Neural Augmentation Using Meta-Learning for Training of Medical Images in Deep Neural Networks

Tina, Sanjay Kumar Dubey, and Ashutosh Kumar Bhatt

Abstract Image data augmentation techniques are state-of-art method for drive of classification and segmentation of multidimensional medical imaging by method of deep neural network approaches. Neural augmentation is considered as type of data augmentation in medical image processing which is widespread and actively used method in enhancing the measures of performance of neural network. The novel approaches introduced on the grounds of deep network which expanded tremendously over the years as it improves the clinical assistance for the doctors in the treatment of patients. The major concern in healthcare domain relies on identification of tumor in the medical imaging modalities at probable early stage in humans, and deep neural network plays vigorous role in the detection of tumors using neural network with possible less layers. Neural network augmentation with the gradient of meta-learning in deep learning models will assess performance of convolutional neural network (CNN) model based on assessment parameters like accuracy and loss function along with augmented images. Deep convolutional network get to trained using meta-learning approach, and then, augmentation will be accomplished. This proposed work implements the neural augmentation with meta-learning approach in neural network subsequently training the dataset to extemporize accuracy rate in training and validation.

Keywords Neural augmentation · Meta-learning · Convolutional neural network · Medical imaging · Brain tumor MRI

Tina (✉) · S. K. Dubey
Amity University, Uttar Pradesh, Noida, India
e-mail: dudeja.tina@gmail.com

S. K. Dubey
e-mail: skdubey1@amity.edu

A. K. Bhatt
Uttarakhand Open University, Haldwani, Uttarakhand, India

A. Tomar et al. (eds.), *Proceedings of 3rd International Conference on Machine Learning, Advances in Computing, Renewable Energy and Communication*, Lecture Notes in Electrical Engineering 915, https://doi.org/10.1007/978-981-19-2828-4_35

1 Introduction

The initiation of artificial intelligence in field of healthcare informatics instigates the improvised and advanced in transformation of clinical technology. The illustrations of abnormalities in parts of organ in body are rapidly intensifying for nearly entire age groups in human beings. However, the initiation of deep learning models in field of medical domain and clinical diagnosis aids in the enhanced medical procedures and better decision-making with improvised image visualization of medical image modalities. The illustrations of abnormality in structures such as brain tumor cases which are rising at a quick rate for certain reasons, for example, age of patient, chemical exposure, radiations, etc. Researchers aim to deliver improved visualization of organ which is affected, so early diagnosis can be apprehended. Over the years, artificial intelligence made substantial improvement in the healthcare informatics which comprises preprocessing of medical computed tomography (CT) image which is accommodating in diagnosing the ailment at initial stage in easy way. Now a days, health care needs well-organized and reliable practices to analyze diseases such as cancer which is the reason of mortality worldwide for humans. The best practice for investigating and identifying tumor is magnetic resonance imaging (MRI). Advanced level grades evaluate that in most cases upper level-staged tumors are damaging as these are developed in brain at a fast rate. In the underlying stage, tumor does not spread much; however, in later stage, there are chances of spreading to parts of the brain. Early diagnosis of tumor is hence recommended as in affected portion of brain, cells are destructive; subsequently, these cells may pass into the circulation systems of brain and spread into the encircling cells [1]. Consequently, it is imperative to identify early phase of brain tumors with the most effective accuracy.

MRI imaging avails a technique for classification of tumors by means of image augmentation and models of deep neural network. Image data augmentation techniques applied on medical imaging modalities provide the diversity on the available dataset by inclusion of image cropping, flips, Gaussian filters, principal component analysis (PCA), color jittering, etc., and through these techniques, capturing of noteworthy structures of actual image dataset can be done. The prospect of enhancement in the data visualization entirely counts on the learning strategies and deep learning strategies including data augmentation diminishes overfitting models by training the dataset [2].

