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Diagnosis of Developmental Venous Anomalies via Susceptibility-Weighted Imaging: A Deep Learning Application Using the DenseNet121 Model

Duyarlılık Ağırlıklı Görüntüleme ile Gelişimsel Venöz Anomalilerin Tanısı: DenseNet121 Modelini Kullanan Derin Öğrenme Uygulaması

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ABSTRACT

AIM: Developmental venous anomalies (DVAs) represent the most common type of cerebral vascular malformation and are typically diagnosed incidentally. Susceptibility-weighted imaging (SWI), a specialized application of magnetic resonance imaging (MRI) technology, is extensively utilized to detect microhemorrhages, iron deposits, and ischemic lesions. This study aimed to determine the accuracy of a deep learning-based model for diagnosing DVAs and to assess its potential applicability in clinical practice.

MATERIAL AND METHOD: This study included 99 patients with DVAs detected on cranial SWI MRI conducted at our hospital between January 2021 and May 2023, as well as 100 controls without DVAs. All imaging data were evaluated by a neuroradiologist with 10 years of experience. The deep learning process was initiated using the DenseNet121 model.

RESULTS: The study cohort consisted of 109 women and 90 men, with a mean age of 41.62 ± 19.69 years. A total of 104 lesions were identified in 99 patients diagnosed with DVAs. The developed model demonstrated high sensitivity (85% ± 5.0), specificity (81% ± 8.2), accuracy (83% ± 3.71), and area under the curve (90.02% ± 2.99) values in detecting DVAs.

CONCLUSION: The findings of this study indicate that the developed deep learning model may be effectively used for the accurate diagnosis of DVAs. This model addresses a significant gap in the literature and offers a strong basis for future research. Testing the model across different populations and conducting external validation studies will further enhance its generalizability and reliability.

Keywords: Developmental Venous Anomaly, Susceptibility-Weighted Imaging, Deep Learning, DenseNet121, Artificial Intelligence

ÖZET

AMAÇ: Gelişimsel venöz anomali (GVA), en yaygın serebral vasküler malformasyon türüdür ve genellikle tesadüfen teşhis edilir. Manyetik rezonans görüntüleme (MRG) teknolojisinin özel bir uygulaması olan duyarlılık ağırlıklı görüntüleme (SWI); mikrokanamalar, demir birikimleri ve iskemik lezyonların tespitinde yaygın olarak kullanılır. Bu çalışmada, derin öğrenme tabanlı bir modelin GVA tanısındaki doğruluğunu belirlemek ve klinik uygulamalardaki potansiyel kullanımını değerlendirmek amaçlanmıştır.

GEREÇ VE YÖNTEM: Bu çalışmaya, Ocak 2021 - Mayıs 2023 tarihleri arasında hastanemizde kraniyal SWI MRG incelemesi yapılan ve GVA saptanan 99 hasta ile GVA bulunmayan 100 kontrol dahil edilmiştir. Tüm görüntüleme verileri, 10 yıllık deneyime sahip bir nöroradyolog tarafından değerlendirilmiştir. Derin öğrenme süreci, DenseNet121 modeli kullanılarak başlatılmıştır.

BULGULAR: Çalışma kohortu 109 kadın ve 90 erkekten oluşmakta olup, ortalama yaş 41,62 ± 19,69 yıl olarak hesaplanmıştır. GVA tanısı alan 99 hastada toplam 104 lezyon tespit edilmiştir. Geliştirilen modelin GVA'ları tespit etmede duyarlılığı (%85 ± 5.0), özgüllüğü (%81 ± 8.2), doğruluğu (%83 ± 3.71) ve eğri altındaki alanı (%90.02 ± 2.99) yüksek bulunmuştur.

TARTIŞMA: Bu çalışmanın bulguları, geliştirilen derin öğrenme modelinin GVA'ların doğru tanısında etkili bir şekilde kullanılabileceğini göstermektedir. Model, literatürde önemli bir boşluğu doldurmakta ve gelecekteki araştırmalar için sağlam bir temel sunmaktadır. Farklı popülasyonlarda test edilmesi ve harici doğrulama çalışmalarının yapılması, modelin genellenebilirliğini ve güvenilirliğini daha da artıracaktır.

