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CONVOLUTION NEURAL NETWORK-BASED DISTINGUISHING COMPUTER-GENERATED IMAGE FROM THE PHOTOGRAPHIC IMAGE

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Abstract-
Scientists have experienced a lot of challenges while detecting, recognizing and classifying images from various photographic sources. However, with the advent of the facilities of convolution neural network systems, the process of image generation from computers has become easier than before. Scientists have pointed out that the CNN method can be highly utilized in distinguishing images from various photographic sources to properly diagnose and predict future steps in healthcare decision-making. On the other hand, CNN uses complex and forward neural networks to distinguish it from its predecessors. Medical scientists have witnessed the merits of using CNNs in image processing and distinguishing due to their high accuracy level. Researchers therefore in this research paper are going to investigate all the essential roles of CNNs in distinguishing computer-processed images from photographic sources.

Primary research has been carried out with 59 individuals to understand the criteria based on which Convolutional Neural Network (CNN) performs more accurately in distinguishing images generated from computer and photography. The survey questions were congested with four key questions and responses for easier understanding. After the collection of the primary data, the researchers conducted secondary research to justify the findings of primary research. Findings suggested that ResNet and "Visual Geometry Group" (VGG) architectures are more accurate in distinguishing images. Image resolution ranging from 240 to 1024 is considered effective for the CNN training. The white Gaussian noise distinction technique is more accurate in this experiment.

Keywords: Machine Learning, Image classification, Image distinction, Artificial Intelligence, computer graphics, virtual reality

I. INTRODUCTION

Nowadays, computer technology is used to generate *photorealistic images* by using graphics tools and software. These technologies are used in making films, video games and virtual reality (VR). These are also known as computer-generated (CG) images which are different from those photographic images [1]. The photographic images include the directly captured images with the help of a camera and lenses [2]. Nowadays, CG images are becoming more realistic and human naked eyes cannot distinguish CG images from photographic images. According to the studies, CG images can be misused in various fields and it can cause potential harm to an individual. Therefore, distinguishing the CG images from the photographic image (PG image) is highly necessary to mitigate the issues [3].

Concerning this, Meena and Tyagi stated that fake images or videos can easily be created using graphical technology and it may result in reputation loss. Marraand colleagues also stated that CG technology is misused for manipulating the original information and to influence social groups to share hatred based on the bias of the CG image [4]. Therefore, it is of utmost importance to develop Artificial Intelligence (AI) technology that can potentially distinguish between CG image and PG image [5].

This paper is going to describe the fruitfulness of "**Convolutional Neural Network**" (CNN) in distinguishing images generated from computers and by photography. IBM has provided the description of CNN where it states that CNN is a branch of Machine Learning and it also performs like a Deep Learning (DL) algorithm to execute image detection [6]. The CNN is composed of input layers, hidden layers, output layers and node layers. The node is activated when the output crosses the threshold values. CNN utilises three layers; such as "*Convolutional Layer", "Fully-concentrated layer",* and *"Poling Layer"* [7].

This research is going to analyse the key criteria of the CNN algorithm to distinguish the CG images from that of PG images. CNN has been used by many developers to execute the distinguishing functions and thus, primary research has been carried out to collect the right method for developing CNN. The paper is organised into past literature that will describe the past studies on CNN and its performance in image classification and detection. The image classification will be based on the distinguishing of CG with

PG images. Thereafter, the current research methodology will be described and after that, the primary data will be analysed and interpreted. Finally, the results will be discussed and concluded.

II. Literature Review

Nowadays, the process of conducting convolution neural network-based systems has experienced positive growth in healthcare practices from the last few decades. Previously, it was quite difficult to distinguish various computer-generated images to detect critical diseases and predict necessary treatment procedures for a sustainable future [8]. However, with the advent of convolution neural networks, healthcare practices around the globe have found a new pathway towards future development [9]. The convolution neural networks (CNN) can be operated from a remote sensing place across a vast network setting that helps in recognising and detecting medical images from photographic sources [10].

Fig. 1: Image processing through the use of CNN
(Source: [10])

Clinical scientists have pointed out from different medical findings that CNN is usually used in computer-generated medical image analysis (fig. 1). From various photographic image sources, CNN-based distinguishing computers focus on essential clinical things such as medical image recognition, detection as well as segmentation of medical objects [11]. However, the convolutional layer presented over a typical neural network can offer each input neuron that is strongly linked with the next hidden layer of CNN.

