# Deepfake Detection using Benford's Law and Distribution Variance Statistic

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**Abstract**—*Deepfake images have been a trending technology for a long time. Though it seems amusing to our eyes how a computer can generate realistic fake images, it has become double trouble for celebrities and Important personnel wherein their faces are morphed to bring down their reputation. Deepfakes can also be used to change the content they speak by morphing lip movements and integrating the video with artificially generated audio. Previous experimentations and research in this field have contributed many methods for detection deepfake media, which unfortunately tends to get fooled by the realism of the artificially generated media. Hence, there is an immediate requirement for a more stable method for deepfake detection. In this paper, we will observe how Benford's law or Law of the First digit can be used to detect deepfake media.*

**Keywords**—Deepfake, Benford's Law, Generative Adversarial Neural Network

## 1. Introduction

Deepfake has been a hot topic in the research and development field in computer science. With the oncoming of Generative Adversarial Neural Networks, there has been a lot of hustle and bustle in generating artificial images and videos. The other side of this technology is a dark side where cyber-crimes are on the rise by manipulating images to generate pornographic images or videos of celebrities and people of national importance. Face morphing and lip-syncing are the most used deepfake methods to generate fake media and bring down the reputation of a person or an organization. Scientist's have been in the hunt for a method to curb the spread of ingenuine media for a long time. The media is spread with reality such that even human eyes tend to get fooled. Various techniques have been tested out to detect these super-realistic images but cyber-criminals exploit the fragility of these detection techniques. A search conducted by Amsterdam based company named Deeptrace during early 2019 pointed to the fact that there were 84% more deepfakes than there were during last year. By the end of 2019, there was an almost 100% increase in the count compared to the start of the year. Even with the state of the art AI systems to detect, real-world examples shows that breakthroughs in Artificial Intelligence and Image Processing Algorithms tend to make artificial images more realistic and much harder to detect thus making the existing systems obsolete. Hence, there is an urgent requirement for a fool-proof technique to eradicate the spread of such misinformation and to develop such a system that can detect potential Deepfake images. This paper will take a look at Benford's Law for detecting Deepfake images where the First-digit law is put to use to detect if any tampering has occurred. Benford's law fits well with natural datasets and deviates if there is any tampering in the dataset. In later sections, experimentation with different transform functions that follow Benford's distribution is also carried out to get accurate results. To evaluate the extent of manipulation, several statistical tests are also evaluated to choose the best one. To test the efficiency of this approach, we will use an image generated and generate the deviance value and Benford's Curve.

### *A - Deepfake*

Deepfakes are artificially generated images that use a trained Neural Network to generate images. Deepfakes can be used to generate realistic computer images or perform editing, or morphing on a given image. AI architecture termed Generative Adversarial Networks (GANs) are used to generate these images. They have two parts for their functioning – Generator and Discriminator. The generator generates the images while the discriminator is involved in predicting if the generated image is fake or real. The ideal situation is when the discriminator cannot differentiate between the real and fake images accurately i.e., both classes have 50% probability.

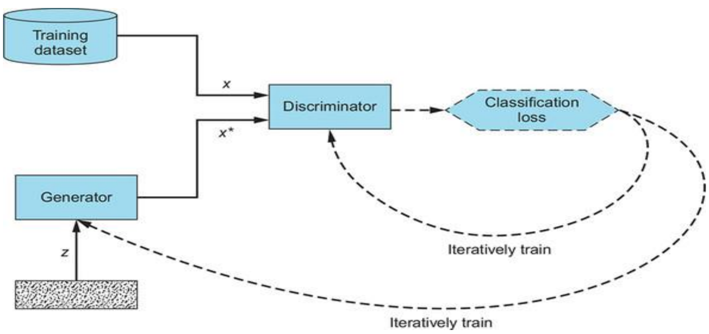


*Fig 1 - Basic GAN Architecture*

GAN is a two-player game – The generator and discriminator are trained side by side to ensure none of them outruns

each other. The discriminator is a CNN model fed with a training dataset of real images while the generator is a generative model which is fed with random noise data. The model generates images using this nose as a base. GAN works based on zero-sum theory. The zero-sum theory is a situation in which one person's gain is another' loss which is explained by the training method of GANs. The training of GANs has two phases where either the discriminator or the generator is penalized :

***Situation 1:*** If the discriminator correctly classifies the real and fake images, generator parameters are updated to make the generation more realistic.

