A New Approach for Aneurysm Detection Based on CNNs

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***Abstract*— An intracranial aneurysm (IA) is an abnormal bulging of a blood vessel caused by a weakening of its wall. This bulge can rupture and cause internal bleeding. Rupture of an internal blood vessel causes subarachnoid haemorrhage. Without detection and treatment, such damage to the artery leads to death. The development of an automated system to help doctors accurately diagnose IA can save many lives. For this reason, we focused on neural networks that would be able to recognize IA. In our work, we propose a CNNs (convolutional neural networks), which is mainly used to classify different types of images, both in transportation and medicine. Conv2D layers are most used in image processing since there is convolution over the image, which causes better classification. Our proposed network got an overall accuracy of 97.36% during the classification of the dataset into vessels and aneurysms, and the accuracy of recognizing aneurysms directly was 84%. We compare the results with other freely available experiments, where the authors obtained the highest overall classification accuracy on POINTCNN models of 90.44% and directly on aneurysms on PN++ models of 88.55%.**

***Keywords*—Detection; Aneurysm; Neural network; *CNN*;**

I. INTRODUCTION

An intracranial aneurysm refers to an irregular protrusion of a blood vessel (typically an artery), resulting from the weakening of the vessel wall, commonly occurring at branching points. As blood flows through the weakened vessel, the increased blood pressure causes a localized area to expand outward, resembling the shape of a balloon. This bulge can burst and cause internal bleeding. Rupture of the IA causes subarachnoid haemorrhage. Without early detection and treatment, such arterial damage leads to severe neurological sequelae and high mortality [1]. The diagnostic approach is challenging as it requires the involvement of physicians, but despite this, it still happens that intracranial aneurysms are not recognised. Therefore, the development of an automated system to help physicians accurately diagnose intracranial aneurysms may save many lives and prevent various types of neurological damage. In the work [2], it is reported that the annual incidence rate of Unruptured Intracranial Aneurysms (UIA) is approximately 0.95%, and the annual rate of UIA rupture ranges from 0.4% to 17.8%. Currently, various diagnostic approaches are employed for detecting intracranial aneurysms. Digital subtraction angiography (DSA) is recommended when considering surgical or endovascular treatment for identifying and evaluating intracranial aneurysms (IA). Additionally, Computed Tomographic Angiography (CTA) and Magnetic Resonance Angiography (MRA) are utilized for diagnosis. However, CTA and MRA offer lower resolution and sensitivity in detection compared to DSA, particularly for IAs smaller than 3 mm [2].

In our study, we present the utilization of a neural network (NN) architecture featuring Conv2D layers for the detection of intracranial aneurysms (IA). Specifically, we train and evaluate our proposed architecture using the publicly available IntrA: 3D Intracranial Aneurysm Dataset for Deep Learning (CVPR 2020 Oral) [27], which contains annotated data. The Conv2D neural network is trained on this annotated dataset to perform aneurysm detection. In the subsequent sections, we provide an overview of the IntrA dataset, followed by a detailed explanation of our proposed architecture. Finally, we present the results of IA detection achieved using this dataset.

II. RELATED WORK

In recent years, this issue has come to the forefront, and several research studies have been conducted on the automatic detection of intracranial aneurysms. The main challenge in diagnosis lies in detecting small IAs, which are frequently misdiagnosed. Previous studies have explored detection systems and techniques such as MRA [3-7] and CTA [8-9]. Invasive DSA examinations have also been conducted, but the available data is relatively limited compared to non-invasive approaches (MRA or CTA). In [10], the authors combined expert knowledge with a fuzzy model for cerebral aneurysm detection. Subsequently, in [11], the authors employed the Otsu method along with Zernike moments and the Maximally stable extremal regions (MSER) detector to extract vascular structures and detect aneurysms. The authors further extended their research in [12], integrating MSER, speeded up robust features (SURF), and Scale-invariant feature transform (SIFT) descriptors to improve aneurysm detection and potentially reduce false-positive rates observed in [11]. In recent years, CNN architectures have gained significant popularity in various domains, including object detection [13-18]. CNN architectures have also been increasingly applied in medical detection, demonstrating promising performance [19-23]. In [24], the authors calculated the intra-vessel distance to derive intensity maps from 3D-DSA images and employed CNNs for classification. However, the generation of intensity maps is computationally demanding, making IA classification time-consuming. In [25], the authors modified the VGG network to perform pixel-by-pixel semantic segmentation of blood vessels and aneurysms, achieving an average AUC value of 0.761.