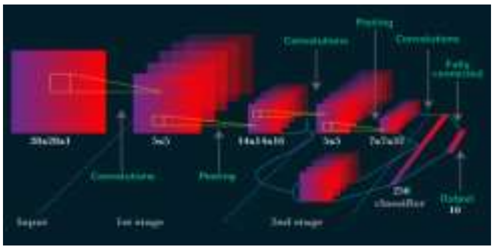

Fig. 2: Use of CNN in Image classification and recognition
(Source: [11])

Modern-day medical science has witnessed various advantages of utilizing the CNN process in medical image processing and distinguishing those computer-generated images from photographic sources [12]. However, in the case of machine learning, CNN deals with feed and forward neural networks that are complex (fig. 2). Medical scientists have reflected their opinions that CNNs can be used for classifying relevant medical images and recognizing their values due to their high level of accuracy [13]. On the other hand, all the incorporated convolutional layers are primarily utilized for medical image processing from an effective perspective. However, the classification and segmentation of medical images also can be highly linked with the auto correlated data through the steps of CNNs [14]. Scientists have spotted that the facilities provided by CNNs can be used for recognizing and classifying any 2D or 3D data array related to the particular industry [15]. One of the important advantages of CNN as compared to its predecessors in the previous decades is that it can automatically detect the essential features of the computer-generated image without any human supervision [16]. Researchers, therefore, show genuine interest to investigate more regarding the use of CNN in distinguishing computer-originated images from photographic sources.

III. Research Methodology

The research selected a primary data collection method and analysed the data. Survey-based primary research has been conducted with ***59 individuals*** who use the ML, DL and AI algorithms. Due to the persistence of ongoing pandemic and low-research budget, the researchers have selected an ***online survey-based primary research*** method. Initially, researchers shared a post on social media concerning the survey. Many individuals responded to the post regarding filling out the survey form. From those individuals, the researchers selected 59 individuals who had more than 1 year of experience in ML, DL and AI. The 59 individuals were then asked to provide their email addresses and via the email address, a ***google survey form*** has been distributed.

The survey form contains many survey questions regarding CNN and its respective criteria for building a high-performance DL algorithm. Demographic data were also collected which will not be analysed as they seemed to be irrelevant for this study. The survey questions and the respective answers were converted to four broad questions for analysis. The responses were also converted to numerical form for easier analysis. After that, percentage values were calculated in Microsoft Excel and the analysis has been interpreted in the following section. To accomplish an effective discussion, the researchers selected journal articles from the last five years (2018-2022) to justify the relevance of primary findings.

Research questions:
Which CNN architecture is best for distinguishing a CG image from that of a PG image?
What are the processing techniques required for building this algorithm to distinguish between the images from PG and CG?

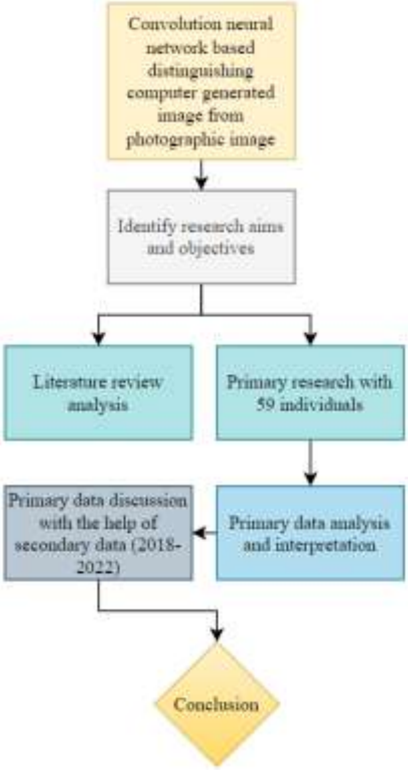

Fig. 3. Research flowchart
(Source: Created by the researchers)

IV. Analysis and Interpretation

The survey questions and their respective responses with percentile values have been provided below. The demographic data has been excluded and the person with more than 1 year of experience has been selected for this survey.
Q1. What do you think is the best CNN architecture for distinguishing images generated by computers and photography?

