A Novel Approach to Reconstruct Visual Data from Brain Using Conditional GAN.

Manish Pawar[1], Sufyan Parkar[2], Chaitanya Dandekar[3], Meet Dhanki[4]

[1]Department of Computer Engineering, Mumbai University, India
Email: i_am_manish@outlook.com
[2]Department of Electronics and Telecommunicatio1 Engineering, Mumbai University, India
Email: sufyanparkar@gmail.com
[3]Department of Electronics and Telecommunication, Mumbai University, India
Email: chaitanyasdandekar47@gmail.com
[4]Department of Mechanical Engineering, Mumbai University, India
Email: meetdhanki@gmail.com

Abstract— *This approach elucidates the extraction of visual data from the human brain using several decoding techniques and deep learning algorithms. The seen or imagined images are recorded using fMRI pattern construction and an optional Generative Adversarial Networks (GAN) used to reconstruct the images from the predicted pattern. A CGAN (Conditional GAN), an improved version of GAN is presented along-with a Classifier, which improves the output of the whole system, thus obtaining a better output resemblance with the original image. The classifier is a pre-trained model of deep neural network, and the generated images mirror the stimulated images (both natural images and artificial shapes). The method successfully generalized the reconstruction to artificial shapes and natural images, indicating the model indeed 'reconstructs' or 'generates' images, and not simply throws an arbitrary result, thus proving that the deep neural network effectively rendered semantically meaningful details to reconstructions by restricting reconstructed pictures to be just like natural pictures.*

Keywords— CGANs, DNN, fMRI, GANs, visual imagery.

I. INTRODUCTION

Humans were always fascinated by the idea of mapping brains to interfaces and the recent advancements in neuroscience and engineering have made this idea a reality. Brain-computer interfaces (BCI) can now allow the brain to connect, communicate and control various machines just by thinking [6]. A BCI collects brain signals, interprets them and returns the command to a connected machine. Machines are improved progressively in a way in which they are able to understand a given situation and take actions accordingly using "Machine Vision" [16]. A Human vision is how a person sees and interprets data. Similarly, Machine Vision stands for the technology by which a machine sees (using a camera) and analyzes the given data in a much more efficient, accurate and precise manner. Machine Vision has already been used extensively and is one of the key features of Industry 4.0.

fMRI (Functional Magnetic Resonance Imaging) [9] is a medical technique generally used to detect abnormalities in the human brain, but its application can be further extended when it is coupled with BCI. This technique calculates brain activity by detecting the blood flow through the brain. It works such as that a higher blood flow through a certain region of the brain indicates neural activity in that region. The changes in blood flows are captured by the machine, this data can be further evaluated by using neural networks, thereby giving us a depiction of human thoughts.

General Adversarial Networks or GANs are the new and extraordinary state-of-the-art models used to generate or synthesize any type of data. They are a strong class of neural networks that follow the unsupervised learning approach. GANs are made up of a system of two adversarial neural network models that compete with each other and are able to analyze and work on refining the result. Since they have the power to generate new data, it can help to decode and have clear visual imaging of the brain's cortical activity. And thus, it enhances traditional neural networks.

This paper proposes an architecture comprising of conditional General Adversarial Networks or CGANs along with a proposed model for decoding visual imagery of the brain's cortical region through a decoder type of neural network. This decoder converts

ISBN:[978-93-5391-287-1] ISSN: [2395-6992] [Vol-6, Issue-3, March- 2020]

fMRI perceiving brain scans to a visual image representation pattern. And this structure is amalgamated with CGAN, which has both adversarial feedback from its Discriminator network as well as classifier feedback from an additional classifier which makes the generation process by Generator converge faster, giving clearer output of what human brain imagines or sees.

II. PREVIOUS WORK

Tomoyasu Horikawa and Yukiyasu Kamitani used a Deep Neural Network (DNN) model to extract features for objects while dreaming taken by the decoded FMRI data collected by the brain during dreaming [1]. The decoders were trained with brain activity and labeled with the feature values of the images from multiple DNN layers. Decoded features were then compared with the features of each category calculated from a very large image database. Barbara Tversky explained how thoughts when visualized into words require various perspectives to put [2]. These may be on a particular language or how its written on a page, the way it's depicted, the proximity between the words, etc. She also explained how visual expressions of the meanings plays an important role in language gesture, and by patterns created by the people around them in detail. Yoichi Miyawaki, Hajime Uchida et al. reconstructed visual images by combining local base images of multiple scales [3]. These images where decoded from FMR activity and relevant voxels were selected. 2100 possible states were accurately reconstructed on a single volume basis by measuring brain activity. The results suggested that their approach provides an effective means to read complex visceral states while discovering information representation in multivoxel patterns.