***Situation 2:*** If the generator fools the discriminator, the discriminator parameters are updated.

***B – Benford's Law***

Benford's Law or First Digit law states that the frequency distribution of leading digits in many real-life/natural datasets follow a logarithmic curve where 1 is the most frequency and 9 being the least. For a digit *d*, the frequency distribution of that digit in a real-life dataset is calculated to be $P(d) = log_{10}( 1+ (1 /d) )$.

The above formula applies to the first digit of the data, namely [1-9] and the following graph holds.

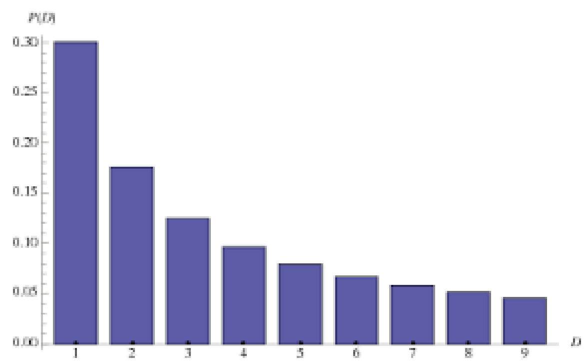


*Fig 2 - Benford's Curve*

Benford's Distribution is illustrated in Fig 3. Any major deviation from these values points to any external modification of the data. Although a negligible deviation from Benford's Law is said to be a "normalcy" for all real-world datasets, any significant deviation is considered to be unacceptable. To further evaluate Benford's Law accurately, statistical deviance tests can be used which gives a numerical deviance value of given data distribution from Benford's Distribution.

P(d) for any digit d in the range [1,9] returns frequency distribution in percentage i.e., For P(d) = X % states that X % of the first digit of the values in the dataset is digit d.

| Digit | Expected Frequency |
|---|---|
| 1 | 30.10% |
| 2 | 17.61% |
| 3 | 12.49% |
| 4 | 9.69% |
| 5 | 7.92% |
| 6 | 6.69% |
| 7 | 5.80% |
| 8 | 5.12% |
| 9 | 4.58% |

*Fig 3 - Digits with their expected frequency in Benford's Law*

## 2. Literature Review

The study paper titled "*A Review: Generative Adversarial Networks*" does an in-depth study into the functioning and working of a GAN network explaining its architecture, interior functioning and its application in the field of computer vision [1]. The workshop paper titled "*Recent Developments in Generative Adversarial Networks: A Review (Workshop Paper) "explains* GAN and its structures along with the recent developments in the field. The paper also describes in detail, certain large scale GAN network which has been optimized for performance improvements and reliability [2]. The works of the paper titled "*Vulnerability assessment and Detection of Deepfake videos*" reflect the method of detection of deepfake media using Machine Learning and Deep Learning. Machine Learning algorithms are trained on deepfake databases which are further used to predict if an image belongs to the set of artificially generated images or a natural image [3]. The paper titled "*Deep Learning in Face Synthesis: A Survey on Deepfakes"* performs a study on deepfake generation, its methods and related tools. The article also discusses certain types of deepfakes that are most common to date [4]. The review paper titled "*Media Forensics and Deepfakes – An overview*" carious out a study where deepfakes, their detection methods using traditional and Deep Learning methods are discussed. The paper also discusses the popular deepfake dataset for generating deepfake detection machine learning models [5]. The paper titled "*Deepfake detection: Current challenges and next steps*" by Siwei Lyu does a review on the types of deepfakes, current detection methods and their fragility in practice. The paper also discusses various types of deepfake media. Finally, future works are discussed which includes techniques to improve existing detection methods [6]. The paper titled "*Benford's Law: What does it say on adversarial images?*" tests Benford's theorem on adversarial images. The experiments the Benford's law by performing it on GAN generated images and performing the Kolmogorov-Smirnov test to evaluate the deviation [7]. The experiments in the paper titled "*Analysis of Benford's Law in Digital Image Forensics*" tests the compliance of images to Benford's law under different compression rations using Discrete Cosine Transform (DCT) as the transform function. The paper also tests Benford's law on images where copy-paste forgery has taken place and on CGI images [8]. The study paper titled "*On some properties of Benford's Law*" by Dominic Strzalka performs a study on Benford's law, the first digit, second digit and nth digit analysis. The paper also extends the study to the application of Benford's law to different number systems and numerical transformations of Benford's law [9]. The paper titled "*Benford's law and the limits of digit analysis*" experiments with Benford's law on a dataset of aggregated annual bank balances to detect accounting fraud. The experiment uses Benford's law along with Mean Absolute Deviation (MAD) to evaluate the deviation of the data from actual Benford's distribution [10]. The experiments carried out in the paper titled "*Detecting Anomalies by Benford's Law*"

