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Research Article

CEREBRUM LESION DETECTION USING A ROBUST VARIATIONAL AUTOENCODER AND MOVE LEARNING USING FCM AND ACM

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Abstract

Mechanized thoughts harm discovery from multi-ghostly MR image while can assist clinicians through enhancing affectability simply as particularity. Directed AI strategies were fruitful in sore discovery. Notwithstanding, those strategies usu-associate rely upon infinite bodily depicted pix for specific imaging conventions and obstacles and regularly do not sum up properly to different imaging obstacles and demograph-ics. Most as of late, different solo fashions, for example, autoencoders are becoming attractive for sore popularity due to the fact that they need not trouble with admittance to bodily mentioned accidents. Regardless of the suc-cess of unaided fashions, using pre-organized fashions on a hid dataset is as but a check. This problem is in view that the brand new dataset might also additionally make use of unique imaging obstacles, demo-designs, and various pre-coping with procedures. Expansion associate, using a medical dataset that has oddities and anomalies could make unaided choosing up trying out for the reason that out-liers can unduly impact the presentation of the found out mod-els. These issues make unaided sore detection an specifically hard undertaking. The method proposed on this road numbers those troubles using a -prong strategy: (1) we make use of a sturdy variational auto encoder version that relies upon on effective measurements, explicitly the - distinction that may be organized with statistics that has anomalies; (2) we make use of an change studying method for studying fashions throughout datasets with different attributes. Our results on MRI datasets evil presence strate that we are able to enhance the precision of harm popularity through adjusting full of life authentic fashions and circulate studying for a variational autoencoder version.

Keywords— Variational autoencoders, sore detec-tion, full of life variational autoencoders, cerebrum imaging, unsuper-vised AI, oddity identity

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I. INTRODUCTION

Precise discovery of accidents with inside the human cerebrum is crucial for early end and treatment. Clinical imaging techniques, for example, MRI are presently popular medical apparatuses for detecting and measuring sores. People dominate in spotting sores through visible assessment after huge getting ready, but the summary and high-priced nature of human identity and de-lineation makes the AI strategies an attractive different choice or supplement. Moreover, AI may want to likely accomplish higher-than-human execution for this precise venture through using multispectral MRI. Exploration depending on controlled AI has efficaciously made essential progress [1, 2, 3] with human-stage or higher performance. Nonetheless, big portions of guide harm delineations are wanted for getting ready controlled strategies. Unsupervised methods, then again, do not want named statistics but for the maximum element are much less precise.

Solo strategies, 1for version, the auto encoder and variational auto encoder (VAE) [4] and their varieties [5] have proven that we are able to harsh the name of the game flows of high-dimensional facts. An common usage of unsuper-vised methods is abnormality distinguishing evidence [6], wherein the goal is to apprehend statistics assessments whose portrayal strays from the normal examples. For a population of cerebrum pix, accepting that accidents and special irregularities show up seldom and in comparison ent regions throughout subjects, we wager that it's far viable to advantage talent with the move that mirrors a stable thoughts shape using a VAE. When this move is found out, we are able to mea-certain the remaking mistake among a given image and the reproduced image to differentiate and limitation anomalies in that image.

A VAE is a probabilistic autoencoder that makes use of the vari-ational decrease sure of the immaterial probability of facts because the goal paintings. It has been proven that VAEs acquire better exactness in indignant location endeavors than popular au-toencoder [7, 8, 9]. VAEs rely with the settlement that the association dataset and the check dataset are investigated from a comparative apportionment. Nonetheless, this supposition might not maintain in authentic settings, for example, medical imaging appli-cations due to the fact that diverse datasets can make use of unique securing and pre-getting ready methods. In a great world, we need to anyways have the choice to apply a pre-organized VAE version to accumulate any other version that adjusts to our dataset. The challenge of circulate grasp ing facilities round tending to this trouble [10]. With the manual of circulate studying, it's far viable to keep the statistics received even as tackling one trouble and use it on an change trouble.