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III. INTRA: 3D INTRACRANIAL ANEURYSM DATASET FOR DEEP LEARNING

The IntrA: 3D Intracranial Aneurysm Dataset for Deep Learning dataset was created by researchers at South China University of Technology. The authors of this dataset have designed the dataset to be applicable to the diagnosis of intracranial aneurysms and neck extraction for clipping surgery in medicine, such as normal estimation and surface reconstruction. 3D models of whole cerebral vessels were created in the dataset. The 3D models are obtained by reconstructing the scanned 2D MRA images. The 2D MRA images were not published by the authors due to GDPR (General Data Protection Regulation). There are 1909 vessel segments in the dataset. The whole dataset is divided into two classes:

- Healthy vessels: the category is referred to as vessels and contains 1694 3D objects.
- Aneurysm: this category contains 215 segments of aneurysms.

Thus, the IntrA dataset consists of artificially created 3D objects based on real data (see in Fig.1) [27].

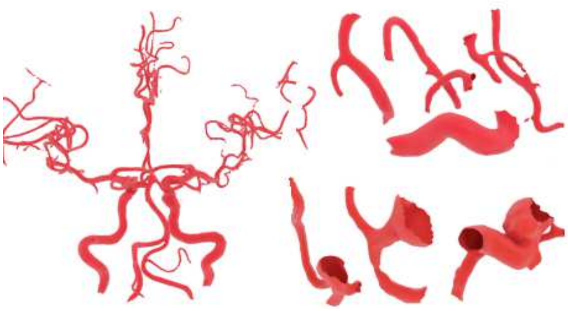

Figure 1. 3D objects containing aneurysms and healthy vessels [27]

IV. PROPOSED ARCHITECTURE CNNS

Convolutional neural networks are currently used in computer vision tasks such as classification. CNNs are because they explicitly assume that records are images, which allows us to encode certain features in the architecture to recognize specific features in images. First, however, we must specify to the network what the object we are looking for in the image looks like. When using CNNs, we need to identify lines, edges, textures, or shapes that are like those contained in the object. We can argue that in a convolutional neural network, each layer learns different levels of abstraction.

Taking this into consideration, we have chosen to employ this specific type of network and adapt the data accordingly to achieve optimal results. Our designed network primarily comprises five Conv2D (2-dimensional convolutional) layers. These layers are subsequently followed by MaxPooling and MLP (Multilayer perceptron) components. The MLP consists of three dense layers, two dropout layers, and one flatten layer. The Conv2D layer operates by applying a convolutional kernel to the input layer, generating a tensor of outputs. MaxPooling, also utilizing 2D operations, performs subsampling along the spatial dimensions, such as height and width. Its function involves selecting the maximum value for each input channel within the input window, while the window moves in steps across the image. The layers within the MLP play crucial roles in the network. The flatten layer transforms the matrix into an output vector, enabling compatibility with subsequent layers. The dense layer, serving as the final layer, comprises fully connected neurons. To prevent overfitting or underfitting, the dropout layer deactivates certain neurons during training. Overall, this network configuration aims to optimize the performance and efficiency of the model in the IA detection task.