Anahtar Kelimeler: Gelişimsel Venöz Anomali, Duyarlılık Ağırlıklı Görüntüleme, Derin Öğrenme, DenseNet121, Yapay Zekâ

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INTRODUCTION

A developmental venous anomaly (DVA) is the most frequently encountered type of cerebral vascular malformation and is often diagnosed incidentally. The advancements in imaging techniques and their increased usage in recent years have led to a greater recognition of DVAs and their associations with clinically significant conditions, such as hemorrhage, infarction, hydrocephalus, and various abnormal imaging findings. [1-5]

Susceptibility-weighted imaging (SWI), a specialized application of magnetic resonance imaging (MRI) technology, is used for the diagnosis and assessment of various medical conditions. It is particularly utilized in the detection of microhemorrhages, iron deposits, and ischemic lesions in the brain and spinal cord. [6] This technique is also employed for the evaluation of neurodegenerative diseases, traumatic brain injuries, and tumors. By providing clearer imaging of low-contrast and hard-to-detect lesions, SWI plays a critical role in early diagnosis and accurate treatment planning. [7, 8]

Artificial intelligence (AI) has revolutionized the field of radiology. It facilitates rapid and accurate results, particularly in image analysis and diagnostic processes. [9] The capability of AI to detect abnormalities with high accuracy reduces the workload of radiologists and improves the quality of patient care. Furthermore, AI algorithms automate routine and repetitive tasks, allowing radiologists to focus on more complex cases. [10] The ongoing development of this technology demonstrates its vast potential for the future of radiology. [11]

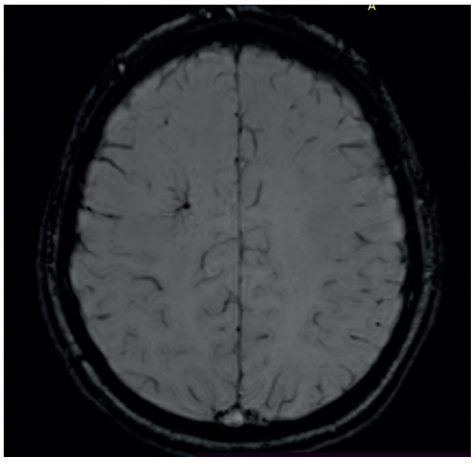
To the best of our knowledge, there are no studies in the literature where DVAs are fully automatically detected using artificial intelligence. In this study, we aimed to develop a deep learning-based model capable of diagnosing DVAs, which are often easily overlooked, dand to evaluate the model's diagnostic performance.

MATERIAL AND METHOD

After obtaining approval from our hospital's ethics committee (E-93471371-514.99-223929313, 06.09.2023), patients who underwent cranial SWI sequences between January 2021 and May 2023 were retrospectively reviewed from our hospital system.

The study focused on specific radiological criteria for the identification of DVAs. The primary criterion for diagnosing DVAs was the convergence of radially oriented veins into a single dilated venous channel, forming the characteristic "caput medusae" appearance. All images were carefully examined according to these criteria, and DVAs were identified based on these specific radiological findings. [12, 13] All images were evaluated by a neuroradiologist. A total of 99 patients aged between 0 and 100 years, with and without a history of cranial surgery, and diagnosed with DVAs were included in the study.

Figure 1. SWI sequence shows GVA in the right frontal lobe.



Additionally, 100 patients aged between 0 and 100 years, with and without a history of cranial surgery, were included as the control group.

MRI Acquisition Technique

For all patients, MRI scans were performed using a 1.5 Tesla (Siemens Aera, Erlangen, Germany) device available in our department. The routine sequences applied for brain MRIs includ-

Table 1. Technical parameters of susceptibility-weighted imaging.

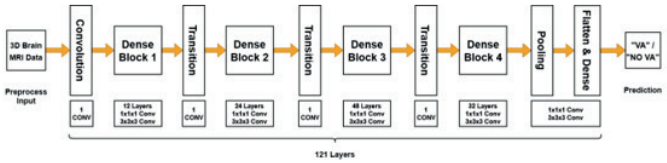
Parameter	Value
Echo time	40 ms
Repetition time	29 ms
Slice thickness	0.7 mm
Flip angle	25
Field of view	185x200 mm
Intersection gap	0 mm
Matrix size	320x250

presents the parameters used for SWI in this study. The evaluations were conducted retrospectively by reviewing the cases on the Picture Archiving and Communication System (PACS) monitors and recording the findings.