Image augmentation addresses the issue of overfitting in labeled dataset which provides a procedure of intensifying a dataset being derivative from information accessible in the prevailing dataset. When the implementation is done on images, then the insight for that is ubiquitous, as its application involves translation, rotation, and other type of modifications in the healthcare imaging which are predominant in the medical dataset to generalize the learning model. Analyzing medical image segmentation and augmentation plays important part suing deep neural learning models such as deep convolutional neural networks, growing convolutional neural networks [3], and support vector machines. As the mixing of varied samples is quite challenging tasks through similar feature space representations for newer sample generation [4].

This paper instigates in generating the augmented images through the process of self-learning methodology which will help to make learn normal and abnormal structures by themselves in directive to reduce complexity in training dataset of medical image besides reducing overfitting. So, the concept of neural augmentation can be utilized in aggregation with meta-learning approach in deep learning framework.

2 Related Work

Data augmentation methods alike adding noise, rotation, flip determine to degree the performance gain specified by augmentation techniques. They avail recommended data augmentation methods which will be beneficial in procedure of decision-making in clinical assistance. F. Baseslice et al. [5] proposed an approach for sparse tensor prototype which is built on weighted regularization by means of MRI through efficient computation. This projected model implements MRI image modalities for given dimensions for 20 slices. The experimentation was exhibited on four diverse contrast models through SSIM and PSNR estimation. The outcomes demonstrate that sparse tensor technique outperformed the improvised regularization for weighted pixels. M. Jaderberg et al. formulated a framework for the intent of synthetics data generation with the intent of word recognition in deep learning architecture. In this paper, NDB, i.e., natural data blending is used to prepare the synthetic data which seems to be further realistic and highly sufficient in order to replicate the real-word data through infinite amount of training data [6]. I. Goodfellow et al. introduced the generative adversarial networks (GANs) which considered as unsupervised learning practice which implements minimum and maximum strategy in the two networks, wherein the first network efforts to make images and detect the counterfeits to make another network engrosses the same method. This is done in course to generate the augmented images from datasets obtainable [7]. J. Lemley introduced the concept of smart augmentation defined by author which addresses the matter of training dataset to lower the overfitting and improvisation in regularization through deep learning approach for combining images to resolve the above stated issues that are reducing the overfitting and regularization method [8]. H.A. Khan proposed the concept for classification of CT images in direction to locate the region of interest (ROI), and then, cropping it for augmentation purpose on large training dataset, they applied edge detection technique. Also, according to the proposed methodology, afterward, training of small dataset, accuracy, and rate of accuracy can be attained which are showed after experiments [9]. The results of proposed models are compared to ResNet framework, VGG-16, and Inception model. V. Olsson proposed practices for augmentation called ClassMix in “ClassMix: Segmentation-Based Data Augmentation for Semi-Supervised Learning.” In this paper, augmentations of medical image were generated using mixing of samples which are unlabeled, and in further procedures, these samples were leveraged based on prediction of network with respect to limitations of any corresponding object. The evaluation of samples was built on semantic segmentation and secondly diverse design and training managements [10].

K. Nishi proposed the strategies of augmentation in approaches of deep learning for the labeled noise. The paper "Augmentation Strategies for Learning with Noisy Labels" has advantage for higher noise ratios, and in that case, copious augmentation needs to be avoided [11]. S. Mounsaveng addresses the issue of hyper-parameters for data augmentation through the proposal of an effective system to train network that will learn to effectively distribute the conversion in directive to improvise the generalization through bi-level optimization. This technique helps to optimize the parameters of data augmentation along with validation set. Also, experiment results justify that proposed method generates the accuracy of image classification better restored from existing data augmentation [12]. A. Krishna proposed the DRL, i.e., deep reinforcement learning that fit in the neural style transfer toward creating the anatomical shapes. It will generate the higher-resolution medical images at varied quantities with smaller datasets [13].