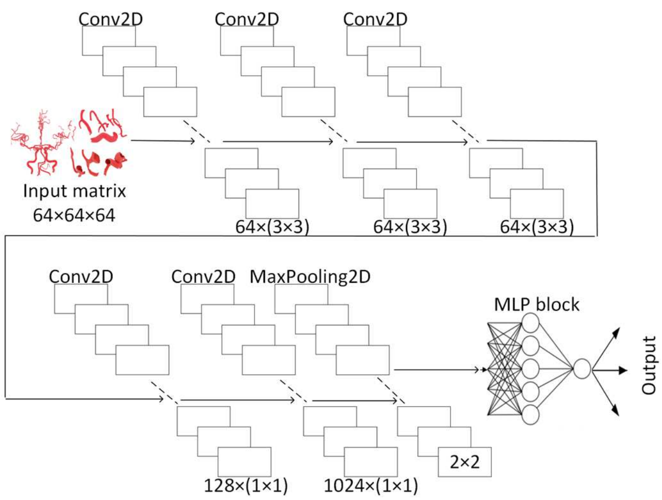

Figure 2. Proposed architecture CNN

The proposed neural network architecture, depicted in Figure 2, involves the input of a 3-dimensional matrix into the network. This architecture consists of two main blocks. The first block comprises six convolutional layers and a MaxPooling layer with a window size of 2×2. The initial Conv2D layer contains 64 filters and a 3×3 kernel. It is followed by two additional Conv2D layers, each with 64 filters and a kernel size of 3×3. A subsequent change occurs, introducing a Conv2D layer with 128 filters and a kernel size of 1×1. The final Conv2D layer in this block consists of 1024 filters and a kernel size of 1×1. The second block, known as the MLP block, follows the convolutional layers. It includes two dense layers with 512 and 256 units, respectively. A Dropout layer with a value of 0.7 is applied, followed by a flattened layer. After the flatten layer, another Dropout layer with a value of 0.2 is employed. Finally, a Dense layer is utilized, with the number of classes as the output and the softmax activation function. This neural network architecture has been designed to effectively process the input data and extract meaningful features for the IA detection task.

Within the neural network, we carefully selected and tuned various parameters to optimize its performance. We chose the Adamax optimizer, which has demonstrated excellent performance in image data classification tasks. The learning rate was set to 0.001. These choices were based on previous research, specifically focusing on hyperparameter optimization [28]. To find the optimal batch size, we conducted experiments using different values. Through rigorous testing, we determined that a batch size of 64 yielded the best results in terms of performance and convergence. Similarly, we explored different numbers of epochs to determine the most suitable value. After comprehensive evaluation, we found that training the network for 25 epochs achieved the best performance, striking a balance between avoiding underfitting and overfitting.

Our experiments were tested on NVIDIA GeForce GTX 1660Ti graphics card. During experiments, we used frameworks such as TensorFlow or Keras. In addition to the mentioned frameworks, we used libraries such as Numpy and Scikit as we worked in the Python environment.

V. Experiment and Results

The all experiments were performed on the IntrA dataset, where we studied the problem from a theoretical point of view. Subsequently, we decided to design NN. The proposed NN was done in a process where we first investigated the connection between the resulting accuracy and the number of convolutional layers. We tested different compositions, whether convolutional layer followed by MaxPooling and batch normalization or other combinations. The best designed network that performed the best is presented in our paper. The experiments of the proposed NN were conducted on the IntrA dataset. This dataset was divided into the ratio of 70:20:10 (Training, Test and Validation sets).

First, we trained the neural network, where we tracked the progression during each epoch, which had an exponential increase to approximately 98%. We also observed a decrease in the Loss Function which got up to 0.138. After each epoch, validation and testing were performed. In the neural network testing routine, we tested the network on 190 data points, where 165 3D matrices were vessels and 25 3D matrices provided information about the aneurysm. During testing, we evaluated metrics such as Precision, Reacall, F1 score and Accuracy (see in Tab.1).

TABLE I. Resulting values of metrics

Metrics	Accuracy	F1 score	Recall	Precision
Results (%)	97,36	93,93	96,53	91,69

After evaluating the resulting metrics, where we can claim accuracy up to 97.36%, we have worked out a confusion matrix where we can observe the classification of the given classes. The confusion matrix (see Tab. 2) is one of the metrics that serves to represent the results very well in the classification, and it is also in the confusion matrix that we can observe that there is almost no error rate in the vessel framework. The neural network with aneurysm classification had several errors, where we observed 4 misclassified 3D matrices but, at the same time, correctly for tridents, up to 21 matrices containing aneurysms.

TABLE II. Confusion Matrix

Targeted/Predicted	1	2
1	21	4
2	1	164

We then compared the results with other studies, where we observed that we were within approximately roughly similar numbers compared to other experiments. The comparison of the results can be seen in Table 3. We can see that in terms of overall F1 score, we achieve the best classification results. The overall increase in this metric is clearly influenced by the excellent classification of the vessel class. For the classification of the aneurysm class, we achieve similar results with an average of 84%.