Uses Benford's Law for System Monitoring with the system logs as the dataset. The paper also explores the conditions which a dataset should adhere to for complying with Benford's law [11]. The paper titled "*Benford's Law for Natural and Synthetic Images*" demonstrates the results of Benford's Law by applying it to various Natural and Synthetic Images. The experiment also involves evaluating $\chi^2$ Divergence, which measures the variance of an image from the actual Benford's distribution [12]. The paper titled "*Benford's Law in Image Processing*" presents the concept of image Steganalysis, where the hidden message in an image is detected by using Benford's Law with Discrete Cosine Function as Transform Function (DCT). The paper demonstrates the Fourier model for Benford's Law for comparison with DCT [13]. The works of the paper titled "*A Proper Transform for Satisfying Benford's Law and Its Application to Double JPEG*" demonstrates the usage of the 2D DCT transform function and use it to analyse tampered and non-tampered images and images under different compression levels – Single and Double compression [14]. The empirical study in the paper titled "*1-D DCT Domain Analysis for JPEG Double Compression Detection*" experiments with the 1-D DCT function for compression detection in images using Benford's Law [15]. The works of the paper titled "*A generalized Benford's law for JPEG coefficients*" presents a statistical model for first digit analysis of an image using Benford's Law with DCT as the transform function. The paper also tests the working of Benford's Law in single and double compressed images [16]. The study paper titled "*Jpeg Image Compression Using Discrete Cosine Transform - A Survey*" does a study on the Discrete Cosine Transform function, its algorithm and related concepts. This function is further demonstrated by taking Image compression as a case study [17]. The experiments of the paper titled "*On the use of Benford's Law to Detect GAN generated images*" test out the method of classification of GAN generated images using Benford's Law with DCT as transform function and a Random Forest Classifier which classifies the images as real or GAN generated depending on the Benford's features. The paper also discusses certain GAN architectures and related datasets which can be used for artificial image generation.

Thus, many approaches have been taken to detect Deep Fake images, both using visual examination (inconsistent blinking, abnormal head and lip movements) and using automated algorithms like Neural Networks (Convolutional Neural Networks). Previous research works also tested Benford's law on Artificially Generated Images proving the variance, but only limited to qualitative analysis. The application of Artificial Intelligence and Visual Examination is shown to have a fragility where more realistic fake images pass through without getting detected and the Benford's Law Visualisation has only qualitative analysis reducing the ability to accurately judge a potential fake image. This research work highlights the application of Benford's Law to Artificially Generated Images with the addition of quantitative and qualitative analysis of the results to detect potential Deep Fake Images.

## 3. METHODS

The experimentation consists of the following parts:

***Generating GAN images:*** We will train a Generative Adversarial Neural Network to generate artificial images based on a dataset. For this particular paper, we will use MNIST handwritten digit dataset on a TensorFlow GAN Network. The input will be images from the dataset and the output will be images that are generated by the GAN network. For this experiment, Benford's curve of both input and output images will be compared to demonstrate the detection technique.