In above mentioned review, it has been seen that labeled dataset in medical imaging is primary concern in the dispersal of neural network in healthcare informatics. Medical image augmentation generally trained the neural network after initial phase or from preprocessing in command to classify whether the brain MRI encompasses tumor or not. The regularization techniques applied are generally pretrained through the deep learning protype which will decrease the generalization error by accumulation of parameters into it. So, effective regularization practice is somewhat necessary to decrease the variance via reduction in the error for validation testing. We applied the neural augmentation can be used in unification through meta-learning approach in learning framework to provide image augmentation where the dataset will be classified by learning the new tasks from existing set of jobs. This technique attempts to generate the augmented medical images with the process of learning approach which will help to make learn images themselves in order to reduce complexity in training data and reduce overfitting.

3 Materials and Methods

3.1 Neural Image Augmentation

It is being suggested to train the neural model on a dataset to learn it in the most ideal manner and furthermore to maintain a strategic distance from the overfitting of issues. Fundamental deep learning models can be improvised over massive dataset by preparing a counterfeit dataset with adjustments in available dataset [1–25]. Neural image augmentation (NIA), as shown in Fig. 3, approach aids in training the dataset to anticipate the matter of overfitting main origin basis with sight of the prospect that further information can be mined or extracted through original dataset available. NIA exaggeratedly inflates the size of training dataset by using the concept of oversampling or data warping, i.e., transformation of prevailing images in the way that their labels are preserved involving augmentations (color, flips, geometric

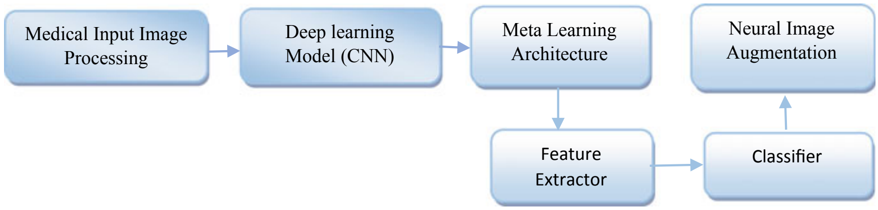


Fig. 1 Flow of neural image augmentation (NIA)

transformations, generative adversial network, and neural style transfer) as shown in Fig. 1. However, oversampling generates synthetic instances thereby adding it to training dataset including feature spacing and mixing of images. Although both the augmentations available does not produce exclusive contrast between dataset. While in training phase, the network takes at most two images as input from same set of similar class, and it get to pass through a layer, and this layer returns the single same-sized image usually called as image from augmentation or augmented image. This output augmented image along with input images again passes through a network called as classification, and its loss is entropy (cross) loss via sigmoid of class score. NIA usually improvised the accuracy in classification besides reduction in overfitting. This approach is quite cooperative in convergence of network in rapid manner.

The persistence of neural style transfer (NST) is extensively castoff in 3D image to synthesize the image to envisage the possible representations. As pragmatic, the un-balanced datasets every so often encountered in procedure of diagnostic systems which foresees the inconsistency for equally training in context to testing set. The neural style algorithm optimizes the loss of data where loss might be style or content and in command to disparity of style of testing data slice to equivalent targeted training dataset portion. This case simultaneously enforces the constraint on newly generated image in order to uphold its content. The neural style transfer algorithm inescapably modifies the testing set images from given dataset through determination of training dataset as it is being laid to get processed through same framework.

3.2 Meta-Learning

The implementation procedure of augmentation plays vital role in choosing the type of network architecture. Through this way, deep convolutional neural network learns the best utilization of feature space representations in the medical dataset with some definite class to obtain the detailed target network by merger structures of further samples. The practices of augmentation can be yet again utilized in image classification in procedure of discourses the issue of envisaging the unlabeled images in the imaging dataset.

The influencing factors in the meta-learning framework are as follows:

Meta-Train:

In meta-learning framework, the aim is to train a meta-model by viewing it solitary for fewer examples per class. Besides that, it tests in contradiction of examples from similar classes which have remained kept out afterward for original dataset. It will be verified in much similar way when obtainable with fewer training examples since novel class of set. Individually, every training instance comprises of set of test and train data points which is termed as episode. Also, it can be alternately called as support (train) and query (test) sets. The classes in training set define N-class classification or N-way task along with labeled examples. The dataset for meta-training has episodes, each having test set also training set, and also, each test dataset comprises hyper-parameters fine-tuning and generalization.

