Brain Anomalies of MRI Segmentation

R. Jayanthi [a], A. Hepzibah Christinal [a], R. Hephzibah [a], D. Abraham Chandy [b], T. Shekinah [c]

[a] *Department of Mathematics, Karunya University, Coimbatore, India*
[b] *Department of Electronics and Communication Engineering, Karunya University, Coimbatore, India*
[c] *Department of Computer Science, Loyola College of Engineering, Chennai, India*

Abstract

For several decades, MRI is used widely in neurological research and in clinical examinations. The most dominant step in preparing MRI brain images is removing unwanted brain regions. The identification of brain lesions through Magnetic Resonance Imaging (MRI) remains challenging. The discovery of tumor in the brain using diverse steps of brain image segmentation is challenging. The use of automated brain tumor detection has just recently been proposed through a variety of methods. Methods based on Unsupervised Anomaly Detection are initiated to detect anatomical variability as the deviation of a healthy model well informed by using a VAE. This paper provides detail about unsupervised anomaly detection with autoencoders. We discussed the dataset that contains healthy and unhealthy images of the brain. In our future work, we planned for anomaly detection and classification using the variational autoencoders by training the model.

Keywords

Unsupervised Anomaly detection, Variational autoencoders, Brain images.

1. Introduction

Anomalies or outliers are those which deviate from the normal or expected one. Anomaly detection has its vast area of applications in Intrusion and Fraud and Medical Anomaly Detection, Detection of damage in industries, Processing of Images, Text Data detection, Networks based on sensors, and other zones.[1]. Anomaly detection unlike other problems handle insignificant and rare events. All the detection methods undergo a complex problem in this detection of anomalies. Latterly emerging deep learning-enabled deep anomaly detection has the three prototypes such as the learning of Feature Extraction and End-to-end Learning of anomaly score along with the Normality-based representations of feature [2]. Anomaly detection with deep learning expands wider in all applications specifically in the medical field. Some challenges in the detection of anomalies include the labelled data availability and difficulty in identifying the noise similar to anomalies [3]. The anomalies are separated into three categories contextual, point, and collective anomalies. Due to the enormous amount of medical data, it is a tedious task to detect the outliers. The models of deep learning for anomaly detection are classified into three categories supervised, semi-supervised, and unsupervised models [4]. The original evidence of details for the surveillance implementation is the Videos. As there are a huge amount of video materials, it contains less or don't have interpretation for supervised learning. The unsupervised models for anomaly detection in videos are based on classes such as the Spatio-temporal predictive models, Reconstruction based models, and Generative models [5]. The Brain Medical Image Segmentation is generally classified as follows: By segmentation manually intensity-based methods such as thresholding, region-growing, classification, Atlas and surface-based methods, active contours, and multiphase active contours, a hybrid method and clustering [6]. Partitioning of MR images manually is a long-widened and thus extravagant technique. In addition, hand labeling is subject to

CVMLH-2022: Workshop on Computer Vision and Machine Learning for Healthcare, April 22 – 24, 2022, Chennai, India.
EMAIL: hepzia@yahoo.com (A. Hepzibah Christinal)
ORCID: 0000-0003-3965-3183 (A. Hepzibah Christinal)

inter-and intra-observer variance. These restrictions on manual methods present a challenge