Yaxing Wang, Chenshen Wu, et al. [4] explained how they made GANS work with a limited amount of dataset. They stated that by studying domain adaptation and applied it to image generation with GANs. They examined the aspects the domain adaptation with the initialization of GANs. They also explained how using pre-trained networks can lessen the convergence time and help improve the quality of images. By drawing conclusions, they also mentioned how density is more important than diversity and how it affects the model overall. Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford and Xi Chen presented new technical features and training methods that they applied to GANs framework [5], achieving tremendous results in semi-supervised classification on MNIST, CIFAR-10 and SVHN. They also presented ImageNet samples with unique resolution and presented that their methods assist the model to learn features of ImageNet classes.

III. PROPOSED METHODOLOGY

A brain-computer interface (BCI) [6] is an interface that links an external device with the brain. In a BCI system, the signal travels from the brain to the device that helps us to record the electrochemical impulses. It works by recognizing specific energy/frequency patterns in the brain. A BCI interface can be invasive (implanted into the brain by neurosurgery), Non-invasive (electrical activity recorded by the electrodes placed on the scalp) or Semi-invasive (devices are inserted into the skull on top of the human brain). Non-invasive interfaces are the safest and are cheaper as compared to the other techniques. However, they can be used to capture only “weaker” human brain signals due to the obstruction of the skull. The most commonly used Non-invasive BCIs are EEG (Electro-encephalography) [7], MEG (Magneto-encephalography) [8] and fMRI (Functional Magnetic Resonance Imaging) [9].

In EEG, electrical activities are recorded using small metal discs (electrodes) which are attached to the scalp. The cells in the brain communicate via electrical impulses. While MEG maps brain activity by recording magnetic fields produced by electrical currents occurring in the brain by using very sensitive magnetometers. An fMRI measures brain activity by observing changes associated with blood flow where cerebral blood flow and neuronal activation are coupled. When a specific region of the brain is in use, blood flow to that area also increases.

Our research is focused on the reconstruction of the imagery data or visual data, that the test subject sees or imagines. We propose a way to achieve that using the technique of fMRI, as fMRI is non-invasive and safe, it is practically easier to implement. In order to obtain the visual data of what the test subject sees or imagines, we need to access the Occipital Lobe and the Parietal Lobe of the Cerebrum in the brain, occipital lobe performs the function of managing the visual perception, depth perception, and reading, while parietal lobe functions in processing sensory information and interpreting visual data, both located in the largest part of the brain that is the Cerebrum in the prosencephalon.

National Conference on
"Role of Engineers in Nation Building" organized by VIVA Institute of Technology, Mumbai
(6th and 7th March 2020)
International Journal of Engineering Research & Science (IJOER)
ISBN:[978-93-5391-287-1] ISSN: [2395-6992] [Vol-6, Issue-3, March- 2020]

A. DECODING VISUAL FEATURES WITH FMRI

Signifying homology between human-machine vision and its brain-based data retrieval, [10] put forth a decoding approach for arbitrary objects seen or imagined by a human brain. They proved that the visual features can be estimated from fMRI patterns, considering those derived from a deep convolutional neural network or DCNN.

Initially, strong associations between visual features' complexity and hierarchical visual cortical regions were proved by computing models for the prediction of visual features of seen objects from multiple brain regions. They represented an object image by retrieving features from object images by 13 visual-type layers like CNN1-8 [11], HMAX1-3 [12-14], GIST [12] & SIFT+BOF [13]. Then, the regressor model or the decoder was trained for the prediction of vectors of visual features of seen or imagined objects. Next, seeing or imagining an object not used for training, the decoder predicted its visual features. Finally, the predicted pattern was compared with the most similar patterns in an annotated image dataset -ImageNet [14].