Meta-Optimizer:

Meta-optimizer is process of meta-learning framework enhances the arrangement of the neural components which are formerly linked with existing deep neural network. Through this strategy, performance can be optimized by fine-tuning the hyperparameters of neural network to improve it. At training dataset, the computational procedure for each task parameters ϕ will be done, and then, updating meta-parameters by means of the gradient descent objective will be computed (with meta-parameters). Then, repeat this iteratively using optimizer like SGD.

Meta-Loss Function:

Though loss function in meta-learning will specify how fine the model along with neural model is performing on the job but in outcome, the meta *learner* is accustomed by means of a gradient descent method for each new task in the cluster of episodes. The objective for learning meta-loss function is castoff to train a classifier through the specified parameters of function M_φ as meta-loss to optimize the trained data f_θ to generate the output of loss value $\mathscr{L}_{\text{Learned}}$. The parameter for θ to compute gradient descent in training of f_θ for the above function is as follows [15]:

$$\theta_{\text{new}} = \theta - \alpha \nabla_\theta \mathcal{L}_{\text{Learned}} \tag{1}$$

$$\mathcal{L}_{\text{Learned}} = M_\varphi(y,\ f_\theta(x)) \tag{2}$$

wherever, y perceives ground truth value in supervised learning. In order to learn a loss function that could be used recommend learning model to acquire parameters for meta-loss function φ through gradient descent calculation. The substantial task is to originate a training indication to acquire loss parameters φ.

4 Proposed Methodology

4.1 Convolutional Neural Network with Meta-Learning

These systems are usually getting train after being visible to a variety to tasks; besides that its capability to acquire new tasks is simultaneously tested. Meta-learning approach trains the model in order to absorb newer tasks and that too in meta-training set. It deals with few optimizations; one is learner who is learning new tasks and other meta-learner who is providing training to learner. Some of methods which are defined in meta-learning approach comprise of learning optimize, metric learn, and recurrent model. The strategy trains a model which can be recurrent model in command to take the dataset in systematic and ordered way. It will process the input which are in training dataset (Fig. 2).

This incorporates the proposed methodology by showing the conjunction of deep learning model laterally with the pretrained model before classification using meta-learning technique for self-learning training to reduce its loss and time complexity. Numerous frameworks in deep learning undergo speedy enhancement in domain of medical image processing which is performed on various platforms. Each hidden layer signifies the image filters for feature extraction, i.e., to excerpt the differential features from input image. The output layer entails of feature maps which has innumerable filtered forms which denote resolution, classification of image, segmentation, image synthesis, etc. [16–25].

In Fig. 3, flow of generation of augmented medical images using meta-learning style has been revealed where the meta-learning approach is used after image preprocessing to pretrain the model in order to quote the features after the medical images in dataset. The neural image augmentation is generally used to develop the existing model or the inference by neural model components. This will integrate the forward pass along with deep learning architectures.