The VAE's goal paintings carries the KL-uniqueness time period which does not adapt properly to anomalies and is therefore now no longer effective. This might also additionally spark off unintentional affects in making use of circulate studying for adjusting pre-organized VAE fashions whilst the traits of the brand new dataset range basically from that of the underlying getting ready dataset. To this end, we endorse the usage of full of life VAE depending on the idea of - distinction from hearty insights [11] for making use of circulate gaining from pre-organized unaided sore region fashions. By extrade ing the energy hyperparameter , we are able to manage how a whole lot effect is conceded to assessments with low probability. We display the adequacy of our technique on thoughts MRI datasets. Our outcomes display that 1the blend of ro-bust VAE and circulate studying licenses us to apply getting geared up facts that has precise imaging limits and economics than that of the check dataset. We display this the use of a quantita-tive dating with VAE fashions.

2. Numerical FORMULATION

In this segment, we first gift a synopsis of VAEs and full of life variational surmising. At that factor we determine a full of life VAE that may be organized on a aggregate of common and harm pix established with the knowledge that the sore loose pix are drawn from a Gaussian move.

2.1. Variational Autoencoder

The VAE is a coordinated probabilistic graphical version whose ~ rear ends are approximated through a neural organization. Let X de-observe the enter facts, $\tilde{x}^{(i)}$ ~ denote the samples of X , and Z characterize its low-dimensional dormant portrayal. 1The VAE contains of an encoder community that figures an approxi-~ j ~ mate returned $q(Z|X)$, and a decoder community that com ~ putes $p(X|Z)$ [4] and $p(Z)$ shows the sooner appropriation which z is created from. The version obstacles and are located 2by amplifying the evidence decrease sure (ELBO) paintings [4] characterize its low-dimensional idle portrayal. 1The VAE contains of an encoder community that procedures an approxi-~ j ~ mate returned $q(Z|X)$, and a decoder community that com ~ putes $p(X|Z)$ [4] and $p(Z)$ method the sooner appropriation which z is produced from. The version obstacles and are located 2by augmenting the evidence decrease sure (ELBO) paintings [4]:

$$(i)) =Eq(Z\sim j\sim x(i)) (i) \sim$$

$$L(; ; \sim x [\log(p(\sim x |jZ))]) (1)$$

$$\sim (i) \sim$$

$$DKL(q(Z|j\sim x))jjp(Z):$$

The preliminary time period (log-opportunity) may be deciphered because the recon-struction misfortune and the following time period (KL dissimilarity) because the reg-ularizer. Utilizing observational tests of assumption, we shape the Stochastic Gradient Variational Bayes cost.

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2.1. Variational Autoencoder

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$$(i)) =Eq(Z\sim j\sim x(i)) (i) \sim L(; ; \sim x [\log(p(\sim x |jZ))]) (1)$$

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The preliminary time period (log-opportunity) may be deciphered because the recon-struction misfortune and the following time period (KL dissimilarity) because the reg-ularizer.

Utilizing actual critiques of assumption, we shape the Stochastic Gradient Variational Bayes cost [4]:

$$\log(p(\tilde{x}(i)|z(j))) \sim j$$

Assuming $p(X|Z)$ is a Gaussian distribution and the out-placed of the community is the imply of this distribution, the log-probability time period simplifies to the imply-squared-error.