In labeling large populations of subjects, which are commonly required for neuroimaging investigation [7]. The main disadvantages of these methods all of which are based on supervised learning are that they require huge and different interpretation datasets, which are infrequent and high-priced to obtain and the end models can only identify lesions similar to those in the training dataset. The collection of training data for unusual diseases, in which collection of such data presents a major challenge, is especially important.[8] In image segmentation, a thresholding technique is one of the simplest and most commonly used. The contour of a brain tumor can be determined with this technique. Therefore, methods in need of partially labeled data or without labeling at all are common. According to [9] segmentation, MR images dealing with patch-based glioma detection of the brain were performed by using unsupervised three-dimensional (3D) stacked denoising autoencoders, but only as a preparing step before the supervised model was applied. An example of a detection method that combines the semi-supervised with unsupervised methods to manage the methods of classification and segmentation is anomaly detection. During deep learning, VAEs are used to learn latent representations of data. In addition, they have been utilized to draw images, perform semi-supervised learning, as well as interpolate between sentences. In UAD, two types of neural networks include generative adversarial networks and variational autoencoders are examined [10]. There are three types of anomaly detection such as supervised, semi-supervised, and Unsupervised. Unsupervised anomaly detection is the most common type. Using an unlabelled dataset, we train a machine-learning model to fit the normal behavior. An unlabelled dataset is used for unsupervised anomaly detection. A huge variety of anomalies is detected using the deep learning model on healthy brain images on independent datasets, and it is analyzed with the supervised U-Net. [11]. Anomaly detection identifies unusual points in a setof normal samples in order to highlight areas to the extent of manual examination. In addition, it is not needed of any manual annotation, is not dependent on unconstrained human errors, and as a replacement, instinctively incorporates the view of normal tissue to identify anomalies. Anomaly detection aims to identify unanticipated, deviated data points on the basis of normal data samples, thusspotlighting the essential regions for the next examination. Unlike manual annotations, no need for supervision. [12]. Anomaly detection is the technique of detecting out-of-the-ordinary items or events in datasets. In contradiction to the old task of classification, detection is most often implemented on unlabelled data, mainly detecting on the datasets with the underlying structure of anomalies. Unsupervised anomaly detection is a problem that is tackled in a diversity of practical implementations, which include fraud, intrusion and network detection, and the bio-science and medical domains. In thisdomain, dozens of algorithms have been presented, however, the academic community at present does not have a universal relative consideration and easily accessible datasets.[13]. This paper addresses these flaws by evaluating nearly 19 algorithms of unsupervised anomaly detection implemented on ten distinct databases from various applications. In modeling and creating graphs with latent components, graph neural networks and variational autoencoder are used often. However, no one knows what thesehidden characteristics are or why they function so effectively. We present the Dirichlet Graph Variational Autoencoder (DGVAE) in this paper, which uses graph cluster memberships as latent components. Our research establishes a link between VAEs-based graph generation and balanced graph cut, opening up new avenues for understanding and improving the internal mechanism of VAEs-based graph production. We initially understand DGVAE's reconstruction term as a principled balanced graphcut. Furthermore, we suggest a new variation of GNN termed Heatts to convert the input graph into, driven by the low pass features in unbiased graph cut [14].

2. Methods

2.1. Unsupervised anomaly detection

The models that are trained is utilized for detection of anomaly and partition in many sectors, as provided below. Methods based on reconstruction, Monte Carlo methods, and Gradient-Based methods [15]. And Anomaly detection has been classification-based methods, Reconstruction-based methods, Density-based methods. Unsupervised anomaly detection approaches include methods based on classification. The OC-SVM is a well-known example of a classification-based approach (OC-SVM). To distinguish normal from abnormal data, the OC-SVM makes a decision for a boundary in the features space connecting the origin and data features [12]. Deep unsupervised representation learning has recent results used in novel approaches to UAD in MRI brain. The basic idea underlying particular studies is to understand a model of the normal structure by compressing and recovering health data. It enables the detection of typical structures resulting from inaccurate retrieval of compressed, samples of anomaly [13]. Obtaining a dataset of this type can be time-consuming and expensive. Because we have trained these algorithms for a specific job, they will perform badly when applied to photos containing previously discovered types of abnormalities. Unsupervised Anomaly Detection (UAD) approaches have been proposed to circumvent these constraints [14]. Rather than building a network to detect pathologic circumstances, an unsupervised network is trained with normal brain MR images to detect pathogenic traits as departures from the norm. The models cannot completely regenerate healthy equivalents of certainly morbid samples of input samples, but different areas produce different differences in error reconstruction statistics of tissue based on normal and abnormal, described as excellent depicter of best performance of UAD [15]. The models with a certain ability can be prepared and is useful for UAD in images of whole-brain at their native aspiration by using skip-connections, having previously demonstrated usefulness in segmentation and image-to-image translation of bio medical images [16].