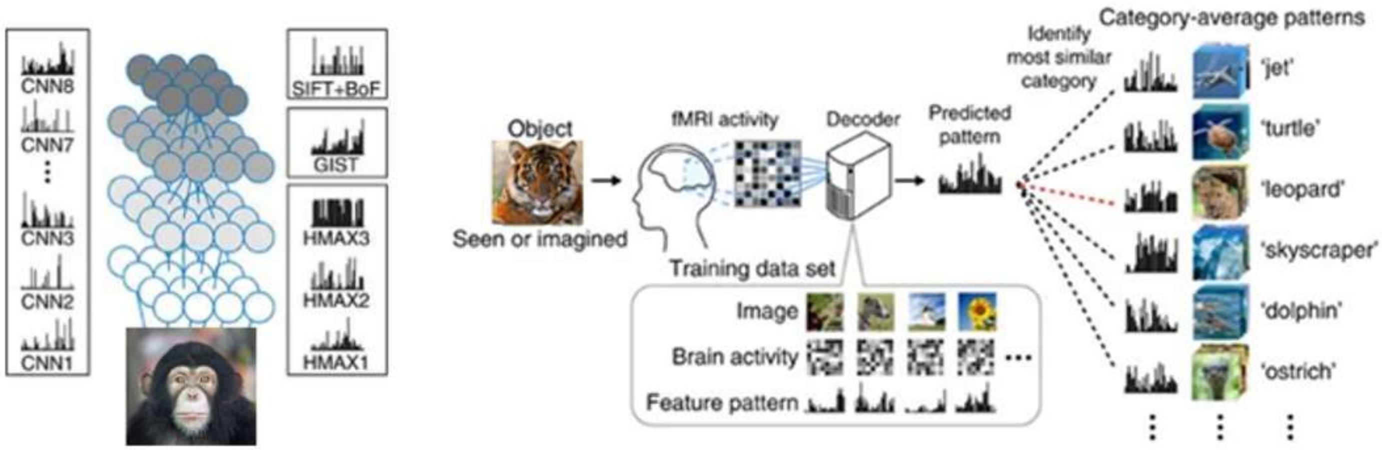

FIGURE : Visual Image Decoder

The entire workflow of the proposed system hinges on how accurate the decoder is. Moreover, the image features produced here by the decoder were not that much limpid.

IV. 3.2 GANS

Introduced by Ian Goodfellow [15] in 2014, General Adversarial Networks (GAN) are the most interesting and advanced phenomena in the last 10 years in deep learning. These networks are capable of generating media, either replica or a brand new one.

GANs comprise two neural networks, one's the Generator which synthesizes new data instances and secondly, the Discriminator evaluating them to review whether the generated one belongs to actual data or not. Discriminator tries it all to distinguish real data from fake created one. The generator tries to improve based on generated data's feedback given by the Discriminator. This goes on and on till the generator becomes a skilled counterfeiter. Thus, generators and discriminators compete against each other, ultimately refining each other's performance.

ISBN:[978-93-5391-287-1] ISSN: [2395-6992] [Vol-6, Issue-3, March- 2020]

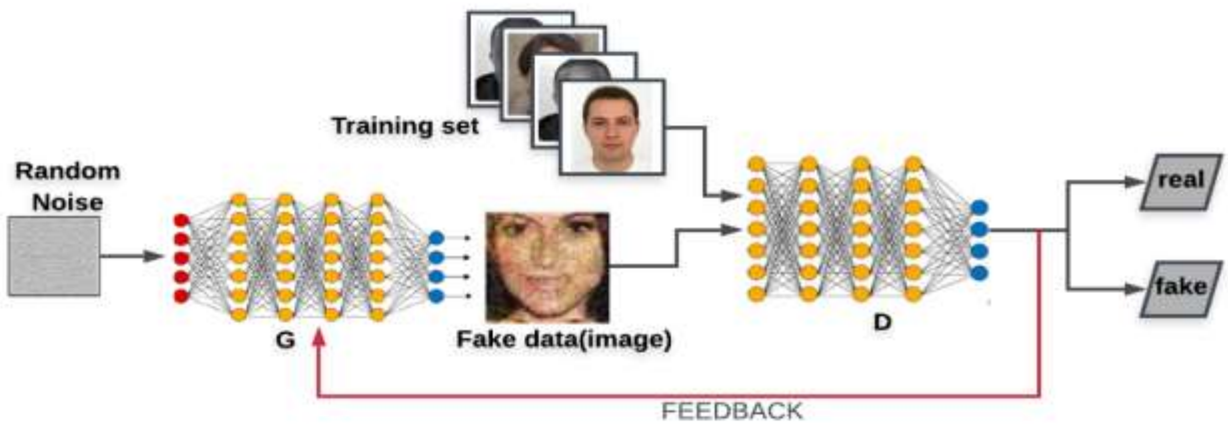

FIGURE : Generative Adversarial Network (GAN) where G - Generator D - Discriminator

Combining the Generative adversarial networks with Section 3.1 methodology, a clearer image with enhanced details can be fabricated from the visual features produced by the fMRI pattern. Normal GANs can't produce much lucid generated images. So, considering conditional GANs, they have a certain condition imposing on the production of data by generator G. CGANs give a slight edge over GANs by predicting the class of required image. Thus, the generator G knows the specific training path rather than going off the way, thus producing classified oriented output.