2.2.Strong Variational Autoencoder

Robust variational surmising relies upon at the ELBO primarily based totally misfortune paintings and replaces the log-opportunity time period with - dissimilarity that is equal to limiting - move entropy [11, 12].The ELBO paintings is given through: $L(q; \cdot) = N \mathbb{E}_q(Z) \mathbb{E}_{p(X|Z)}[H(p(X|Z))] - \mathbb{E}_q(Z) \mathbb{E}_{p(X|Z)}[H(p(X|Z))]$ (three) $\sim \sim DKL(q(Z)||p(Z))$: wherein $p(\cdot)$ is posterior distribution, the empirical distri- $(Z, X)_{j=1}^N \sim (i)$ bution is $p^{\wedge}(X) = \prod_{i=1}^N p(X; x_i)$ wherein is the Dirac δ characteristic and Z represents the latent variable, N is the P range of samples, and carries the generative version's pa-rameters. The -move entropy is given through [12]: $H(p(X|Z)) = -\int p(X|Z) \log p(X|Z) dX = -\int p(X|Z) \log p(X|Z) dX + Z + 1$ (4) By changing log-probability with -move entropy withinside the VAE formulation, we gain a brand new fee characteristic which is powerful to outliers [13]. For a Gaussian distribution, the ELBO-fee of RVAE for the j th pattern simplifies to [13]: $L(\cdot; \cdot; \tilde{x}(i)) = \frac{1}{2} \log \frac{1}{2\pi} - \frac{1}{2} \frac{(\tilde{x}(i) - \mu)^2}{\sigma^2} - \frac{1}{2} \log \sigma^2$ (5) Similar to the VAE, we use stochastic gradient variational bayes fee minimization the usage of sampling to optimize -ELBO to teach the sturdy VAE. Next, we describe the usage of VAE and sturdy VAE in com-bination with switch studying for lesion delineation tasks. three. THE MODEL AND EXPERIMENTS $\log(p(\tilde{x}(i)|z(j)))$ 1203960-82550 We used the VAE structure proposed in [14] that includes 3 consecutive blocks of convolutional layer, a batch normalization layer, a rectified linear unit (ReLU) activation characteristic and fully-related layers withinside the bottleneck for the encoder and a fully-related layer and 3 consecutive blocks of deconvolutional layers, a batch normalization layer and ReLU, and a very last deconvolutional layers for the decoder. The length of the enter layer is three sixty four. Authorized certified use restrained to: Auckland University of Technology. Downloaded on June 06,2020 at 02:53:37 UTC from IEEE Xplore. Restrictions apply. 690880914400 FLAIR $q\phi(Z|X)$ Z $p(X|Z)$ T2 T1 5080-14262105080-1426210

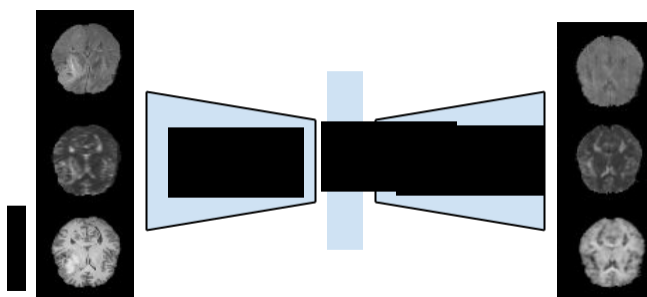
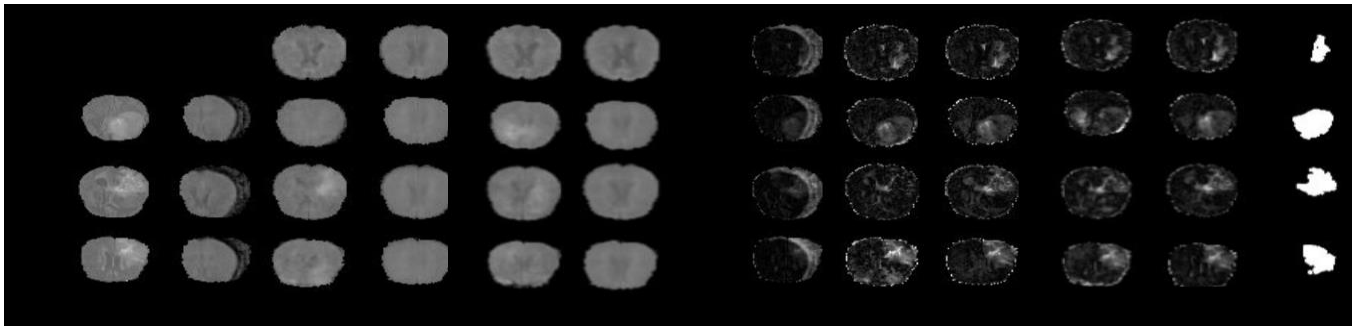


Fig. 1. VAE community and enter, output pattern for ISLES dataset .