TABLE I. RESPONSES OF QUESTION 1
(SOURCE: CREATED BY THE RESEARCHERS)

Google form options	**Total participants**	**Collected responses**	**Percentile calculation**
LeNet	59	2	3%
AlexNet	59	4	7%
ResNet	59	18	31%
VGG ("Visual Geometry Group")	59	9	15%
Xception	59	9	15%
GoogleNet	59	11	19%
NIN (Network in Network)	59	6	10%

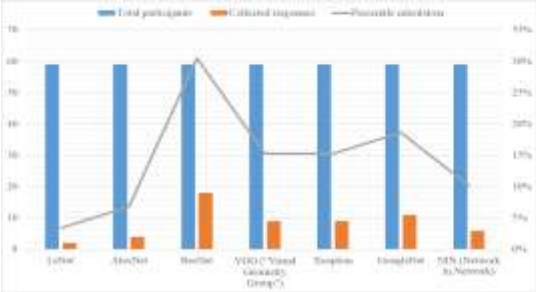

Fig. 4. Graphical representation of survey question 1
(Source: Created by the researchers)

The above responses (Table I, Fig. 4) shows that most of the people agreed with using ResNet for image distinguishing experiments (31%). They stated that ResNet requires fewer parameters and is used in image classification and detection. Thus, it can perform better in distinguishing images. Many of them also agreed with using GoogleNet (19%). Some of them (15%) agreed that Xception can also distinguish images of CG from PG. The least of the respondents agreed with the rest of the CNN architectures.

Q2. What do you think can be the best resolution for distinguishing CG images from PG images?

TABLE II. RESPONSES TO QUESTION 2
(SOURCE: CREATED BY THE RESEARCHERS)

Google form options	**Total participants**	**Collected responses**	**Percentile calculation**
32 x 32	59	1	2%
90 x 90	59	1	2%
256 x 256	59	6	10%
512 x 512	59	9	15%
900 x 900	59	14	24%
1024 x 1024	59	18	31%
2048 x 2048	59	10	17%

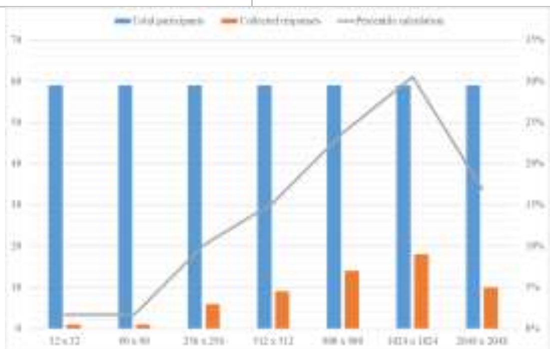

Fig. 5. Graphical representation of survey question 2
(Source: Created by the researchers)

The above question has been asked to understand whether the resolution has any impact on the accuracy of CNN architectures or not (Table II, fig. 5). In that question, 31% of the respondents agreed that images of 1024 x 1024 resolution are the best to train the architectures. Moreover, the architecture can distinguish images of this resolution. 24% agreed that 900 x 900 images are enough to train the algorithm. 17% of individuals responded that 2048 x 2048 resolution is better for distinguishing images; however, the dataset will require a large storage system. Thus, 512-1024 resolution is the best range. A few of them selected resolutions ranging from 32x to 256x.

Q3. Do you think the CNN algorithm requires any extra feature extractor or classifier or the algorithm can alone extract the features?

TABLE III. RESPONSES TO QUESTION 3

(SOURCE: CREATED BY THE RESEARCHERS)

Google form options	Total participants	Collected responses	Percentile calculation
The algorithm can alone extract the features and classify it	59	25	42%
CNN can extract features; however, cannot classify it	59	14	24%
CNN can classify the images; however, a feature extractor is required	59	13	22%
CNN requires both feature extractor and classifier	59	7	12%

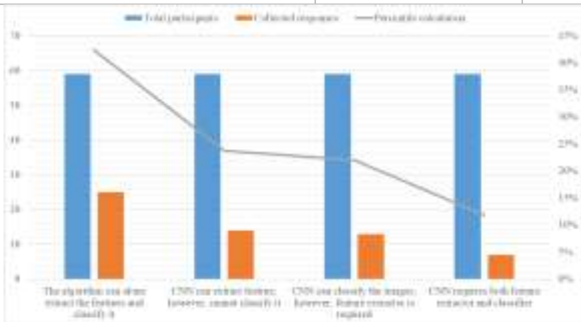

Fig. 6. Graphical representation of survey question 3
(Source: Created by the researchers)

The third question has been asked to understand whether CNN requires any extractor and classifier or not. In this question, 42% of respondents agreed that CNN has its *autoencoder* and can extract features. Moreover, no extra classifier is required in the case of CNN. 24% agreed that CNN can extract features of CG and PG images; however, it requires a classifier. 22% stated the opposite. A few of them (12%) stated that an external autoencoder is required for both feature extraction and classification (Table III, Fig. 6).