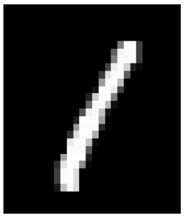

*Fig 3 (a)*

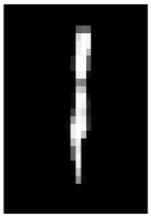

*Fig 3 (b)*

*Fig 3 (a) represents the actual sample from MNIST Handwritten Digits Datasets; Fig (b) represents a GAN generated image from the same dataset.*

***Choosing appropriate Transform Function:*** Transform function is essential for few problems where it violates the condition specified in Section 2. In the case of images in the pixel domain, there is a value constraint of [0 - 255]. To remove the limits, transform functions are applied to the image. This paper tests two transform functions for their efficiency – Discrete Cosine Transform (DCT) and Discrete Fourier Transform (DFT).

### 3.1 Discrete Cosine Transform

Discrete Cosine Transform uses the cosine function for generating a DCT Coefficient matrix with dimensions 8x8 which can be used to perform the conversion of the image from pixel domain to frequency domain. *F(u,v)* corresponds to a matrix value where *(u,v)* is the index of the matrix. *f(x,y)* is the image pixel value at position *(x,y).*

$$F(u,v)=\frac{2}{N}C(u)C(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2y+1)v}{2N}\right]$$

$$\text{for } u=0,\ldots,N-1 \text{ and } v=0,\ldots,N-1$$

$$\text{where } N=8 \text{ and } C(k)=\begin{cases}1/\sqrt{2} & \text{for } k=0\\ 1 & \text{otherwise}\end{cases}$$

*Fig 4 - Mathematical Representation of DCT*

DCT divides the image into blocks of 8x8. These values are then passed to the DCT function to generate DCT Coefficient Matrix (T). The pixel values in the actual 8x8 block in the source image is scaled to [-127,127] (M). The DCT converted matrix is obtained by D = TMT' where T is the Coefficient Matrix and M is the 8-bit monochromatic version of the source image.

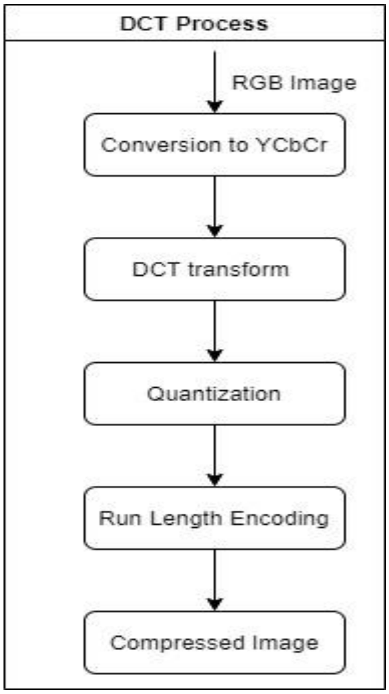


*Fig 5 - DCT Process*

*Fig 6 (a);*

*Fig 6 (b)*

*Fig 6 (a) represents an original or source image; Fig 6 (b) represents its DCT transform*

### 3.2 Discrete Fourier Transform

Discrete Fourier Transform (DFT) is an exponential transform function that is used to convert an image from pixel domain to frequency domain. In this paper, Fast Fourier Transform (FFT) is used in place of DFT to reduce the workload when using large-sized images and get faster transforms. In FFT, DFT is implemented but with much efficient computation techniques to execute the algorithm faster. *F(x,y)* is the DCT coefficient at position *(x,y)* produced by using the image pixel value *f(m,n)* at position *(m,n)*.

$$F(x,y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(m,n)\, e^{-j2\pi\left(x\frac{m}{M}+y\frac{n}{N}\right)}$$

*Fig 7 - Mathematical Representation of DFT*

*Fig 8 (a);*

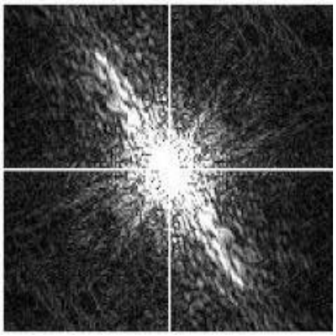

*Fig 8 (b)*

*Fig 8 (a) Represents an original image; Fig 8 (b) represents the DFT of that image.*