TABLE III. Compared results

Network	Vessels (%)	Aneurysm (%)	F1-score overall
PNN++ [27]	98,52	88,51	90,29
PointCNN [27]	98,95	85,81	90,44
SpiderCNN [27]	97,28	87,90	87,22
N-PointNet [29]	98,53	92,15	92,60
Our proposed	99,39	85,98	93,93

VI. Conclusion

In this paper, we are working to create a NN that can best classify aneurysms to help doctors screen for the disease and prevent deaths. We have tested the proposed architecture on the IntrA dataset, which is a dataset of artificially generated data based on real data obtained from MRA.

Our work, we proposed architecture that is simple CNNs, a neural network that is not memory intensive, and can classify 97.36% whether there is an aneurysm in the image or a classical vessel. In terms of overall results, we achieved best accuracy of 97.36%, and the F1 parameter acquired a value of 93.93%. We also evaluated the Recall metric, where we obtained a value of 96.53%, and the Precision metric, where we obtained a value of 91.69%. We then compared our results with other freely available results on other networks. We compared our results with those of PNN++, PointCNN, SpiderCNN [27] and N-PointNet [29], which are very commonly used for this problem and achieve well results. Our results are comparable to those of these networks, even in the overall classification.

The research was conducted as part of the project: APVV-21-0502: BrainWatch: System for automatic detection of intracranial aneurysms. We are working on this project as a team within the Laboratory of Digital Video Processing (LoDVP). For this reason, similar research is being carried out within a parallel published paper: Automated Detection of Cerebral Aneurysms using Deep Learning Techniques.

In our following work, we planning to improve the overall accuracy of the proposed NN for this purpose to improve the classification of the brain aneurysm. Therefore, we further consider appropriate data processing and other available or different interpretations of neural networks. Since our goal is to create a model that will help physicians detect aneurysms and thus prevent deaths.

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REFERENCES

[1] Suarez JI, Tarr RW, Selman WR. Aneurysmal subarachnoid hemorrhage. N Engl J Med. 2006;354(4):387–96.

[2] Thompson BG, Brown RD, Amin--Hanjani S, et al. Guidelines for the management of patients with unruptured intracranial aneurysms. Stroke 2015;46:2368–400.

[3] Stember JN, Chang P, Stember DM, Liu M, Grinband J, Filippi CG, Meyers P, Jambawalikar S. Convolutional neural networks for the detection and measurement of cerebral aneurysms on magnetic resonance angiography. J Digit Imaging. 2018;32:1–8.

[4] Sichtermann T, Faron A, Sijben R, Teichert N, Freiherr J, Wiesmann M. Deep learning-based detection of intracranial aneurysms in 3D TOF-MRA. Am J Neuroradiol. 2019;40(1):25–32.

[5] Ueda D, Yamamoto A, Nishimori M, Shimono T, Doishita S, Shimazaki A, Katayama Y, Fukumoto S, Choppin A, Shimahara Y, et al. Deep learning for mr angiography: automated detection of cerebral aneurysms. Radiology. 2018;290(1):187–94.

[6] Kohout J, Chiarini A, Clapworthy GJ, Klajnšek G. Aneurysm identifcation by analysis of the blood-vessel skeleton. Comput Methods Programs Biomed. 2013;109(1):32–47.

[7] Hentschke CM, Beuing O, Paukisch H, Scherlach C, Skalej M, Tönnies KD. A system to detect cerebral aneurysms in multimodality angiographic data sets. Med Phys. 2014;41(9):091904.

[8] Park A, Chute C, Rajpurkar P, Lou J, Ball RL, Shpanskaya K, Jabarkheel R, Kim LH, McKenna E, Tseng J, et al. Deep learning-assisted diagnosis of cerebral aneurysms using the headxnet model. JAMA Netw Open. 2019;2(6):195600

[9] Adams WM, Laitt RD, Jackson A. The role of MR angiography in the pretreatment assessment of intracranial aneurysms: a comparative study. Am J Neuroradiol. 2000;21(9):1618–28.

[10] Rahmany I, Khlifa N. A priori knowledge integration for the detection of cerebral aneurysm. Biomed Eng/Biomedizinische Technik. 2018;63(4):445–52.

[11] Rahmany I, Laajili S, Khlifa N. Automated computerized method for the detection of unruptured cerebral aneurysms in DSA images. Curr Med Imaging Rev. 2018;14(5):771–7.