2.2. Variational autoencoders (VAEs)

The unsupervised learning which trains the neural network to understand the process of reconstruction is an autoencoder. It contains two parts such as the encoder and the decoder. The solitary hidden layer neural network has an encoder and decoder which is represented in Equations 1 and 2. W symbolize weight and b symbolize the bias of the neural network and the nonlinear transformation function is denoted by σ.

$$h = (W_{gy}y + b_{yg}) \qquad (1)$$

$$z = (W_{gy}h + \ b_{gy}) \qquad (2)$$

$$||y - t|| \qquad (3)$$

Equation (1) shows how an affine mapping follows a nonlinearity to map an input norm y to a hidden variable g. The decoder in equation (2) uses the same transformation as the encoder to reconstruct the hidden representation g return to the original space of input. The reconstruction error, as denoted in the equation, is the variation between the input variable y and reconstruction t [17]. With just normal examples, we describe a new back-to-back relatively supervised DL strategy for anomaly detection and localization in videos. The idea behind this research is that samples of normal may be assigned to at the minimum one Gaussian constituent of a GMM, but outliers can be assigned to none of the Gaussian components. The Gaussian Mixture Variational Autoencoder is a method used to learn the contents of the feature of samples that are normal using a Gaussian Mixture Model assisting with deep learning training. The image as input and the output feature map having relative spatial coordinates are retained using a Completely Convolutional Network (FCN) without a totally associated layer is used for the structure of encoder-decoder [18]. This paper Proposed autoencoders, denoising Autoencoder and Variational Autoencoders. Autoencoders are neural networks in artificial neural networks that are used to efficiently code unlabelled data. Regenerating the input from the encoding allows the encoding to be validated and adjusted [12]. An unsupervised method for detecting anomalies within whole-brain MR images is proposed by building a model for the normal variation of brain structure, coupled with spatial autoencoders. There have been significant developments in excessively intense anomaly detection in MRI data because of AEs. AUD in brain MRI requires skip-connections for high reconstruction [19]. We used skip connections-based spatial autoencoders in order to determine the variations of the normal brain by analysing the MR of individuals who are healthy [20]. The freely accessible two datasets such as 3D Variational Auto Encoders perform best their 2D counterparts, emphasizing the benefit of volumetric context. Furthermore, our 3D erasing technologies enable for significant presentation enhancements. The performance of 3D VAE with input erasing achieves a DICE score having 31.40 percent in comparison to 25.76 percent for the 2D VAE. They presented deep learning for three-dimensional approaches for UAD in brain paired with erasing on 3D and show the steps of three-dimensional perform their two-dimensional counterparts for segmentation. The spatial erasing strategyalso gives access to a different design of the variational approximation distribution to the true posterior of an expanded VAE model with a Markov chain interchanging among the decoder and the encoder, which is the foundation of this method. The method can be used to practice a VAE model from the staring or as post-production on a VAE that has already been trained without access to real data. Our research shows that encoders trained using our self-consistency method produce representations that are vigorous (unaffected) by input deviations [22]. For the modeling of images and to accompany labelsor captions, a unique variational autoencoder is built. The latent image features are decoded using the Deep Generative Deconvolutional Network (DGDN), while the image encoder is a DCNN; the CNN isutilized to estimate a distribution for the latent DGDN attributes. The generative models are used for connecting the latent code for labels and captions. Averaging across the distribution of latent codes is used to predict the names for testing new images; this is computationally efficient due to the learned CNN-based encoder. Because the framework can model the image in the occurrence or lack of linked identifications, a new feature has been included [23]. The joint distribution is studied in two forms such as from observed data fed through the encoder to give codes, and from the simple prior produces the latent codes and produced through the decoder to give data in the novel types. Lower bounds for marginal log-likelihood suitable for the data which is data and coding are studied. The Kullback-Leibler divergence of joint density functions is to be reduced by using the variational bound while also maximizing the two marginal log-likelihoods. A new type of adversarial training has been devised to aid learning. They conducted a set of procedures in which they illustrated the reconstruction of data andproduction on a variety of platforms [24]. further speed increases while reducing the need for big data sets. [21].