3.1. Data and Preprocessing

For the underlying making ready, we applied 20 focal hub cuts of cerebrum MRI datasets from a mix of 119 topics from the Maryland MagNeTS study [15] of neurotrauma and 112 topics



of TrackTBI-Pilot [16] dataset, each on hand for down load from <https://fitbir.nih.gov>. We applied 2D cuts in preference to three-D images to make certain we had an tremendous sufficient dataset for making ready the VAE. These datasets comprise T1, T2 and FLAIR images for every challenge, and feature insufficient sores. The 3 imaging modalities (T1, T2, FLAIR) have been inflexibly coregistered interior challenge and to the MNI chart ee-e book ref-erence, and re-examined to 1mm isotropic goal. Skull and different non-thoughts tissue have been taken out making use of BrainSuite (<https://brainsuite.org>). Accordingly, we re-molded every instance into sixty four dimensional images and done histogram adjustment to a sore loose challenge that energy standardized through the estimation of the 99th percentile voxel. We applied 191 topics for making ready and forty topics for valida-tion haphazardly inspected from MagNeTS and TrackTBI-Pilot datasets. Investigations for pre-organized version: In this trial, we examine the presentation of a pre-organized version on a dataset that turned into pre-treated likewise to the guidance set. We applied 20 focal pivotal cuts of 15 topics from the ISLES (The Ischemic Stroke Lesion Segmentation) facts base [17] as a check set and done comparative pre-dealing with with recognize to the guidance set. Investigations for re-making ready fashions (VAEbr, RVAEbr): In this examination, we re-teach VAE and RVAE fashions

with none guidance making use of a mixture of the underlying dataset and a merchandising ditional 20 self sustaining topics from the BRATS dataset (<https://www.smir.ch/BRATS/Start2015>). We applied 20 focal hub cuts from the the rest of the 20 topics of BRATS 2015 as check facts. Trials for circulate studying (PreVAE, Pre-RVAE): In this closing check, we assume that we simply technique the pre-organized fashions but the guidance datasets applied for pre-organized fashions aren't on hand. We refreshed the pre-organized fashions making use of 20 topics from the BRATS 2015 dataset. Like the examinations for re-making ready the fashions, we attempted the refreshed fashions on 20 focal pivotal cuts from 20 topics of the BRATS 2015 dataset.

3.2. Results

The excellent mistake maps amongst recreated and specific snap shots had been figured for department of the sores. A me-dian channel of length 7x7 turned into carried out to cast off separated pixels. The separated harm mistake maps had been applied to plan ROC (Re-ceiver Operating Characteristic) bends from which we com-puted the AUC (Area Under The Curve) Hand-observed sores had been applied to symbolize floor truth. Just the pixels withinside the thoughts cowl had been applied for AUC calculation. A version in-placed image from the ISLES take a look at dataset and its remaking utilising the pre-organized VAE version is seemed in Figure 1. The AUC for this trial turned into 0.ninety three. Test aftereffects of re-getting ready the

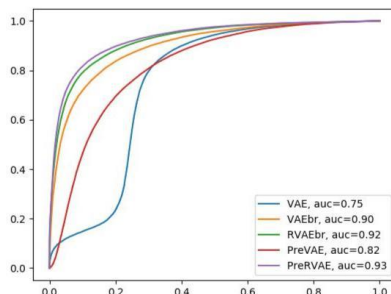
fashions and utilising flow getting to know are delineated in Figure 2 with the ROC bends and AUC esteems seemed in Figure 3. Figure 2A indicates that RVAE failed to recreate the accidents even as the sores are extra clean withinside the reproduced snap shots from the VAE version.