Q4. What do you think is the best pre-processing technique for an image distinguishing experiment?

TABLE IV. RESPONSES TO QUESTION 4
(SOURCE: CREATED BY THE RESEARCHERS)

Google form options	Total participants	Collected responses	Percentile calculation
Ensemble model	59	26	44%
"White Gaussian noise" pre-processing	59	25	42%
State-of-the-art technique	59	8	14%

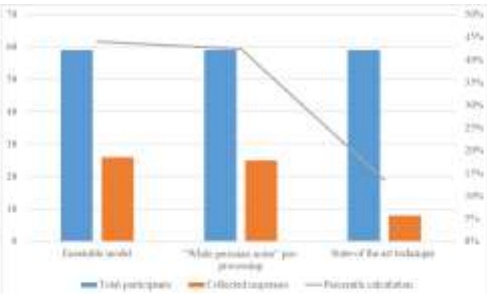

Fig.7. Graphical representation of survey question 4
(Source: Created by the researchers)

The final survey question is about finding the best pre-processing technique for CNN architectures (Table IV, Fig. 7). Several pre-processing techniques are used in image classification, detection and distinguishing images. 44% of the respondents agreed that the *Ensemble model* for CNN is the best to distinguish the CG images from PG images. 42% of the respondents agreed that white Gaussian noise and noise-distinct features are the best techniques. A few of them agreed with the State-of-the-art technique (14%).

V. Discussion and Findings

The primary data have found some important information regarding image distinguishing experiments of CG and PG images. CNN contains more than one architecture and selecting the best architecture is essential to improve the accuracy in distinguishing images. According to the primary research, ResNet architecture is considered the best for distinguishing the two types of images.
According to Sudiatmika and Rahman, VGG architecture performs better in distinguishing forgery images [17]. Other studies also used VGG architecture to perform similar experiments. The commonly used VGG architectures are VGG 16 and VGG 19. An author distinguished CG images from PG by using VGG 12 and ResNet14 [18]. The key problem in distinguishing images is the *"binary classification"* problem. They observed that VGG and ResNet both perform better than State-of-art techniques. The state of art is a hand-crafted technique and is less accurate than CNN techniques [19]. Moreover, the VGG and ResNet CNNs are more stable than "state of art" methods [20].
Concerning this, the current research found that noise distinct feature identification (white Gaussian noise) is more feasible in distinguishing two images [21]. This suggests that the CG images are less noisy than the PG images [22]. The below figure has shown the PG and CG images where it can be seen that CG images possess less noise than PG images. Therefore, it is an excellent feature for distinguishing the images [23].

(a) (b)

Fig. 8. (a) image generated by computer and (b) photographic image is noisier than CG image
(Source: [14])

The current study has found that respondents are recommending *900x to 1024x* images for this distinguishing experiment. This suggests that, below these two resolutions, images tend to lose minute details and contrast variance. Higher resolution images are acceptable; however, the training will require a large storage system. In this case, JPEG compression is also required sometimes to improve the accuracy [24]. Some authors used images of less than 512x resolution (233x233 and 240x240) to experiment. Their study showed 93-98% accuracy in image distinction. Therefore, the images of 240-1028x can be selected for performing this experiment [25].
Finally, it has been found that CNN architecture does not require any external autoencoder. Studies suggest that other algorithms such as Artificial Neural Network (ANN) require external autoencoders; however, CNN does not require it [26].

VI. CONCLUSION

The research has been conducted to understand the criteria for CNN to accurately distinguish the CG image from the PG image. The researchers performed a primary online survey to accomplish the research objectives. A total of 59 individuals have been selected to answer some questions related to CNN and its image distinction property. The results were analysed and justified using secondary journal articles. It has been found that VGG and ResNet are the two best architectures of CNN to distinguish images generated by computers and photography. In this case, CNN is the best algorithm because it does not require any external autoencoder. The study has found that the white Gaussian noise distinction technique is more accurate in distinguishing images.

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