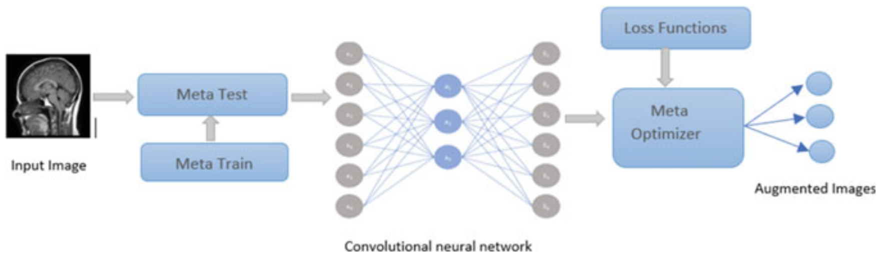


Fig. 2 Convolutional neural network model with meta-learning approach

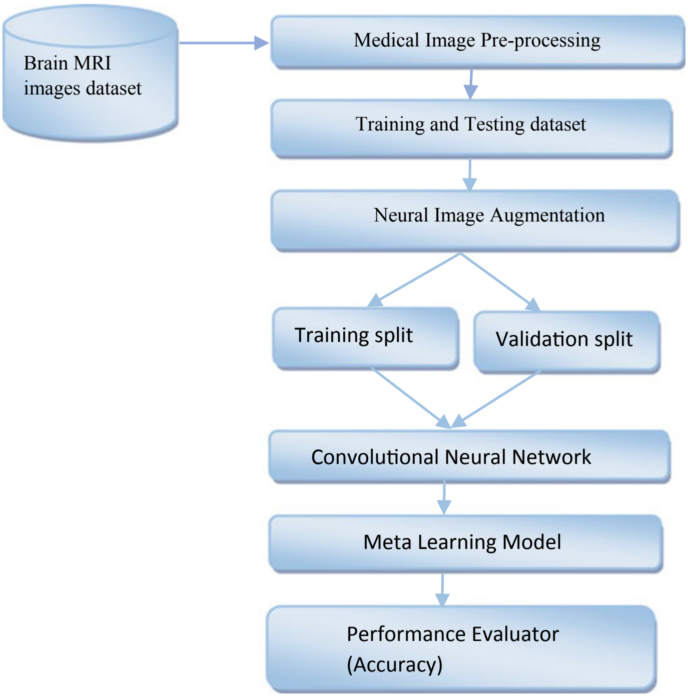


Fig. 3 Flow graph for implementation of meta-learning approach in neural augmentation

4.2 Training Procedure for Meta-Learning

Deep networks are generally get trained for purpose of object recognition where the visual representation of brain MRI which will make information of the inherited object explicit with the contented in hierarchy of its processing. The focus point of the representation is to compare the actual content with that of comprehensive pixel values. The information which is being inherited can visualize directly and that too layer by layer through the reconstruction method from feature maps. In higher layers, the pixel values do not constraint to the reconstruction; besides that it will capture the higher-level content and arrangement in given input image.

In Fig. 4, model of meta-learning insights the hyperparameters aimed at the training in regular mode via consideration of omega (ω) in command to specify either learning rate, also the strength ("regularization"). The parameter θ is implemented on model f_θ, and through that multi-tasks are adapted by the approach of set of meta-batches $\mathcal{T}_m$. The tasks of batch set $\mathcal{T}_m$ are sampled either randomly or through MAB, i.e., multi-armed bandit in which sampling is done through observation and for each task of $\mathcal{T}_m$, a sample from T_j. After that sample A_j^{tr}, a training set with N_{tr} volume and A_{val}, a validation set with N_{val} volume. The adaptation along with learning rate α is calculated as:

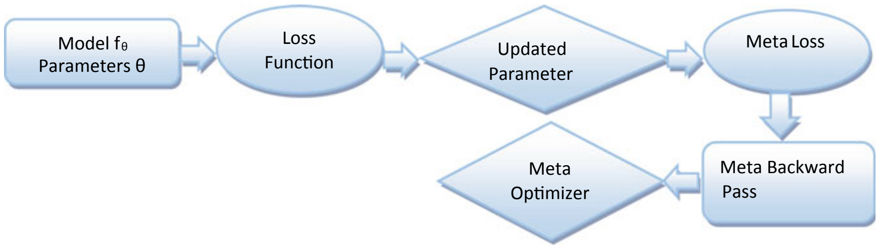


Fig. 4 Training process for meta-learning model

$$\theta' j(t) = \theta(t) - \alpha \frac{\alpha \partial (lk) f \theta(t) D j(\text{tr})}{\partial \varsigma}$$