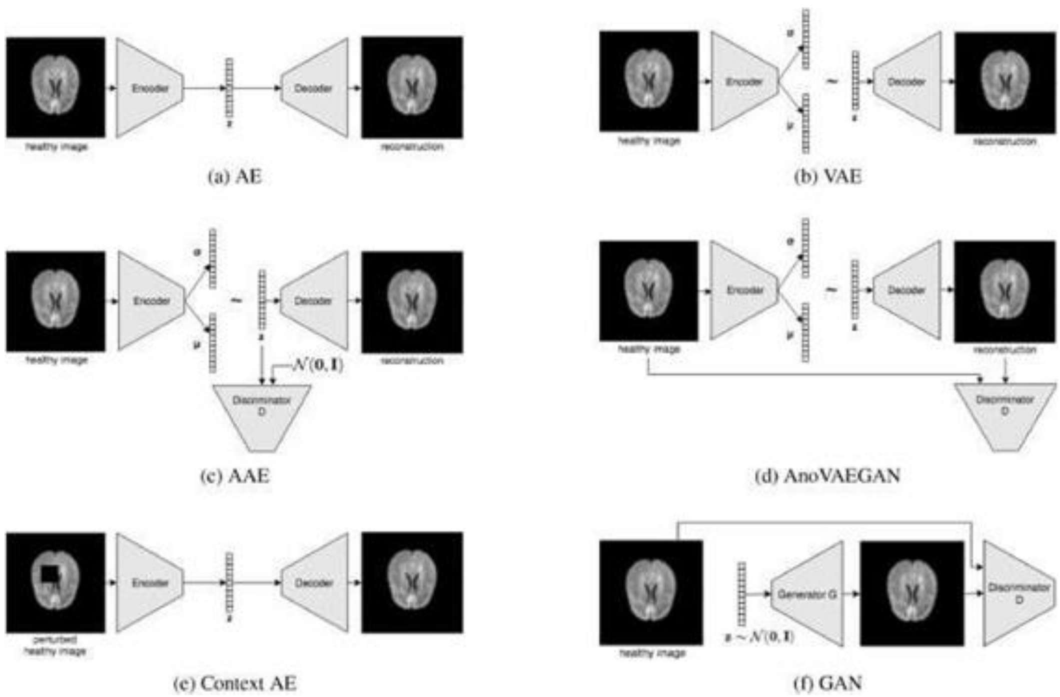

Figure 1: Representation of various Autoencoders

3. Experiment

The dataset is taken freely accessible Kaggle dataset repository. We will be implementing the coding using the python software in windows 10 with the 64-bit operating system. We have 155 healthy brain images and 98 affected images. The images are classified into two classes such as the Healthy (class 1)and Unhealthy (class 2) images. In this paper, we are going to use these datasets for the anomaly detection and classification of healthy and unhealthy images. The data will be separated into healthy and unhealthy images and the model will be trained where 80% is used for training and 20% for testing. In our future work, we will perform the process of anomaly detection and classification. We will use the variational autoencoders and train them and take results based on their performance.

4. Conclusion

This paper is about unsupervised anomaly detection using variational autoencoders. This paper discusses about Unsupervised anomaly detection in brain images. Autoencoders are neural networks in artificial neural networks that are used to efficiently code unlabelled data. Regenerating the input from the encoding allows the encoding to be validated and adjusted. An unsupervised method for detecting anomalies within entire brain images is proposed by modelling the normal variation of brain structure, coupled with spatial autoencoders. Here, we give a detail about the variational autoencoders. The Kaggle dataset containing healthy and unhealthy brain images will be used for our experimentation purpose. The autoencoders will be trained and will be used for the goal of identifying anomalies and classification. We will carry out our experiments and further results will be given in our future work.

5. References

[1] Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. *ACM computing surveys (CSUR)*, *41*(3), 1-58.

[2] Pang, G., Shen, C., Cao, L., & Hengel, A. V. D. (2021). Deep learning for anomaly detection: A review. ACM Computing Surveys (CSUR), 54(2), 1-38.

[3] Alloqmani, A., Abushark, Y. B., Khan, A. I., & Alsolami, F. Deep Learning based Anomaly Detection in Images: Insights, Challenges and Recommendations. image, 4, 5.

[4] Chalapathy, R., & Chawla, S. (2019). Deep learning for anomaly detection: A survey. arXiv preprint arXiv:1901.03407.