Deep Learning Method

To enhance the accuracy of the analyses conducted on MRI images, various preprocessing and modeling techniques were employed. Initially, all MRI images were normalized to a range of 0 to 1, which facilitated more stable and rapid model learning by standardizing pixel values. In addition, all MRI images were resized to 120x120x36 dimensions, ensuring consistent processing across different-sized images. The model was trained in 3D using the 121-layer DenseNet architecture. [14] DenseNet121 is a deep learning model based on a densely connected network structure.[5] The input layer transforms the images into a consistent size, and densely connected blocks optimize the flow of information by ensuring that units in each layer receive the outputs of all previous layers. The 3D convolution layer is used to process volume data, especially in 3D data sets. Transition layers reduce the size of feature maps, accelerating the learning process. The features extracted in the final layer are used for classification. DenseNet121 effectively facilitates learning with fewer parameters due to its dense interlayer connections.

Figure 2. DenseNet121 model [14]



In choosing our deep learning architecture, we prioritized the ability to process volumetric data efficiently and to maintain robust feature representation with relatively few parameters. We analyzed several alternative 3D architectures:

- ResNet (3D): While residual connections facilitate deeper networks, the sequential nature of information flow will result in lower sensitivity to small anatomical changes compared to DenseNet.

- 3D U-Net: This model excels in voxel-wise segmentation tasks but not suitable for classification problems.
- EfficientNet (3D extension): Despite its strong parameter efficiency, longer convergence times will present practical limitations.

DenseNet121 was selected due to its densely connected blocks, which ensure that each layer receives feature maps from all preceding layers. This design enhances gradient flow, mitigates vanishing gradient issues, and promotes feature reuse advantages particularly valuable when working with limited datasets.

The data was split into training, validation, and testing sets at a 70:10:20 ratio to enhance the generalization capability of the model. The developed model was trained for a maximum of 100 epochs using the training and validation data. During the training process, the performance of the model was monitored, and early stopping criteria were applied to achieve optimal performance. The trained model was evaluated using the test dataset. Performance metrics, including accuracy, sensitivity, and specificity, were calculated. In addition, five-fold cross-validation was applied. The entire dataset was divided into five parts, with each part being used as the test set in turn, and the average performance was reported. This approach was used to assess the generalization capability of the model and its performance across different datasets.

RESULTS

The study included 109 women and 90 men, with a mean age of 41.62 ± 19.69 years. A total of 104 lesions were identified in 99 patients diagnosed with DVAs. Among these lesions, 45 were located in the frontal lobe, 30 in the cerebellar hemispheres, 9 in the parietal lobe, 7 in the frontoparietal region, 4 in the temporal lobe, 4 in the brainstem, 4 in the occipitoparietal region, and 1 in the occipital lobe.

Table 2. Distribution of locations of GVA

Location	N (%)
Frontal lobe	45 (%43.2)
Cerebellar hemispheres	30 (%28.8)
Parietal lobe	9 (%8.6)
Frontoparietal region	7 (%6.7)
Temporal lobe	4 (%3.9)
Brainstem	4 (%3.9)
Occipitoparietal region	4 (%3.9)
Occipital lobe	1 (%0.9)

Two of the lesions showed evidence of previous hemorrhage, and two others presented with peripheral gliosis. In 15 patients, cavernomas were identified in the vicinity of DVAs. In 2 patients, cavernomas were located distant from the DVA site. Additionally, 1 patient had an AVM located in a region distant from the DVA.

The sensitivity, specificity, and accuracy of the DenseNet-121 model were calculated as 85%, 81%, and 83%, respectively, with an AUC value of 90%.

Figure 3. Confusion matrix (average values for five-fold cross-validation)

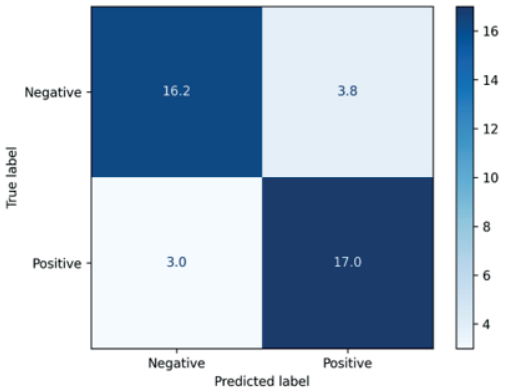


Figure 3 shows the confusion matrix prepared based on these findings. In addition to Figure 3, which presents the normalized confusion matrix across the 5-fold cross-validation, we have included in