4.3 Augmentation Using Meta-Learning Procedure

Algorithm: Augmentation Using Meta-Learning Approach on Dataset

1. Input: ω_0, θ_0, w_θ, n_w, n_θ
2. Input: Train the dataset trainset, validation dataset valset, test dataset testset.
3. for $i = 1$ to epoch do
4. for $t = 1$ to T dob, then generate N_w policys according to $p_{\theta t}$
5. Call Procedure: Meta-train for augment training from from A_{train} with N_w policy, respectively;
6. Obtain the validation loss f_{val}(wt) j on A_{val}; Restore the network parameters, ˆwt = wt; end for
7. Utilize validation loss $f_{\text{val}}(w_{\text{t}})\, j$,policys c_j ($j = 1,\ldots,N_\theta$) to update θ_t according to Eq. 8; end for
8. end for, est the network on A_{test};
9. Return final validate set.

5 Experiments and Discussions

The dataset consists images which are anatomical in nature of around 120 patients from The cancer Genome Atlas (TCGA) and The cancer imaging Archive (TCIA). The accurate dimensions of each 3D images are 256 × 320 × 320 with fluid-attenuated inversion recovery (FLAIR) sequence. The state of dataset is heterogeneous, and foundation is also nonuniform in nature, whereas the dataset splits into non-overlapping subset each batch size. The experiment illustrates that meta-learning procedure can implement loss function to include further information accessible in

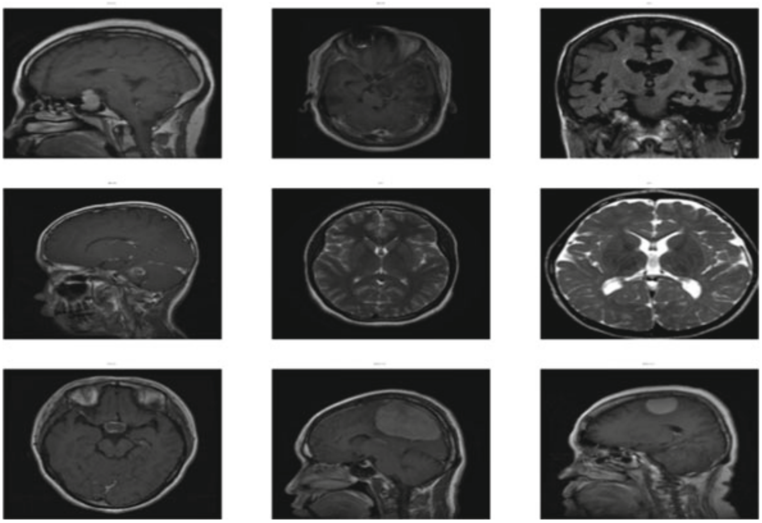


Fig. 5 Training set for applying meta-learning parameters

duration of meta-training. In Fig. 5, the training medical image dataset is attained after implementation of hyperparameters involved in meta-learning.

In above Fig. 6, gap among validation and training accuracy determines the attained gap to estimate the overfitting. The proposed model emphasizes on reduction of gap among dataset of training and validation to interpret the accuracy (Fig. 7).

6 Conclusion

The neural augmentation has the potential to improvise the performance in addition to accuracy on the available testing medical dataset. The mentioned approach will train the medical imaging data inevitably using prior learning approaches in our trained dataset in process of augmentation in deep neural network. The training loss besides validation accuracy perhaps achieves better results. In future, the application of generative adversial networks can be implemented on deep neural network utilizing a superfluous discriminator model-based model can be obtained for better results. The foremost focus is on mutual information present in a class so that a model could be constructed to provide augmentation. The proposed approach "Neural Augmentation" with inbuilt concept of meta-learning which will be helpful in automatic training of appropriate augmentations in deep neural network. Meta-learning framework in deep learning model leverages to self-learn new tasks which embraces wide spectrum for learning techniques in neural network.