Subsequently, it has a tendency to be presumed that the RVAE can seize the regions of the accidents all of the extra exactly with the aid of using com-puting the blunder amongst specific and reproduced snap shots. The AUC of the pre-organized VAE turned into 0.75. At the factor whilst the VAE is re-organized with none training utilising the BRATS dataset (VAEbr), the AUC has elevated to 0.nine. In any case, the estimation of AUC dwindled to 0.eighty two whilst flow getting to know is carried out to the pre-organized VAE version (PreVAE). The AUC of the RVAE version that turned into re-organized utilising the underlying and the BRATS datasets (RVAEbr) turned into 0.92. The AUC elevated to 0.ninety three whilst flow getting to know turned into carried out to the RVAE version (PreRVAE). The estimations of beta for those trials had been picked us-ing the approval dataset. We picked a beta really well worth that maintains RVAE from remaking accidents in approval dataset. 4. Conversation

CONCLUSION

In the wake of getting ready the VAE utilising ostensibly typical (irregularity free) records, we will put it to use for peculiarity discovery and explicitly for ID of uncommon buildings in scientific snap shots. We zeroed in on outlining accidents from MRI exams which can also additionally have contrasting features and pre-getting ready. This reasons debasement withinside the presentation of VAE. Using the electricity of RVAE, we depicted a device that empowers us to tweak the version for brand spanking new take a look at units with contrasting spe-cific ascribes. We applied a pre-organized version and re-organized it with the greater topics from the brand new dataset for version refinement. The heartiness of RVAE powers the version to simply examine regular highlights among those records exams in preference to their unusual highlights (accidents). We have proven quan-titatively and subjectively that RVAE outflanks VAE each whilst version refinement.

A beyond document at the BRATS 2015 dataset [7] introduced AUC of 0.nine utilising VAE. 690880914400 AB Original VAE VAEbr RVAEbr PreVAE PreRVAEVAE VAEbr RVAEbr PreVAE PreRVAEGTruthFig. 2. (A) Original and reproduced take a look at snap shots utilising numerous fashions. (B) Absolute replica mistake of the take a look at snap shots and associated hand-portrayed accidents (GTruth). VAEbr: VAE version re-organized with none training utilising the underlying records and the BRATS exams, RVAEbr: RVAE version re-organized with none training utilising the underlying records and BRATS exams, PreVAE: flow taking in of VAE from the pre-organized VAE version utilising greater BRATS exams, PreRVAE: flow taking in of RVAE from the pre-organized VAE version utilising greater BRATS exams. True Positive Rate 125730-1502410 False Positive Rate



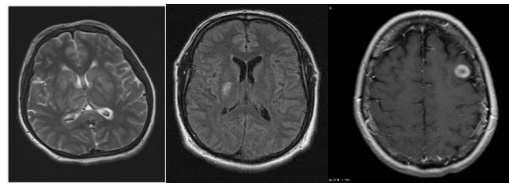
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Fig. 3. ROC bends of numerous fashions.

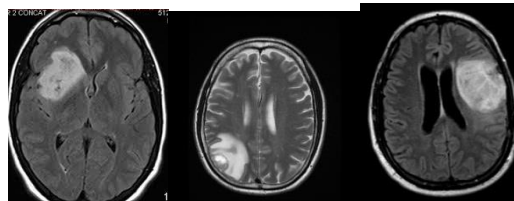
RVAE outflanks VAE each whilst organized with none training utilising BRATS exams however the underlying records (RVAEbr as opposed to VAEbr) and whilst up-dated utilising the pre-organized fashions (PreRVAE as opposed to PreVAE). We achieved a similar diploma of execution with the aid of using utilising only a subset of this dataset and a pre-organized version from an exchange dataset.

EXPERIMENTAL RESULTS

The proposed approach was tested on the database of 10 images out of which 6 images output is discussed. The recorded entities where as follows: the image name, Area of tumour, execution time and the detection decision (tumour present and tumour absent). Some of the table entires are given below in Table 1, 2 and 3. Out of 6 images, two images named IN_0000M.jpg are normal and rest are Abnormal MRI Brain images, Fig. 2 show the Database of 6 images considered.