A. PROPOSED MODEL (CGAN + DECODED VISUAL IMAGERY)

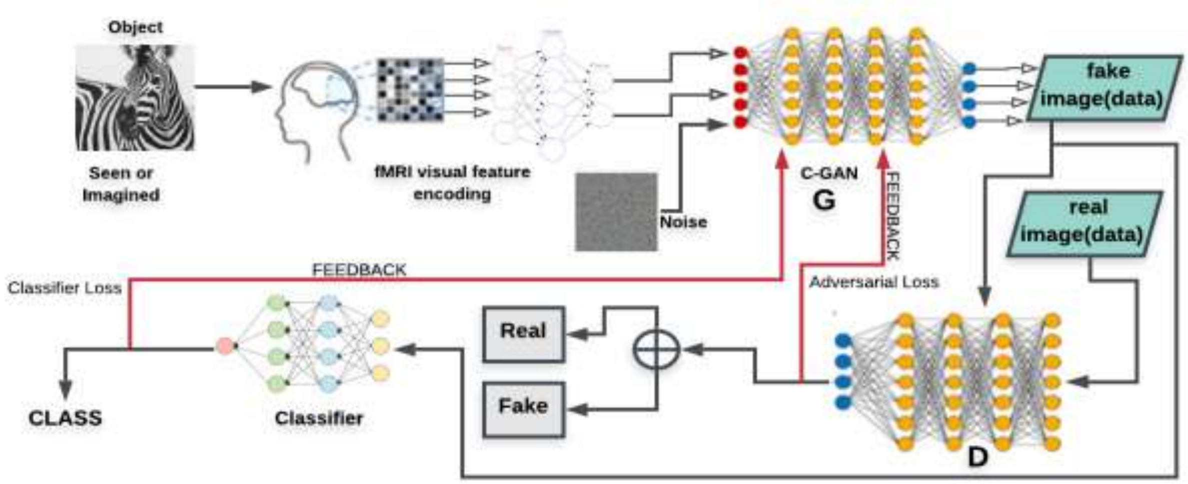

FIGURE : Conditional GAN combined with Visual Image Decoder

Here, initially, any object or image is considered to be seen or imagined by the human test subject. Then from fMRI scans, visual features of the image are encoded by a deep CNN model (encoder). Just like section 3.1's fMRI encoded image pattern is generated. This is fed to the Generator (G) of a Conditional GAN or CGAN. The Generator uses random noise as an input. The

ISBN:[978-93-5391-287-1] ISSN: [2395-6992] [Vol-6, Issue-3, March- 2020]

discriminator (D) is supplied with the image generated by G as well as the real image and accordingly, it tries to distinguish between real and fake. The D tries hard to discriminate G's synthesized image and thus providing an adversarial feedback to G.

Additionally, we propose an extra classifier model that will enhance the CGANs generated data. This classifier is pre-trained with ImageNet [17] dataset and thus on feeding the fake image, it'll match its features within the dataset and output the correct predicted class of fake image. Thus, a classifier-loss type of feedback (by the classifier) is sent to G of CGAN. This will help G to move in a correct predicting direction while synthesizing the image. Thus, G receives feedback not only from D, but also from the Classifier. So, both adversarial and non-adversarial feedbacks help the model to converge faster than the traditional GANs.

Moreover, the performance of GANs can be ameliorated by many enhancements over GANs using tuning as follows,

i. Minibatch Discrimination - Here real images and generated images are fed to the discriminator in different batches to resolve the issue of images getting similar when the model collapses.

ii. Historical Averaging - In this technique, a track of the model parameters for the last 't' models is recorded and maintained. Also, the average of the model is updated.

iii. Experience Replay - The model can sometimes tend to become too greedy in defeating what the generator is currently generating, Experience Replay maintains the most recent generated images only, that is then fed to the discriminator, hence preventing overfitting of the discriminator for a particular instance of the generator

iv. Using Labels - Adding labels in the latent space can help accelerate the training of the GAN.

v. Virtual Batch Normalization - This can be regarded as the de facto standard in many deep networks. The mean and variance of the batch normalization is derived from the current minibatch.