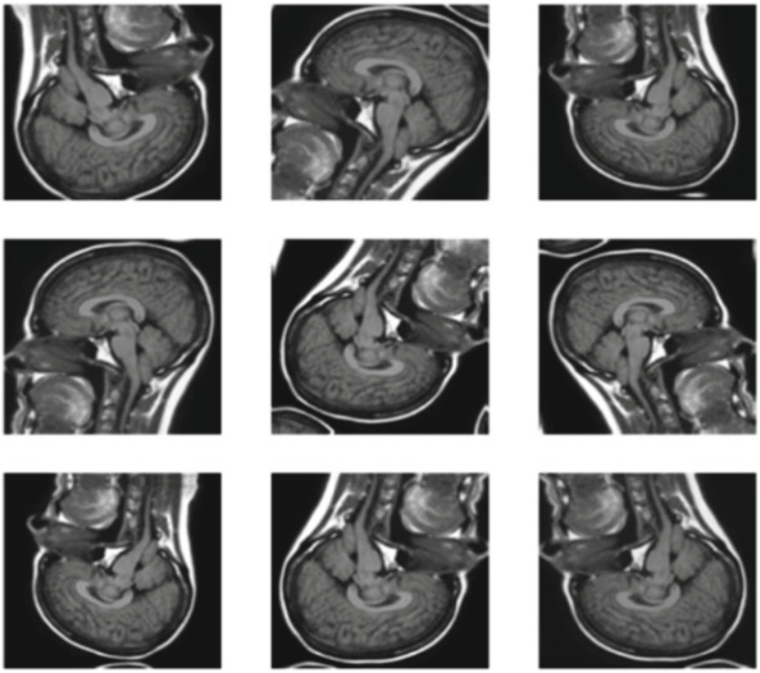
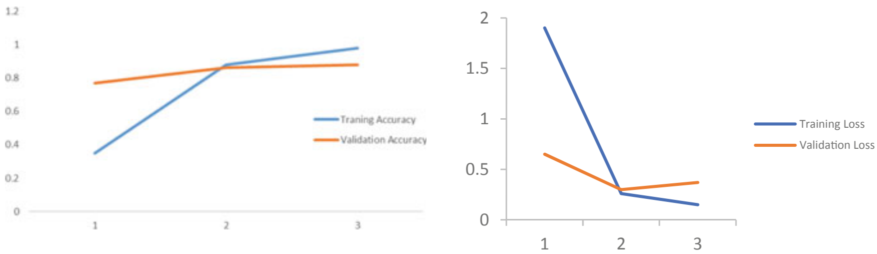


Fig. 6 Augmented set of images after implementing meta-learning approach



a) Training and Validation Accuracy b) Traning and ValidationLoss

Fig. 7 Accuracy and loss line graphs with respect to training and validation

References

1. Yao JC, Hassan M, Phan A, Dagohoy C, Leary C, Mares JE et al (2008) One hundred years after "carcinoid": epidemiology of and prognostic factors for neuroendocrine tumors in 35,825 cases in the United States. J Clin Oncol 26(18):3063–3072. https://doi.org/10.1200/JCO.2007.15.4377.PubMed
2. Dong C, Loy CC, Tang X (2016) Accelerating the super-resolution convolutional neural network. In: European Conference on Computer Vision