[12] Rahmany I, Arfaoui B, Khlifa N, Megdiche H. Cerebral aneurysm computer-aided detection system by combing MSER, SURF and SIFT descriptors. In: 2018 5th international conference on control, decision and information technologies (CoDIT); 2018. New York: IEEE. p. 1122–7

[13] Krizhevsky A, Sutskever I, Hinton GE. Imagenet classifcation with deep convolutional neural networks. Advances in neural information processing systems. Cambridge: MIT Press; 2012. p. 1097–105.

[14] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv :1409.1556. 2014.

[15] Ren S, He K, Girshick R, Sun J. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems. Cambridge: MIT Press; 2015. p. 91–9.

[16] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A. Going deeper with convolutions. In: Proceedings of the IEEE conference on computer vision and pattern recognition. New York: IEEE; 2015. p. 1–9.

[17] Redmon J, Divvala S, Girshick R, Farhadi A. You only look once: unifed, real-time object detection. In: Proceedings of the IEEE conference on computer vision and pattern recognition. New York: IEEE; 2016. p. 779–88.

[18] Redmon J, Farhadi A. Yolov3: an incremental improvement. arXiv preprint arXiv:1804.02767. 2018.

[19] Albarqouni S, Baur C, Achilles F, Belagiannis V, Demirci S, Navab N. Aggnet: deep learning from crowds for mitosis detection in breast cancer histology images. IEEE Trans Med Imaging. 2016;35(5):1313–21.

[20] Setio AAA, Ciompi F, Litjens G, Gerke P, Jacobs C, Van Riel SJ, Wille MMW, Naqibullah M, Sánchez CI, van Ginneken B. Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks. IEEE Trans Med Imaging. 2016;35(5):1160–9.

[21] Nakao T, Hanaoka S, Nomura Y, Sato I, Nemoto M, Miki S, Maeda E, Yoshikawa T, Hayashi N, Abe O. Deep neural network-based computer-assisted detection of cerebral aneurysms in MR angiography. J Magnet Reson Imaging. 2018;47(4):948–53.

[22] Hirasawa T, Aoyama K, Tanimoto T, Ishihara S, Shichijo S, Ozawa T, Ohnishi T, Fujishiro M, Matsuo K, Fujisaki J, et al. Application of artifcial intelligence using a convolutional neural network for detecting gastric cancer in endoscopic images. Gastric Cancer. 2018;21(4):653–60.

[23] Saha M, Chakraborty C, Racoceanu D. Efcient deep learning model for mitosis detection using breast histopathology images. Comput Med Imaging Gr. 2018;64:29–40.

[24] Jerman T, Pernus F, Likar B, Špiclin Ž. Aneurysm detection in 3d cerebral angiograms based on intra-vascular distance mapping and convolutional neural networks. In: 2017 IEEE 14th international symposium on biomedical imaging (ISBI 2017). New York: IEEE; 2017. p. 612–5

[25] Podgoršak AR, Bhurwani MM, Rava RA, Chandra AR, Ionita CN. Use of a convolutional neural network for aneurysm identifcation in digital subtraction angiography. In: Medical imaging 2019: computer-aided diagnosis, vol. 10950. Bellingham: International Society for Optics and Photonics; 2019. p. 109504.

[26] Jin H, Yin Y, Hu M, Yang G, Qin L. Fully automated unruptured intracranial aneurysm detection and segmentation from digital subtraction angiography series using an end-to-end spatiotemporal deep neural network. In: Medical imaging 2019: image processing, vol. 10949. Bellingham: International Society for Optics and Photonics; 2019. p. 109491.

[27] Yang, X., Xia, D., Kin, T. and Igarashi, Takeo, IntrA: 3D Intracranial Aneurysm Dataset for Deep Learning, The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2020.

[28] R. Vrskova, P. Kamencay et. al, "Hyperparameter Tuning of ConvLSTM Network Models," 44rd International Conference on Telecommunications and Signal Processing (TSP 2021).

[29] Jiaqi Wang, Juntong Liu, Zhengyuan Xu et al. N-PointNet: A multi-layer embedded deep learning model for 3D intracranial aneurysm classification and segmentation, 04 April 2023.