### 3.3 Comparison of DCT and DFT Transform Functions

DCT and DFT functions have been compared and contrasted with respect to chosen efficiency criteria – Close Resemblance to Benford's Distribution and Time Complexity. From the Experimentations conducted, Discrete Cosine Transform has been chosen due to its close resemblance with Benford's Distribution and less time complexity compared with DFT or FFT.

| Digit | Frequency |
|---|---|
| 1 | 29.0 % |
| 2 | 19.0 % |
| 3 | 14.0 % |
| 4 | 10.0 % |
| 5 | 8.0 % |
| 6 | 7.0 % |
| 7 | 5.0 % |
| 8 | 5.0 % |
| 9 | 4.0 % |

*Table 1 (a)*

| Digit | Frequency |
|---|---|
| 1 | 32.0 % |
| 2 | 17.0 % |
| 3 | 13.0 % |
| 4 | 10.0 % |
| 5 | 8.0 % |
| 6 | 7.0 % |
| 7 | 6.0 % |
| 8 | 5.0 % |
| 9 | 4.0 % |

*Table 1 (b)*

*Table 1 (a) Represents DFT of an original image; Table 1 (b) Represents the DCT of an original image.*

### 3.4 Analysis of Images using Benford's Law

The core part of this experimentation comes down to the analysis of the obtained images using Benford's Law. There are two images to explore Benford's Law – GAN-generated artificial image and the original sample of the same image from the dataset. The analysis of this distribution follows a pipeline. The input RGB is passed through the DCT function to generate a frequency-domain version of the image. The first-digit analysis is then performed on this version by extracting the frequency of the first digits in the pixel values. These values are then used to generate a distribution plot.

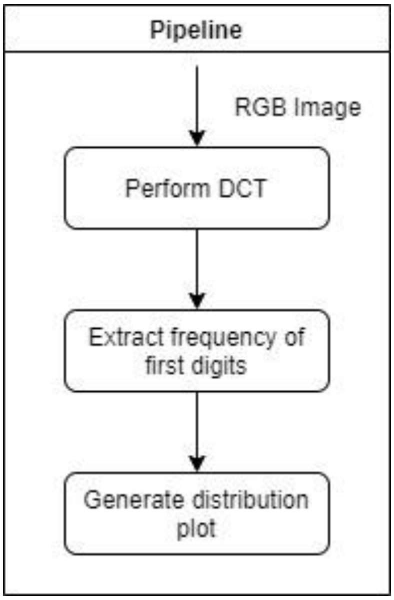


**Fig 9 - Pipeline for Benford's Law**

### 3.5 Inference of the Distribution plot

The generated distribution plots can be analyzed in comparison with Benford's distribution to conclude the tampering of the image. The amount of variance from the original Benford's distribution can be taken as a metric for preliminary analysis of the image. Fig 10 (a) represents the plot of Benford's curve for GAN-generated image and Expected Distribution. GAN generated image plot dips a few points below the expected distribution. This can be normal in few samples where there is a negligible deviation and necessarily does not indicate tampering of the image. Fig 10 (b) Represents Benford's Curve for GAN-generated image and Original Image. There is a significant variance between the two images indicating tampering. Fig 10 (c) shows Benford's Curve for Original Image and Benford's Curve. There is a slight upward deviation of the original image from the Expected Distribution. Since this is a negligible deviation, this can be considered as a similar case to Fig 10 (a).