3. Mittal M, Mohan L, Kaur S, Kaur I, Verma A (2019) Deep learning based enhanced tumor segmentation approach for MR brain images. Applied Soft Computing Journal 78:346–354. https://doi.org/10.1016/j.asoc.2019.02.036
4. Long J, Shelhamer E, Darrell T (2015) Fully convolutional networks for semantic segmentation. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 3431–3440
5. Baselice F, Ferraioli G, Pascazio V, Sorriso A (2019) 'Denoising of MR images using Kolmogorov-Smirnov distance in a non local framework.' Magn Reson Imag 57:176–193. https://doi.org/10.1016/j.mri.2018.11.022
6. Verma V, Lamb A, Kannala J, Bengio Y, Lopez-Paz D (2019) Interpolation consistency training for semi-supervised learning. In: Proceedings of the 28th International Joint Conference on Artificial Intelligence, pp 3635–3641. AAAI Press
7. Jaderberg M, Simonyan K, Vedaldi A, Zisserman A (2014) Synthetic data and artificial neural networks for natural scene text recognition [Online]. Available: http://arxiv.org/abs/1406.2227
8. Goodfellow I, et al (2014) Generative adversarial nets. Proc Adv Neural Inf Process Syst, 2672–2680
9. Lemley J, Bazrafkan S, Corcoran P (2017) Smart augmentation learning an optimal data augmentation strategy. IEEE Access 5:5858–5869. https://doi.org/10.1109/ACCESS.2017.2696121
10. Khan HA, Jue W, Mushtaq M, Mushtaq MU (2020) Brain tumor classification in MRI image using convolutional neural network, 17(10):6203 6216
11. Olsson V, Tranheden W, Pinto J, Svensson L (2021) Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), pp 1369–1378
12. Nishi K, Ding Y, Rich A, Höllerer T (2021) Augmentation strategies for learning with noisy labels. http://arxiv.org/abs/2103.02130
13. Mounsaveng S, Laradji I, Ben Ayed I, Vazquez D, Pedersoli M (2021) Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), pp. 1691–1700
14. Bhujle HV, Vadavadagi BH (2019) 'NLM based magnetic resonance image denoising—A review.' Biomed Sig Process Control 47:252–261. https://doi.org/10.1016/j.bspc.2018.08.031
15. Bechtle S, Molchanov A, Chebotar Y, Grefenstette E, Righetti L, Sukhatme G, Meier F (2021) Meta learning via learned loss, pp 4161–4168. https://doi.org/10.1109/icpr48806.2021.9412010
16. Elhoseny M, Shankar K (2019) 'Optimal bilateral filter and convolutional neural network based denoising method of medical image measurements.' Measurement 143:125–135. https://doi.org/10.1016/j.measurement.2019.04.072
17. Yun S, Han D, Chun S, Joon Oh S, Yoo Y, Choe J (2019) Cutmix: Regularization strategy to train strong classifiers with localizable features. In: 2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27–November 2, pp 6022–6031. IEEE
18. Venu SK, Ravula S (2021) Evaluation of deep convolutional generative adversarial networks for data augmentation of chest x-ray images. Future Int 13(1):1–13. https://doi.org/10.3390/fi13010008
19. Singh SP, Wang L, Gupta S, Goli H, Padmanabhan P, Gulyás B (n.d.) Review_3D_Deep_Learning_Medical_Images, 1–13
20. Kim M, Yan C, Yang D, Wang Q, Ma J, Wu G (2020) Deep learning in biomedical image analysis. Elsevier, In Biomedical Information Technology (Second Edi). https://doi.org/10.1016/B978-0-12-816034-3.00008-0
21. Milletari F, Navab N, Ahmadi S (2016) V-Net: Fully convolutional neural networks for volumetric medical image segmentation. In: 2016 Fourth International Conference on 3D Vision (3DV), pp 565–571
22. Guo L, Zhao L, Wu Y, Li Y, Xu G, Yan Q (2011) Tumor detection in MR images using one-class immune feature weighted SVMs. IEEE Trans Magn 47(10):3849–3852
23. Singh L, Chetty G, Sharma D (2012) A novel machine learning approach for detecting the brain abnormalities from MRI structural images. In: IAPR International Conference on Pattern Recognition in Bioinformatics, Springer, Berlin, Heidelberg, November, pp 94–105

24. Jafar A, et al (2021) AI and machine learning paradigms for health monitoring system: Intelligent data analytics, SBD, volume 86. Springer Nature, Berlin, 513 p. https://doi.org/10.1007/978-981-33-4412-9. ISBN 978-981-33-4412-9
25. Tomar A, et al (2020) Machine learning, advances in computing, renewable energy and communication, LNEE volume 768. Springer Nature, Berlin, 659 p. https://doi.org/10.1007/978-981-16-2354-7. ISBN 978-981-16-2354-7