V. CONCLUSION AND FUTURE SCOPE

This work proposes how we create visual images that were imagined or seen by humans, using CGANs and fMRI technology. The CGANs, an additional enhanced model over GAN, were given a pre-trained classifier to predict the class of the fake image. An extra classifier and its feedback helped to improve the accuracy of the generator network in lesser iteration which would have taken much more time using only GANs. Some limitations of generative adversarial networks include the high computational power needed for training and also the high amount of data required. Also, variational autoencoders are an option to these adversarial networks since they converge faster, but don't have a diverse scope like GANs. Moreover, implementing variations of GANS like pa-GANS, task-GANS can help GANS to improve its synthesizing.

The proposed model can be used to identify a psychopath easily by his behavior. This model can also be used for providing specific treatments to psychopaths. In BCIs, EEG has excellent temporal resolution but poor spatial resolution, whereas fMRI has high spatial resolution and low temporal resolution. Recent advances in hardware sensing have made it possible to simultaneously capture EEG and fMRI signals, but refined signal processing and machine learning approaches are still needed to optimally integrate these two modalities to achieve both high temporal resolution and high spatial resolution. Then, brain stimulation techniques like transcranial magnetic stimulation (TMS) can be better used to treat brain disorders. The rapid development of BCIs also raises ethical concerns. Both structural and functional brain signals are related to mental states and traits, which could potentially be used to reveal sensitive private information [6]. So, ethics and regulations are also very important to the healthy development of BCIs. Using fMRI and deep image reconstruction techniques one can extract information from a subject that is unwilling to share. Writers can create stories imagining anywhere, anytime. Images can be created or shared by just imagining also various augmented reality and virtual reality concepts can be enhanced using basic brain computing applications.

International Journal of Engineering Research & Science (IJOER)
ISBN:[978-93-5391-287-1] ISSN: [2395-6992] [Vol-6, Issue-3, March- 2020]

REFERENCES

[1] Horikawa T, Kamitani Y. 2017. Generic decoding of seen and imagined objects using hierarchical visual features. Nature Com. 8:15037.
[2] Tversky, B. "Visualizing thought." Topics in Cognitive Science, 3, 499-535, 2011. doi:10.1111/j.1756-8765.2010.01113.x.
[3] Miyawaki, Y., Uchida, H., Yamashita, O., Sato, M.-A., Morito, Y., Tanabe, H. C., et al. (2008). Visual image reconstruction from human brain activity using a combination of multiscale local image decoders. Neuron 60, 915–929. doi: 10.1016/j.neuron.2008.11.004
[4] Yaxing Wang, Chenshen Wu, Luis Herranz, Joost van de Weijer, Abel Gonzalez-Garcia, and Bogdan Raducanu. Transferring GANs: generating images from limited data. In ECCV, 2018.
[5] T. Salimans, I. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen. Improved techniques for training gans. arXiv preprint arXiv:1606.03498, 2016.
[6] J. J. Vidal, "Real-time detection of brain events in EEG," Proc. IEEE, vol. 65, pp. 633–664, May 1977.
[7] D. Millet, "The Origins of EEG," 7th Annual Meeting of the International Society for the History of the Neurosciences, Los Angeles, CA, June 3, 2002.
[8] D. Cohen, "Magnetoencephalography: Evidence of magnetic fields produced by alpha rhythm currents", *Science*, vol. 161, pp. 664-666, 1972.
[9] Rinck P (2014) Magnetic resonance: a critical peer-reviewed introduction. In: Magnetic resonance in medicine. The basic textbook of the European magnetic resonance forum, 8th edn., Chap 21.
[10] Horikawa T, Kamitani Y. 2017. Generic decoding of seen and imagined objects using hierarchical visual features. Nature Com. 8:15037
[11] A. Krizhevsky, I. Sutskever, and G. Hinton. Imagenet classification with deep convolutional neural networks. In NIPS, 2012.
[12] Oliva, A., & Torralba, A. Modeling the shape of the scene: A holistic representation of the spatial envelope. In IJCV (2001).
[13] Csurka, G., Bray, C., Dance, C., & Fan, L. (2004). Visual categorization with bags of keypoints. In Workshop on statistical learning in computer vision, ECCV (pp. 1–22).
[14] Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., & Fei-Fei, L. ImageNet: A large-scale hierarchical image database. In CVPR. (2009).
[15] Goodfellow, I. J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014b). Generative adversarial networks. In NIPS'2014.
[16] C. Steger, M. Ulrich, C. Wiedemann, Machine Vision Algorithms and Applications, Germany, Weilheim: Wiley-VCH Verlag GmbH & Co. KGaA, 2008.