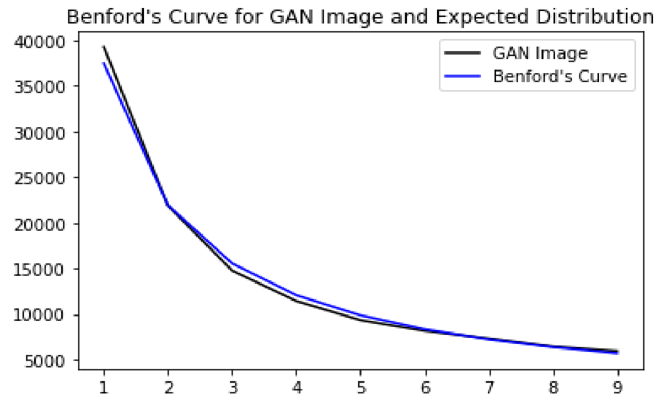


*Fig 10 (a)*

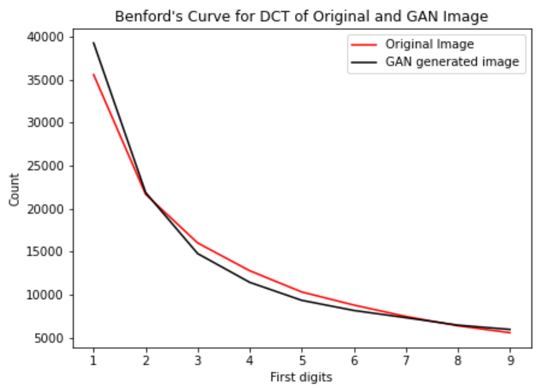


*Fig 10 (b)*

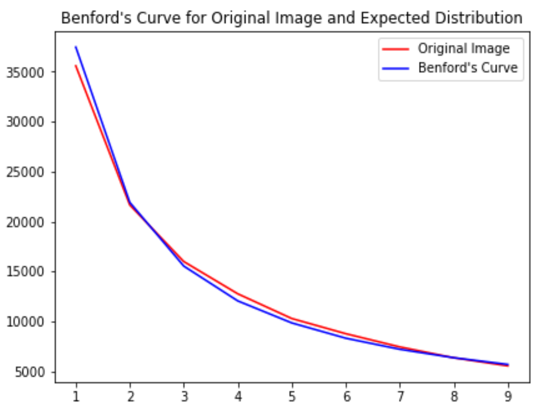


*Fig 10 (c)*

*Fig 10 (a) -Benford's Curve for GAN image and Expected Distribution; Fig 10 (b) - Benford's Curve or Original Image and Expected Distribution; Fig 10 (c) - Benford's Curve for GAN image and Original Image Distribution*

### 3.6 Evaluating out-of-the-dataset cases

The general analysis procedure of Benford's Law is by comparing it with the original image. In real-world cases, the original is often not available for analysis and only the potentially manipulated image/media is only available. Contrasting of Expected Distribution and Obtained media will not yield accurate results due to the previously discussed exceptional samples where the original media deviates negligibly but might be non-tampered. Such scenarios require the use of statistical tests where the numerical difference between the distributions are compared. In this paper, we will be comparing three commonly preferred statistical tests to judge deviation from Benford's Law – *Chi-Squared test, Kolmogorov-Smirnov test and Euclidean test.*

***Chi-Squared test:*** Chi-squared test gives a numerical value of how much a given distribution varies from the actual/expected distribution. This can be used to judge the variance of an image from Benford's distribution.

$$\chi^2 = \sum \frac{(f_e - f_o)^2}{fe}$$

$f_e$ is expected frequency,

$f_o$ is observed frequency

***Kolmogorov-Smirnov test:*** Kolmogorov-Smirnov test or KS test returns the difference of largest absolute distance between the distributions for all values of x.

$$D_n = sup_x \mid F_n(x) - F(x) \mid$$

$D_n$ is the largest absolute difference of values between two distributions

$F_n(x)$ is the observed distribution

$F(x)$ is the expected distribution

$sup_x$is the supremum of the set of distances that returns the largest absolute difference between distances

***Euclidean Test:*** Euclidean test performs the square root of the sum of squares of difference of the distribution values. It is a commonly used distance-based metric to measure the distance between two values.

$$d(X_o, X_e) = \sqrt{\sum}(X_o - X_e)^2$$

$d(X_i, X_o)$ is the distance between the points $X_o$ and $X_e$

$X_o$ is the observed frequency

$X_e$ is the expected frequency

### 3.7 Evaluating Statistical Tests

Evaluation of statistical tests can be performed by taking the efficiency of the test to display the deviance (if any) clearly. From the values in the table, Euclidean Test displays the distance more clearly compared to the other two tests. The difference in Chi-Squared and KS Test can only be seen after long decimal places while in Euclidean Test the difference is visible only after a few decimal places. This makes Euclidean more suitable for accurately judging the distance between two image distributions.

