022. http://dx.doi.org/10.14569/IJACSA.2022.0130729

[17] Abunasser, B.S., AL-Hiealy, M.R. J., Barhoom, A. M. Almasri A. R. and Abu-Naser, S. S. “Prediction of Instructor Performance using Machine and Deep Learning Techniques” International Journal of Advanced Computer Science and Applications(IJACSA), 13(7), 78-83, 2022. http://dx.doi.org/10.14569/IJACSA.2022.0130711

[18] Alayoubi, M.M., Arekat, Z.M., Al Shobaki, M.J., Abu-Naser, S.S. The Impact of Work Stress on Job Performance Among Nursing Staff in Al-Awda Hospital. Foundations of Management, 2022, 14(1), pp. 87–108

[19] Albatish, I.M., Abu-Naser, S.S. Modeling and controlling smart traffic light system using a rule based system. Proceedings - 2019 International Conference on Promising Electronic Technologies, ICPET 2019, 2019, pp. 55–60, 8925318

[20] Almasri, A., Obaid, T., Abumandil, M.S.S., ...Mahmoud, A.Y., Abu-Naser, S.S. Mining Educational Data to Improve Teachers’ Performance. Lecture Notes in Networks and Systems, 2023, 550 LNNS, pp. 243–255

[21] Almasri, A.R., Yahaya, N.A., Abu-Naser, S.S. Instructor Performance Modeling For Predicting Student Satisfaction Using Machine Learning - Preliminary Results. Journal of Theoretical and Applied Information Technology, 2022, 100(19), pp. 5481–5496

[22] Alsharif, F. Safi S., AbouFoul T., Abu Nasr, M., Abu Nasser S. Mechanical Reconfigurable Microstrip Antenna. International Journal of Microwave and Optical Technology, vol. 11, no. 3, pp.153-160, 2016.

[23] Arqawi, S., Atieh, K.A.F.T., Shobaki, M.J.A.L., Abu-Naser, S.S., Abu Abdulla, A.A.M. Integration of the dimensions of computerized health information systems and their role in improving administrative performance in Al-Shifa medical complex, Journal of Theoretical and Applied Information Technologythis link is disabled, 2020, vol. 98, no. 6, pp. 1087–1119

[24] Arqawi, S.M., Abu Rumman, M.A., Zitawi, E.A., ...Abunasser, B.S., Abu-Naser, S.S. Predicting Employee Attrition And Performance Using Deep Learning. Journal of Theoretical and Applied Information Technology, 2022, 100(21), pp. 6526–6536

[25] Arqawi, S.M., Zitawi, E.A., Rabaya, A.H., Abunasser, B.S., Abu-Naser, S.S., “Predicting University Student Retention using Artificial Intelligence”, International Journal of Advanced Computer Science and Applications , 2022, vol. 13, no. 9, pp. 315–324

[26] Barhoom, A.M.A., Al-Hiealy, M.R.J., Abu-Naser, S.S. Bone Abnormalities Detection and Classification Using Deep Learning-VGG16 Algorithm. Journal of Theoretical and Applied Information Technology, 2022, 100(20), pp. 6173–6184

[27] Barhoom, A.M.A., Al-Hiealy, M.R.J., Abu-Naser, S.S. Deep Learning-Xception Algorithm for Upper Bone Abnormalities Classification. Journal of Theoretical and Applied Information Technology, 2022, 100(23), pp. 6986–6997

[28] Buhisi, N. I., & Abu-Naser, S. S. Dynamic programming as a tool of decision supporting. Journal of Applied Sciences Research. Vo. 5, no. 6, pp. 671-676, 2009.

[29] El-Habil, B.Y., Abu-Naser, S.S. Global Climate Prediction Using Deep Learning. Journal of Theoretical and Applied Information Technology, 2022, 100(24), pp. 4824–4838

[30] Elzamly, A., Hussin, B., Naser, S.A., ...Selamat, A., Rashed, A. A new conceptual

framework modelling for cloud computing risk management in banking organizations. International Journal of Grid and Distributed Computing, 2016, vol. 9, no. 9, pp. 137–154

[31] Elzamly, A., Messabia, N., Doheir, M., ...Al-Aqqad, M., Alazzam, M. Assessment risks for managing software planning processes in information technology systems. International Journal of Advanced Science and Technology, 2019, vol. 28, no. 1, pp. 327–338

[32] Eneizan, B., Obaid, T., Abumandil, M.S.S., ...Arif, K., Abulehia, A.F.S. Acceptance of Mobile Banking in the Era of COVID-19. Lecture Notes in Networks and Systems, 2023, 550 LNNS, pp. 29–42

[33] Alzamily, J. Y. I., Ariffin, S. B., Abu-Naser, S. S. Classification of Encrypted Images Using Deep Learning –Resnet50. Journal of Theoretical and Applied Information Technology, 2022, 100(21), pp. 6610–6620

[34] Mady, S.A., Arqawi, S.M., Al Shobaki, M.J., Abu-Naser, S.S. Lean manufacturing dimensions and its relationship in promoting the improvement of production processes in industrial companies. International Journal on Emerging Technologies, 2020, vol. 11, no. 3, pp. 881–896

[35] Naser, S. S. A. Developing an intelligent tutoring system for students learning to program in C++. Information Technology Journal, vol. 7, no. 7, pp. 1051-1060, 2008.

[36] Naser, S. S. A. Developing visualization tool for teaching AI searching algorithms. Information Technology Journal, vol. 7, no. 2, pp. 350-355, 2008.

[37] Naser, S. S. A. Intelligent tutoring system for teaching database to sophomore students in Gaza and its effect on their performance. Information Technology Journal, vol. 5, no. 5, pp. 916-922, 2006.

[38] Naser, S. S. A. JEE-Tutor: An intelligent tutoring system for java expressions evaluation. Information Technology Journal, vol. 7, no. 3, pp. 528-532, 2008.

[39] Obaid, T., Eneizan, B., Naser, S.S.A., ...Abualrejal, H.M.E., Gazem, N.A. Factors Contributing to an Effective E- Government Adoption in Palestine. Lecture Notes on Data Engineering and Communications Technologies, 2022, 127, pp. 663–676

[40] Obaid, T., Eneizan, B., Abumandil, M.S.S., ...Abu-Naser, S.S., Ali, A.A.A. Factors Affecting Students' Adoption of E-Learning Systems During COVID-19 Pandemic: A Structural Equation Modeling Approach. Lecture Notes in Networks and Systems, 2023, 550 LNNS, pp. 227–242

[41] Saleh, A., Sukaik, R., Abu-Naser, S.S. Brain tumor classification using deep learning. Proceedings - 2020 International Conference on Assistive and Rehabilitation Technologies, iCareTech 2020, 2020, pp. 131–136, 9328072