[5] Kiran, B. R., Thomas, D. M., & Parakkal, R. (2018). An overview of deep learning based methods for unsupervised and semi-supervised anomaly detection in videos. Journal of Imaging, 4(2), 36.

[6] Aghdam, R. B., Ghiasi, A. S. B., Fatemi, P., & Hashemi, N. S. (2017). Challenges in Brain Magnetic Resonance Image Segmentation. American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS), 27(1), 122-138.

[7] Makropoulos, A., Gousias, I. S., Ledig, C., Aljabar, P., Serag, A., Hajnal, J. V., ... & Rueckert, D. (2014). Automatic whole brain MRI segmentation of the developing neonatal brain. IEEE transactions on medical imaging, 33(9), 1818-1831.

[8] Sujji, G. E., Lakshmi, Y. V. S., & Jiji, G. W. (2013). MRI brain image segmentation based on thresholding. International Journal of Advanced Computer Research, 3(1), 97.

[9] Vaidhya, K., Thirunavukkarasu, S., Alex, V., & Krishnamurthi, G. (2015, October). Multi-modal brain tumor segmentation using stacked denoising autoencoders. In BrainLes 2015 (pp. 181-194). Springer, Cham.

[10] Lambert, B., Louis, M., Doyle, S., Forbes, F., Dojat, M., & Tucholka, A. (2021, April). Leveraging 3D Information in Unsupervised Brain MRI Segmentation. In 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI) (pp. 187-190). IEEE.

[11] Baur, C., Denner, S., Wiestler, B., Navab, N., & Albarqouni, S. (2021). Autoencoders for

unsupervised anomaly segmentation in brain MR images: a comparative study. Medical Image Analysis, 69, 101952.
[12] Zimmerer, D., Kohl, S., Petersen, J., Isensee, F., & Maier-Hein, K. (2019). Context-encoding Variational Autoencoder for Unsupervised Anomaly Detection--Short Paper. arXiv preprint arXiv:1907.12258.
[13] Baur, C., Denner, S., Wiestler, B., Navab, N., & Albarqouni, S. (2021). Autoencoders for unsupervised anomaly segmentation in brain MR images: a comparative study. Medical Image Analysis, 69, 101952.
[14] Iwano, N., Adachi, T., Aoki, K., Nakamura, Y., & Hamada, M. (2021). RaptGen: A variational autoencoder with profile hidden Markov model for generative aptamer discovery. bioRxiv.
[15] Baur, C., Denner, S., Wiestler, B., Navab, N., & Albarqouni, S. (2021). Autoencoders for unsupervised anomaly segmentation in brain MR images: a comparative study. Medical Image Analysis, 101952.
[16] Baur, C., Wiestler, B., Albarqouni, S., & Navab, N. (2020, April). Bayesian skip-autoencoders for unsupervised hyperintense anomaly detection in high resolution brain MRI. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 1905-1909). IEEE.
[17] An, J., & Cho, S. (2015). Variational autoencoder based anomaly detection using reconstruction probability. Special Lecture on IE, 2(1), 1-18.
[18] Jang, Y., Choi, H., Park, J. C., Jun, J., & Kim, D. S. (2015, October). Variational auto-encoder with convolutional neural network for complex image classification task. In Society for Neuroscience Annual Meeting 2015. Society for Neuroscience Annual Meeting 2015.
[19] Baur, C., Wiestler, B., Albarqouni, S., & Navab, N. (2020, April). Bayesian skip-autoencoders for unsupervised hyperintense anomaly detection in high resolution brain MRI. In 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI) (pp. 1905-1909). IEEE.
[20] Baur, C., Wiestler, B., Muehlau, M., Zimmer, C., Navab, N., & Albarqouni, S. (2021). Modeling Healthy Anatomy with Artificial Intelligence for Unsupervised Anomaly Detection in Brain MRI. Radiology: Artificial Intelligence, 3(3), e190169.
[21] Bengs, M., Behrendt, F., Krüger, J., Opfer, R., & Schlaefer, A. (2021). Three-dimensional deep learning with spatial erasing for unsupervised anomaly segmentation in brain MRI. International journal of computer assisted radiology and surgery, 16(9), 1413-1423.