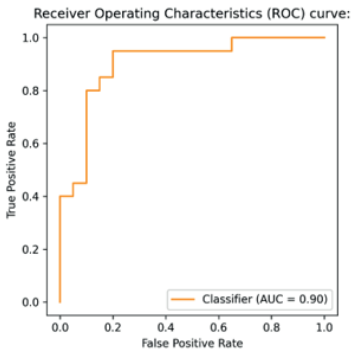
Table 3. Absolute counts of true positives (TP, orange), false positives (FP, blue), true negatives (TN, green), and false negatives (FN, yellow)

Fold-1		Fold-2		Fold-3		Fold-4		Fold-5	
18	2	17	3	17	3	14	6	15	5
4	16	2	18	4	16	3	17	2	18

the absolute counts of true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) aggregated over all folds. Providing these raw numbers enhances the transparency and interpretability of our model's performance.

Using receiver operating characteristic (ROC) curve analysis, the area under the curve (AUC) value was calculated to be 90.02% (95% confidence interval: 88.65–96.29) (Figure 4).

Figure 4. ROC analysis



DISCUSSION

In our study, we demonstrated that the developed model was able to identify DVAs with high sensitivity, specificity, and accuracy. As the first study of its kind in the literature, we established the capability and reliability of our model in diagnosing this condition. In clinical practice, the integration of AI-based tools like our model holds significant promise for improving diagnostic efficiency. Given the subtle imaging features of DVAs and their potential to be overlooked, especially in routine scans or high-volume settings, the model could function as a second reader to support radiologists by flagging suspected lesions for closer evaluation. This adjunctive role may reduce interpretation errors and enhance diagnostic confidence. Furthermore, the model can be incorporated into

automated triage systems to prioritize cases with probable DVAs for expedited review. Such integration into clinical workflows may be particularly beneficial in screening settings or institutions with limited subspecialty expertise in neuroradiology. As artificial intelligence continues to evolve, we believe that tools like ours can contribute meaningfully to both quality improvement and workload management in neuroimaging.

DVAs are associated with clinically significant conditions and require careful evaluation. These anomalies can lead to changes in cerebral blood flow and, albeit rare, can result in serious neurological complications. Routine imaging methods may not always be sufficient for diagnosing DVAs, which presents challenges in clinical management. In particular, small and atypical anomalies carry the risk of being overlooked and potentially delaying the correct diagnosis and treatment of patients. [15, 16]

The findings of this study revealed that the distribution of lesion localization was as follows: 45 in the frontal lobe, 30 in the cerebellar hemispheres, nine in the parietal lobe, seven in the frontoparietal region, four in the temporal lobe, four in the brainstem, four in the occipitoparietal region, and one in the occipital lobe. This distribution is consistent with previous findings in the literature, which report that DVAs most frequently occur in the frontoparietal and cerebellar regions. [16] This underscores the importance of considering the anatomical localization of DVAs in clinical diagnosis processes.

The prevalence of DVAs ranges from approximately 3% to 7% [5]. DVAs are also defined as cerebral venous angiomas or cerebral venous medullary malformations. These anomalies have a thicker wall without an elastic lamina or smooth muscle layer. [17] Due to this structural difference, DVAs can pathologically respond to changes in flow or pressure, potentially leading to complications. DVAs are usually incidental findings; however, patients may rarely present with intracranial hemorrhage. Furthermore, the literature suggests that DVAs are correlated with ischemic stroke and epilepsy. Some studies have observed pathological findings such as gliosis, neuronal degeneration, ischemic changes, and demyelination in the parenchymal venous drainage areas associated with DVAs. [18] These findings indicate that DVAs are not merely structural abnormalities but can also negatively affect brain parenchyma. Therefore, the clinical significance and potential complications of DVAs must be taken into account. It has also been observed that DVAs often coexist with other developmental anomalies. [15] This suggests that DVAs may be part of a broader spectrum of vascular anomalies rather than isolated pathologies. Thus, in the diagnosis and management of DVAs, it is crucial to consider possible accompanying anomalies. These findings emphasize the need for a multidisciplinary approach in the clinical evaluation and treatment of DVAs.