| | Chi-Squared | KS Test | Euclidean Test |
|---|---|---|---|
| Original Image | 0.00166915 | 0.11111111 | 0.01757071 |
| GAN Image | 0.00166215 | 0.11111111 | 0.01737901 |

*Table 2 – Distribution Variances for Original GAN Image*

## 4. Results

- Benford's Law fits well for natural images which have no modification to their pixels in any manner.
- GAN generated images will have a significant variation from Benford's Distribution.
- Discrete Cosine Transform will perform better both in terms of time complexity and Benford's Curve accuracy.
- The deviance test will give a quantitative analysis of the results providing a better judgement.
- Out of the three deviance tests, Euclidean Distance gives a better approximation of the variance between the Expected Curve and Benford's Curve of the image.

## 5. Discussion

From the above experimentation, we can infer that Benford's Law fits good (with negligible variation) for natural images. GAN generated images will have a significant numerical deviation from Benford's Distribution either towards the upper or lower direction because of their modification. The amount of this variance is to be taken into account to judge if the image has been artificially generated or manipulated – the more the variation, the more chance is there for that image to be Deepfake. In the comparison of the transform function for Benford's Law, this paper concludes that Discrete Cosine Transform (DCT) has the advantage for Discrete Fourier Transform (DFT) in computational performance and also in representing the Benford's Distribution with better accuracy. This experimentation also consisted of the evaluation of three major deviance tests – Chi-Squared, KS Test and Euclidean Test. From comparing the results of the three tests, Euclidean Test was found to display the deviance better in comparison to other distance measures because of its relatively higher sensitivity to distribution variance.

Fig 11 shows a super-realistic image that has been developed using Style GAN architecture developed by Nvidia. On applying Benford's Law and performing the deviance test, it is shown to be 0.02 which shows a significant variance. The relatively less deviance compared to other deepfakes is due to the reason that this image has been generated completely from scratch by a Neural Network unliked Face swapping where manipulation occurs in the source image.

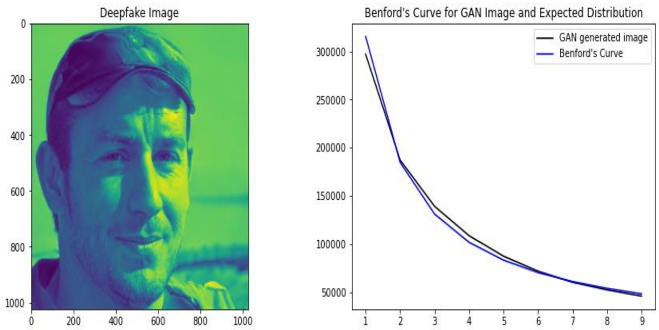


*Fig 11 – Deepfake from Style GAN Architecture and its Benford's Curve*

Thus, we can conclude that the stability of Benford's Law can act as a good method for preliminary analysis of Deepfake images. Combining Benford's Law with Deep Learning techniques and visual methods will provide a strong solution set for analyzing and detecting artificially manipulated or generated images. Quantitative Analysis of the image like deviance test will give a more in-depth insight into the nature of the image.

### Limitations

The limitation of the above experimentation is the lack of a threshold value to accurately judge if the image is deepfake or not. Naturally, Benford's Law tends to show a negligible variance even for natural images. This single experimentation alone will not be a sufficient solution to detect Deepfakes, instead, a combination of quantitative, qualitative and visual methods will help in efficiently classifying artificial images.

### 6. CONCLUSION AND FUTURE WORK

Thus, this experiment highlights the drawbacks of traditional and existing methods in detecting deepfakes. The paper also proposes the idea of using Benford's Law with quantitative and qualitative analysis along with existing methods to better detect potential deepfake images. The experimentation also consists of the comparison of two transform functions – DCT and DFT. This work also tests the efficacy of various distribution variance techniques to judge the variance of an image from its naturality. To further improve this work, the following future works may be carried out:

- To devise a better transform function for media like images that would make Benford's curve suit better for natural images.
- To devise a threshold value for distribution variance to accurately judge natural images from artificial images.

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