IN_0000N.jpg IN_0002AB.jpg IN_0003AB.jpg



IN_0007N.jpg IN_0009AB.jpg IN_0011AB.jpg

Fig.2 Database of images considered

Table 1 TABLE OF DETECTION RESULTS

IMAGE NAME	IMAGE SIZE	DETECTION RESULT
IN_000N	255x255	Tumour absent
IN_0002AB	255x255	Tumour absent
IN_0003AB	255x255	Tumour present
IN_0007N	255x255	Tumour present
IN_0009AB	255x255	Tumour present
IN_00011AB	255x255	Tumour present

Table 2 TABLE OF TUMOUR AREA COMPARISON

IMAGE NAME	ESTIMATED TIME (SEC)	
	FCM	CNN
IN_0000N	3.96	0.38
IN_0002AB	5.16	0.31
IN_0003AB	5.55	0.31
IN_0007N	4.12	0.39
IN_0009AB	5.59	0.43
IN_00011AB	5.55	0.31

Table 1 give the idea of accurate detection of the normal and abnormal brain by showing a message of tumour present or absent. The proposed method gives 98% accuracy in detection and 96% and 89% accuracy in segmentation using FCM and CNN respectively.

Table 2 show the estimated time comparison respectively of both the proposed methods.

FIG 3 With tumour



FIG 4 Without tumour

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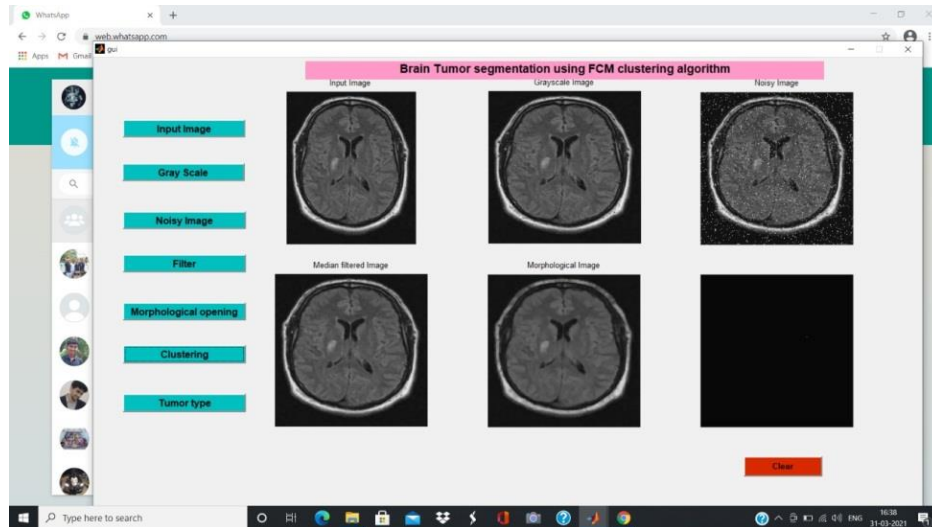


Fig 3 and Fig 4 show the GUI made for the user-friendly operation of the automatically proposed method. All are shown on single GUI screen for comparing easily. Different Clusters gives the different elements of the brain such as white matter, gray matter, edema and CSF and tumour is present, etc.

On GUI screen, a message is shown for time and tumour detection separately for FCM and CNN and estimated time calculated is shown in edit box as shown in fig above.

CONCLUSION

In this paper an algorithm using Matlab GUI has been developed for the segmentation and detection of brain tumour from MRI brain scanned images based on various operations like pre-processing. Noisy filter, Median filter, Morphological opening operations and Clustering image. The FCM algorithm where successfully implemented. Comparison of these algorithm is done on the basis of time, tumour. The proposed work method gives 98% accuracy in detection and 96% and 89% accuracy in segmentation using FCM and CCN respectively. The results obtained conclude that the efficiency of fcm is comparatively better than CNN algorithm for overlapped datasets. In future, this system can be implemented with some other algorithm which will give more accuracy and save more time.

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