Deep learning algorithms offer significant advantages in the detection and diagnosis of brain pathologies. These algorithms have the capacity to accurately recognize complex patterns and abnormalities in brain images. [16] They have the potential to provide the early and accurate diagnoses of pathologies that are difficult to detect, such as tumors, microhemorrhages, and neurodegenerative diseases. In addition, deep learning models can improve clinical decision-making processes by accelerating manual analysis and reducing human error. [19]

DenseNet models have proven beneficial in assisting radiologists by improving diagnostic accuracy and expediting the process. Numerous studies have utilized DenseNet models and directly compared model performance with that of radiologists. In one study using the DenseNet-based CheXNeXt model [20], the performance of the model in detecting 14 chest diseases was found to be comparable to that of radiologists. When compared with nine radiologists using a dataset of 420 images, the model performed equally well in detecting ten pathologies, better in one, and slightly worse in three. In addition, the model completed image analysis much faster than the radiologists. In another study evaluating various deep learning models for distinguishing between normal and abnormal chest X-rays [21], the aim was to alert radiologists and clinicians to potential abnormal findings. The study included the DenseNet model, among others, and demonstrated that such models could achieve accuracy equivalent to that of experienced radiologists. These results indicate that DenseNet models can perform as well as, or sometimes better than, radiologists in specific diagnostic tasks, leading to enhanced efficiency and consistency in clinical diagnosis. Our model may serve as an adjunct to current imaging methods, providing clinicians with more reliable data and accelerating the diagnostic process. This offers a significant advantage in evaluating early intervention and treatment options.

This study has some important limitations. Due to the retrospective design, the evaluation relied on the analysis of past data, which may have increased the possibility of missing or biased data. The dataset used for training and testing the model consists of a relatively small sample. This may limit the generalizability of the model, particularly when applied to images acquired from different hospitals, imaging devices, or patient populations, where performance may decrease. Since the data were obtained from a single center using similar imaging protocols, it may be difficult for the model to achieve the same level of success in diverse clinical settings. No external validation was performed; therefore, the reproducibility and reliability of the results in different datasets or populations have not been confirmed. The study utilized only a single magnetic resonance imaging (MRI) modality (SWI). The exclusion of other modalities or multimodal data limited our ability to assess the model's performance under different imaging conditions. Additionally, the model's decision-making process could only be explained to a limited extent. In clinical practice, it is important to understand which regions of the image the model relies on when making predictions. Although a basic evaluation in this direction was conducted in this study, a more comprehensive interpretability strategy was not implemented. Finally, the model parameters and hyperparameters used during training could have been optimized over a wider range. This represents another limitation that may have influenced the model's performance.

These limitations indicate that the findings should be interpreted cautiously and supported by more comprehensive and prospective studies. The strongest aspect of our study is that, to the best of our knowledge, it is the first in the literature to evaluate DVAs using deep learning algorithms.

For future studies, we recommend validating the model using datasets collected from multiple institutions, including centers with different MRI vendors, scanner strengths, and imaging protocols. Such an approach will help assess the model's robustness and adaptability across various technical settings. Furthermore, applying the model to diverse patient populations—such as pediatric and geriatric groups, as well as individuals with concurrent cerebrovascular abnormalities will offer insights into its performance in broader clinical scenarios. These efforts will be essential for determining the model's generalizability and clinical utility on a larger scale.

CONCLUSION

In conclusion, the findings of our study demonstrate the utility and usefulness of the developed model in routine clinical practice. Additionally, we believe that the artificial intelligence model we developed may be effectively used in the follow-up of patients with DVAs. With its high accuracy rate in diagnosing DVAs, our model fills a significant gap in the literature and provides a solid foundation for future research. Testing the model across different populations through external validation studies will further enhance its generalizability and reliability.

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REFERENCES

1. Linscott LL, Leach JL, Jones BV, Abruzzo TA. Developmental venous anomalies of the brain in children - imaging spectrum and update. Pediatr Radiol. 2016;46:394-406. doi: 10.1007/s00247-015-3525-3

2. Mooney MA, Zabramski JM. Developmental venous anomalies. Handb Clin Neurol. 2017;143:279-282. doi: 10.1016/B978-0-444-

63640-9.00026-6

3. San Millan Ruiz D, Gailloud P. Cerebral developmental venous anomalies. Childs Nerv Syst. 2010;26:1395-1406. doi: 10.1007/s00381-010-1253-4

4. Idiculla PS, Gurala D, Philipose J, Rajdev K, Patibandla P. Cerebral Cavernous Malformations, Developmental Venous Anomaly, and Its Coexistence: A Review. Eur Neurol. 2020;83:360-368. doi: 10.1159/000508748

5. Hon JM, Bhattacharya JJ, Counsell CE, Papanastassiou V, Ritchie V, Roberts RC, et al. The presentation and clinical course of intracranial developmental venous anomalies in adults: a systematic review and prospective, population-based study. Stroke. 2009;40:1980-1985. doi: 10.1161/STROKEAHA.108.533034

6. Weng CL, Jeng Y, Li YT, Chen CJ, Chen DY. Black Dipole or White Dipole: Using Susceptibility Phase Imaging to Differentiate Cerebral Microbleeds from Intracranial Calcifications. AJNR Am J Neuroradiol. 2020;41:1405-1413. doi: 10.3174/ajnr.A6636

7. Rubin A, Waszczuk L, Trybek G, Kapetanakis S, Bladowska J. Application of susceptibility weighted imaging (SWI) in diagnostic imaging of brain pathologies - a practical approach. Clin Neurol Neurosurg. 2022;221:107368. doi: 10.1016/j.clineuro.2022.107368

8. Haller S, Haacke EM, Thurnher MM, Barkhof F. Susceptibility-weighted Imaging: Technical Essentials and Clinical Neurologic Applications. Radiology. 2021;299:3-26. doi: 10.1148/radiol.2021203071

9. Rana M, Bhushan M. Machine learning and deep learning approach for medical image analysis: diagnosis to detection. Multimed Tools Appl. 2022:1-39. doi: 10.1007/s11042-022-14305-w

10. Panayides AS, Amini A, Filipovic ND, Sharma A, Tsaftaris SA, Young A, et al. AI in Medical Imaging Informatics: Current Challenges and Future Directions. IEEE J Biomed Health Inform. 2020;24:1837-57.

11. Kocak B, Durmaz ES, Ates E, Kilickesmez O. Radiomics with artificial intelligence: a practical guide for beginners. Diagn Interv Radiol. 2019;25:485-495. doi: 10.1109/JBHI.2020.2991043

12. Saba PR. The caput medusae sign. Radiology. 1998;207:599-600. doi: 10.1148/radiology.207.3.9609879

13. Gözgeç E, Oğul H. Coexistence of Intracranial Developmental Venous Anomaly and Cavernoma; When, Where and How. J Gen Med . 2021;31(4):349-53. doi: 10.54005/geneltip.1036524

14. Huang G, Liu Z, Maaten LVD, Weinberger KQ. Densely Connected Convolutional Networks. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)2017. p. 2261-2269. doi: 10.1109/CVPR.2017.243

15. Boukobza M, Enjolras O, Guichard JP, Gelbert F, Herbreteau D, Reizine D, et al. Cerebral developmental venous anomalies associated with head and neck venous malformations. AJNR Am J Neuroradiol. 1996;17:987-994.

16. Lee C, Pennington MA, Kenney CM, 3rd. MR evaluation of developmental venous anomalies: medullary venous anatomy of venous angiomas. AJNR Am J Neuroradiol. 1996;17:61-70.

17. Pereira VM, Geibprasert S, Krings T, Aurboonyawat T, Ozanne A, Toulgoat F, et al. Pathomechanisms of symptomatic developmental venous anomalies. Stroke. 2008;39:3201-3215. doi: 10.1161/STROKEAHA.108.521799

18. Santucci GM, Leach JL, Ying J, Leach SD, Tomsick TA. Brain parenchymal signal abnormalities associated with developmental venous anomalies: detailed MR imaging assessment. AJNR Am J Neuroradiol. 2008;29:1317-1323. doi: 10.3174/ajnr.A1090

19. Smith LGF, Milliron E, Ho ML, Hu HH, Rusin J, Leonard J, et al. Advanced neuroimaging in traumatic brain injury: an overview. Neurosurg Focus. 2019;47:E17. doi: 10.3171/2019.9.FOCUS19652

20. Rajpurkar P, Irvin J, Ball RL, Zhu K, Yang B, Mehta H, et al. Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med. 2018;15:e1002686. doi: 10.1371/journal.pmed.1002686

21. Tang YX, Tang YB, Peng Y, Yan K, Bagheri M, Redd BA, et al. Automated abnormality classification of chest radiographs using deep convolutional neural networks. NPJ Digit Med. 2020;3:70. doi: 10.1038/s41746-020-0273-z