Factors Affecting CNN Performance for Binary Steganalysis

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***Abstract*—Binary steganalysis is a prediction of whether an image is a cover image (does not contain a secret message) or a stego image (contains a secret message). CNNs are now widely used to find hidden messages embedded in images. CNN optimization strategies such as the use of Spatial Rich Model (SRM) Filter and Batch Normalization, Spatial Dropout layer, and three Fully Connected Layers before softmax have shown improved accuracy on three binary steganalysis CNNs namely Xu Net, Ye Net, and Yedroudj Net as well as two CNNs for image classification (VGG-16 and VGG-19), but which computational elements are relevant to the accuracy of binary steganalysis CNNs remains unknown. Therefore, this study will investigate the factors that affect the performance of CNNs of binary steganalysis that have not been tested before, such as GBRAS Net and Ntivuguruzwa Net. The data set used in this research is Bossbase 1.01 inserted with secret messages using the S-Uniward steganography algorithm with a message length of 0.4 bpp. GBRAS Net and Ntivuguruzwa Net have three main parts, namely the preprocessing module, the convolution module, and the classification module. The test results show that SRM filter and batch normalization play an important role in accuracy, but the addition of spatial dropout layers and three fully connected layers in GBRAS Net and Ntivuguruzwa Net does not always provide an increase in accuracy.**

***Keywords*—steganalysis, digital image, forensics, deep learning**

I. Introduction

Information security includes preventing access to information by unauthorized parties, protecting the confidentiality of private information, preventing attempts to change information, and so on [1]. Steganography is one of the techniques used to improve information security, which aims to hide the existence of messages to avoid suspicion from other parties. Steganalysis is the opposite of steganography; if steganography aims to hide a secret message, then steganalysis detects whether there is a secret message hidden in a medium. The main goal of steganalysis is binary classification, which means that the system predicts whether a suspect image is a cover image (which does not contain a secret message) or a stego image (which contains a secret message). This is useful for preventing stegosploit (hacking with digital image media), as well as detecting secret messages hidden through steganography, for example, in military or terrorism cases.

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As deep learning methods develop, the steganalysis paradigm has also changed from machine learning to deep learning [2], [3]. Various deep learning algorithms have been applied in binary steganalysis, the majority of which currently use the Convolutional Neural Network (CNN). The first binary steganalysis research was Qian Net [4], which was the beginning of the development of deep learning binary steganalysis. The result of Qian Net is the classification of an image is a cover image or stego image, but the test results of Qian Net accuracy (61.4%) still cannot exceed the Spatial Rich Model and Ensemble Classifier (63.5%) to detect the WOW (Wavelet Obtained Weights) steganography algorithm with a message length of 0.2 bpp. