2022 International Conference for Advancement in Technology (ICONAT)
Goa, India. Jan 21-22, 2022

Design and Evaluation of GAN based Regression Model

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2022 International Conference for Advancement in Technology (ICONAT) | 978-1-6654-2577-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICONAT53423.2022.9726040

***Abstract* – Generative Adversarial Networks (GANs) are capable of generating realistic photos of objects, scenes and people that do not exist in real life. This is made possible due to the successful ability of GANs in modeling high dimensional data, handling missing data, providing multi-modal outputs and multi plausible answers. These positive features and capabilities of GANs have spearheaded research in the area of visual modeling using GAN. In this paper, an attempt is made to design a GAN model for solving regression problems. In order to assess the performance evaluation of proposed GAN model for regression problem, four basic functions and seven datasets from standard repositories are employed. It is observed that the proposed GAN model gave satisfactory results and can be employed for various other regression problems too.**

Keywords* – *Curve Fitting, Deep Learning, GAN, Machine Learning, Regression.

I. Introduction

Generative Adversarial Networks (GANs) have become an exciting and rapidly changing field with an approach towards delivering generative models using deep learning methods, such as convolutional neural networks (CNNs). GANs have been used for various diverse applications such as target sceneries based fashion recommendation is reported in [1], effective generation of traditional complex and creative historical art design patterns is reported in [2], generating synthetic multispectral satellite images imitating closely the actual natural spectral images from Sentinel-2 level-1C product is reported in [3], generating three dimensional visual images to simulate high energy physics detection overcoming the stringent requirement of a scientific simulation is reported in [4], generating larger levels in video games having aesthetic appeal with fewer duplicate levels that are playable is reported in [5], generating samples for different flight states such as take off, landing, cruising etc. to improve operational security, fault diagnosis, flight quality and reliability of unmanned aerial vehicles (UAVs) is reported in [6], producing synthetic images of aged versions of faces using progressive face aging framework is reported in [7], generating speech samples which are closer to natural speech for approximating real emotional speech is proposed in [8], generating realistic energy consumption data for training energy forecasting models in smart grid by learning from real data is proposed in [9] and many more. Various applications of GANs have also led to evolution of different types of GANs based on their applications, architecture or evolution such as conditional GAN [10], cycle GAN [11], style GAN [12], Least square GAN [13], Disco GAN [14], vanilla GAN [15], deep convolution GAN [16], Laplacian Pyramid GAN [17], super resolution GAN [18], auxiliary classifier GAN [19], info GAN [20], Wasserstein GAN [21] and many more.

GANs have been mostly used for applications related to imaging, modeling, gaming and videos. In this paper an attempt is made to design a conditional GAN based model for solving regression problems and the performance evaluation of the proposed model is carried out using standard functions and datasets from standard databases/repositories.

II. Proposed GAN Model for Regression

Generative adversarial networks (GANs) are an ingenious way of training a model that can generate new data instances that never existed. The block diagram of a basic GAN model is shown in Fig. 1 and it can be observed that a GAN model comprises of two blocks: Generator and Discriminator. Generator network is used to generate fake data samples that look like real samples and discriminator network is used to assess the samples and classify between real and fake samples. The generative network learns mapping from input samples of noise (*z*) to generate output samples with a data distribution of interest. The switch before discriminator in Fig. 1 symbolizes that the discriminator can take both real and generated inputs. Training of a GAN is considered as solving minmax problem, wherein a good discriminator should assign high probabilities to real samples and low probabilities to samples generated by generator. Basically GAN is a competitive game with generator trying to fool the discriminator and discriminator trying not to get fooled.

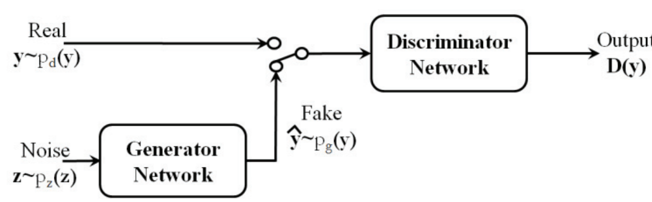


Fig. 1. Block diagram of basic GAN model

Conditional GAN (CGAN) is an extension to GAN with a conditioning variable ***x*** fed as input to both generator and discriminator as shown in Fig. 2. The training dataset for CGAN contains input output pair (***x***,***y***), instead of only single samples ***y***. In CGAN, the generator learns a conditional distribution $p_g(\boldsymbol{y}|\boldsymbol{x})$ that approximates the true conditional data distribution $p_d(\boldsymbol{y}|\boldsymbol{x})$. The samples generated by generator are used as additional samples to train the CGAN. These features of CGAN motivated us to design our proposed regression model using CGAN.

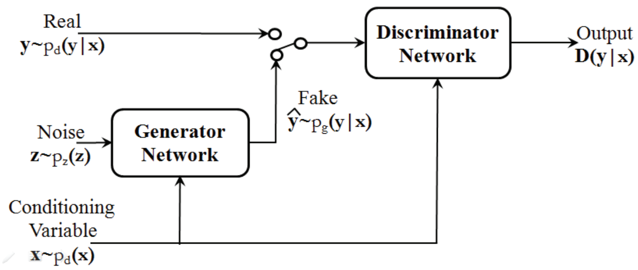


Fig. 2. Block diagram of Conditional GAN model

Double input architecture and noise injection architecture proposed in [22], are the two types of generator network architecture evaluated for proposed regression model. In double input architecture, the noise input (z) is fed to its own group of network layers in generator, whereas in noise injection architecture, the noise (z) is fed to the hidden layers at each layer of the network, as illustrated in Fig. 3(a) and Fig. 3(b) respectively. The dashed box in Fig. 3(a) and 3(b) represents concatenation block. The discriminator architecture employed for proposed model is given in Fig. 4, which is common for both double input and noise-injection architectures.

In Fig. 3 and Fig. 4, L_x, L_y, L_z, L_g and L_d represents the details about the number of layers and nodes for conditional variable input, real/fake input, noise input, generator architecture and discriminator architecture respectively for proposed model. Details about these parameters for proposed generator and discriminator architectures are reported in Table I for double input architecture and Table II for noise injection architecture. It can be observed from Table I and Table II that CGAN designs are basically split into small, medium and large based on the number of layers and nodes, as presented in Table I and Table II. The proposed GAN based regression model is designed and evaluated using the Python scripts and resources available in [22].

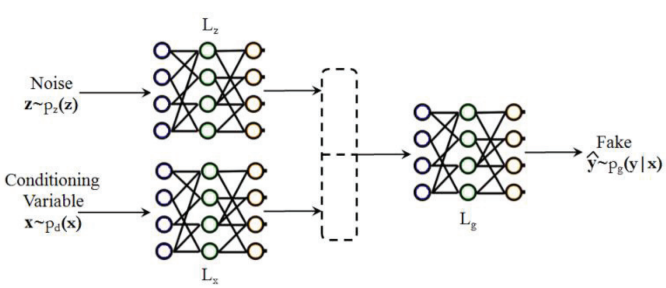


Fig. 3(a). Illustration of double input architecture for generator module

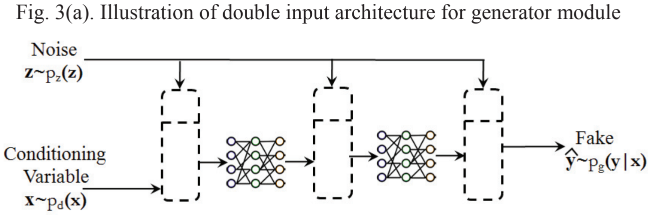


Fig. 3(b). Illustration of noise injection architecture for generator module

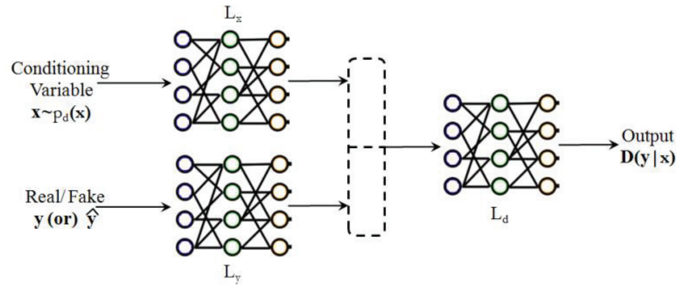


Fig. 4. Illustration of discriminator architecture

TABLE I. DETAILS FOR DOUBLE INPUT CGAN ARCHITECTURE

CGAN Design	Generator			Discriminator		
	L_x	L_z	L_g	L_x	L_y	L_d
Small	2×16	1×16	2×16	2×16	2×16	2×16
Medium	2×32	2×32	4×64	2×32	2×32	4×64
Large	3×64	3×64	5×128/64*	3×64	3×64	5×128/64*

*First two layers with 128 nodes, followed by three layers with 64 nodes.

TABLE II. DETAILS FOR NOISE INJECTION CGAN ARCHITECTURE

CGAN Design	Generator	Discriminator		
	L_g	L_x	L_y	L_d
Small	4×16	2×16	2×16	2×16
Medium	6×64	2×32	2×32	6×64
Large	8×128/64*	2×64	2×64	6×128/64*

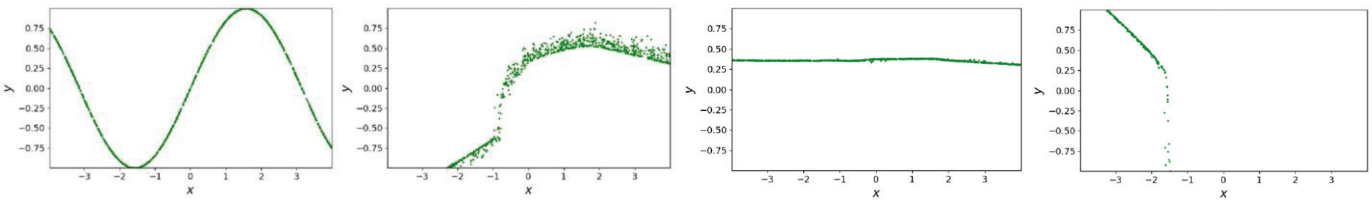
*First two layers with 128 nodes, followed by four layers with 64 nodes.

III. EXPERIMENTAL RESULTS

In order to assess the efficacy of double input and noise injection architecture for proposed GAN model to solve regression problems, a sinusoidal waveform is considered for regression using these two architectures and the results are reported in Fig. 5 for 199 epochs with three different network sizes i.e., small, medium and large. It can be observed from Fig. 5 that the results for CGAN regression model with noise injection generator architecture converged satisfactorily over double input generator architecture. It is also observed that under noise injection generator architecture, the medium sized network performed satisfactorily over other sizes. These experimental results recommended the use of noise injection generator architecture with medium sized network for proposed CGAN regression model.

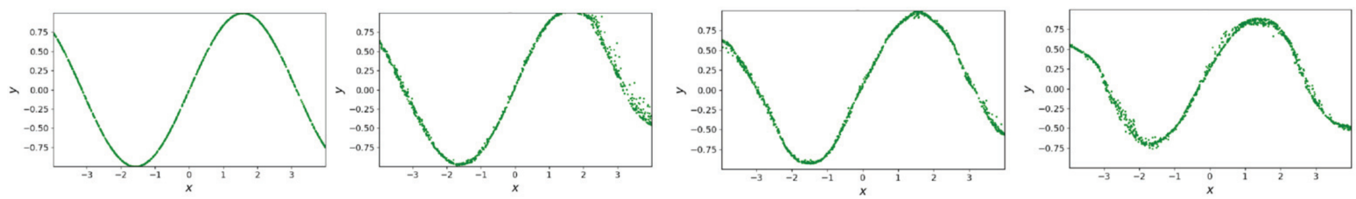
In order to extend the evaluation of proposed model, three more functions (Sinc, x^2 and x^3) were generated and the results are reported in Fig. 6 for various epochs. It is observed in Fig.6 how the waveforms converged for an increase in number of epochs with acceptable waveform obtained after 2000 epochs. The variation of mean square error (MSE) with respect to the number of epochs for Sine, Sinc, x^2 and x^3 are presented in Fig.7, indicating that the MSE reduced for increase in epochs. It is confirmed from Fig. 6 and Fig. 7 that the proposed regression model is capable of generating any curve based on the regression problem within acceptable limits of MSE.

In order to further assess the performance of proposed regression model for real-world regression problems, samples from standard datasets and repositories were considered. Details and description about the datasets considered for the evaluation of proposed regression model using CGAN is reported in Table III, along with the number of samples used for training the model, followed by validation and testing.



Ground Truth | Small | Medium | Large

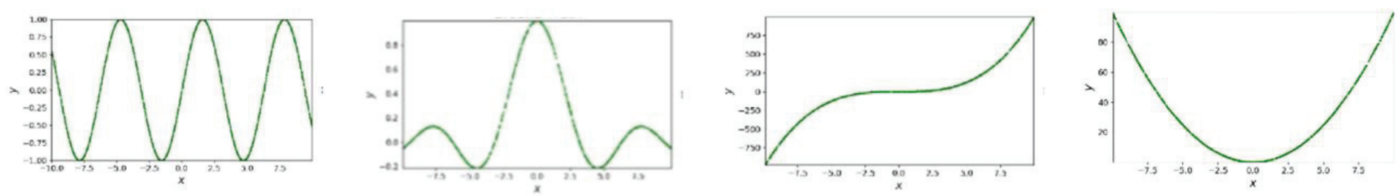
(a) Results for Double Input Generator Architecture



Ground Truth | Small | Medium | Large

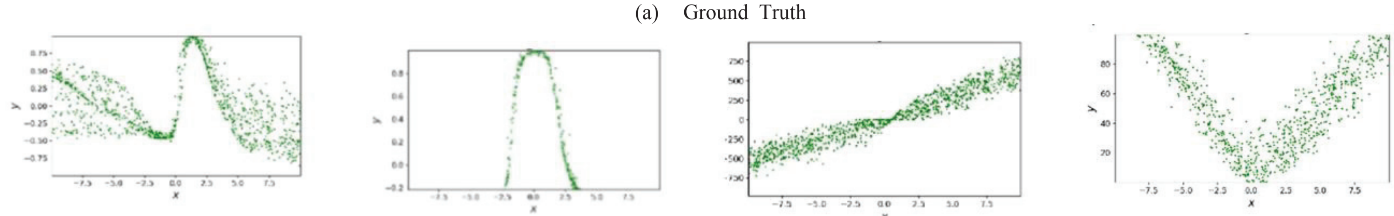
(b) Results for Noise Injection Generator Architecture

Fig. 5. Evaluation of two generator architectures and three network sizes for a sinusoidal waveform input

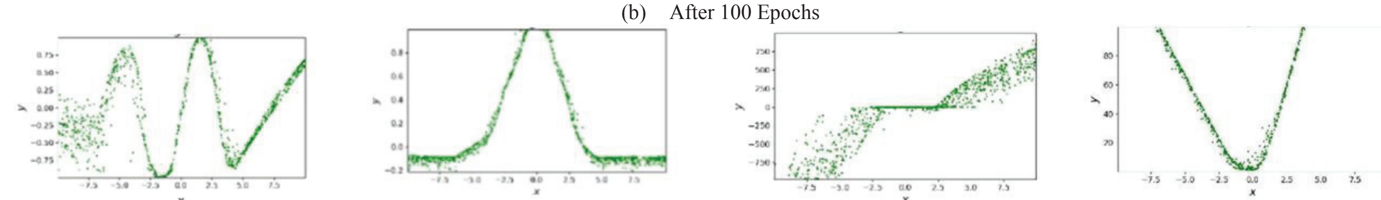


Sine | Sinc | x^3 | x^2

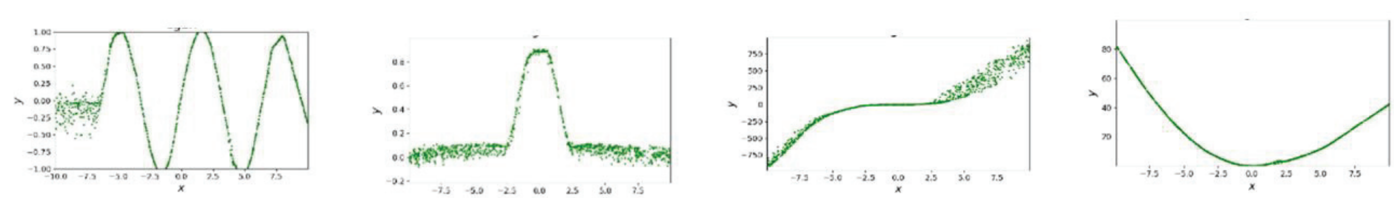
(a) Ground Truth



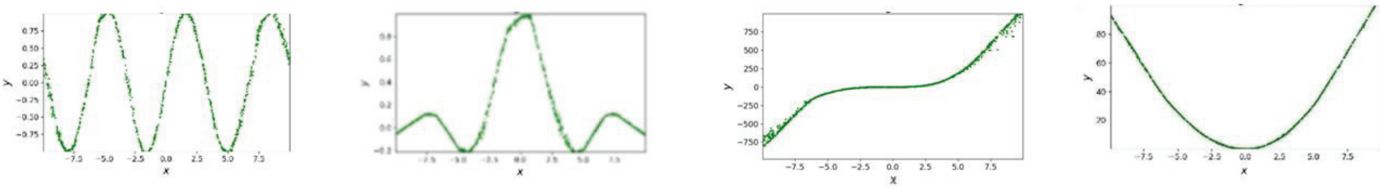
(b) After 100 Epochs



(c) After 200 Epochs

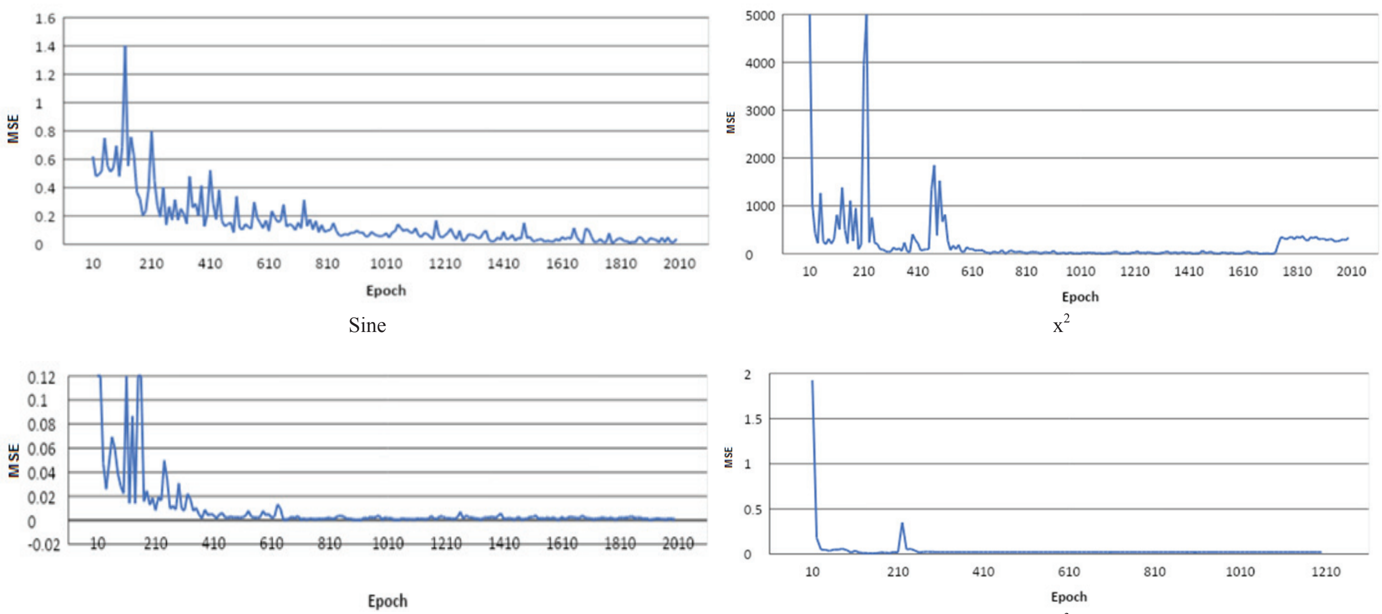


(d) After 1200 Epochs



(e) After 2000 Epochs

Fig. 6. Experimental results of proposed CGAN regression model for four different functions.



Sine

x^2

Sinc

x^3

Fig. 7. Variation of MSE with respect to Epochs for different functions.

Experiments were carried out using the proposed GAN based regression model for the datasets listed in Table III and the MSE results obtained over epochs are presented in Fig. 8. It can be observed from Fig. 8 that the MSE values for all the datasets converged for an increase in number of epochs, indicating that the proposed GAN based regression model can be used to predict outputs for various other regression problems too.

TABLE III. DETAILS OF DATASET USED FOR PROPOSED GAN BASED REGRESSION MODEL

Dataset	Source	Output	#Features	#Training	#Validation	#Testing	#Total
Housing	CMU	Median House Value	8	16512	2064	2064	20640
Airfoil Self Noise	UCI	Scaled Sound pressure level	5	1053	225	225	1503
Advertising	Kaggle	Sales	3	100	80	80	260
Housing Age	CMU	House Age	3	16512	2064	2064	20640
Concrete	UCI	Compressive Strength	8	722	154	154	1030
Power	UCI	Net hourly electrical energy	4	6698	1435	1435	9568
Microwave	NASA	Temperature	1	631	134	134	899

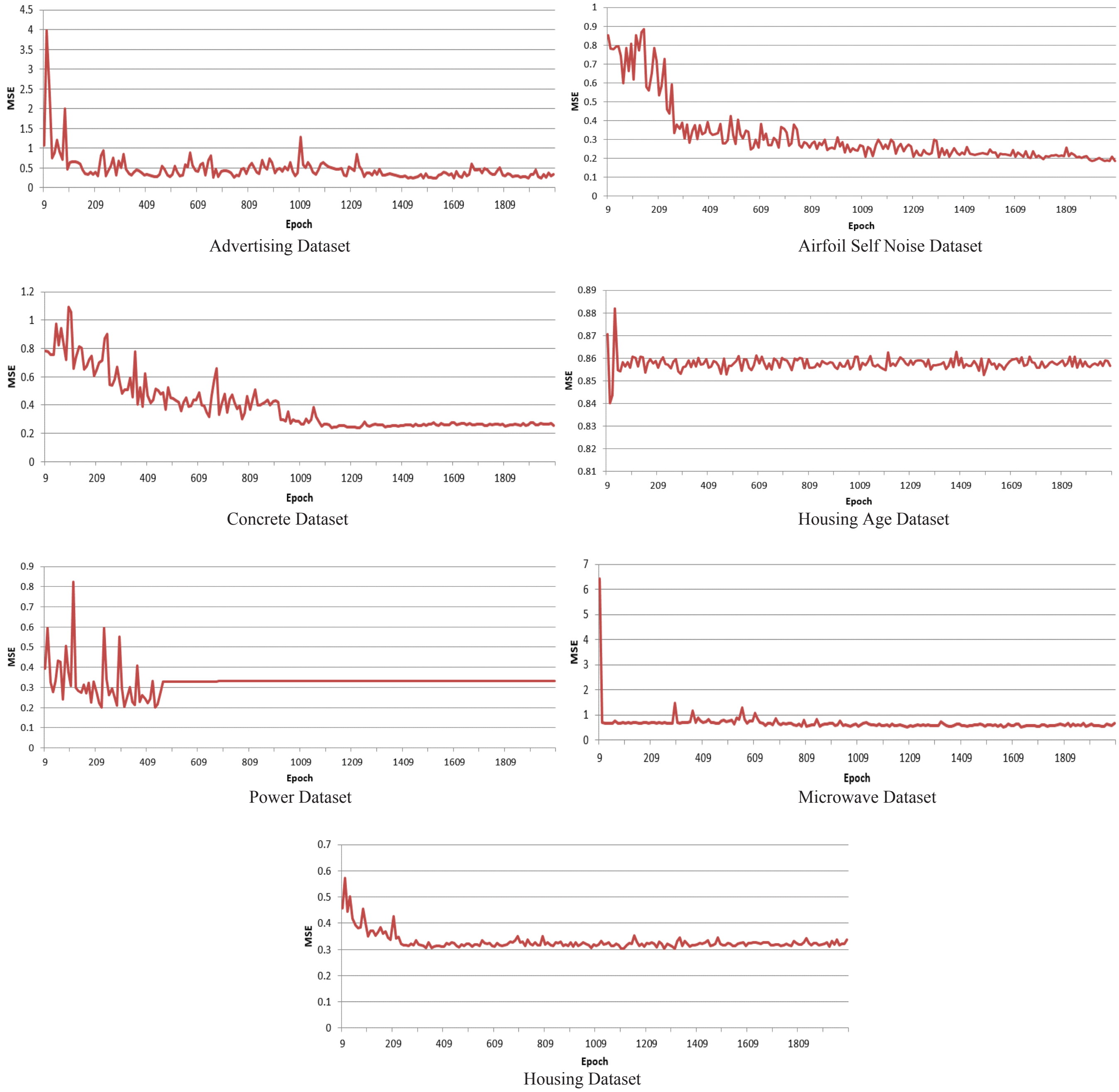


Fig. 8. Variation of MSE with respect to Epochs for different datasets.

IV. Conclusion

In this paper, design and evaluation of a GAN based regression model to solve real-world regression problems demanding prediction of outputs with curve fittings is proposed. In order to assess the performance evaluation of proposed model, four standard functions and seven standard datasets from well known repositories were considered for curve fitting and the proposed model gave satisfactory results with acceptable levels of MSE based on the datasets. The results obtained from proposed GAN based regression model indicate that the same can be employed for various other datasets and applications too.

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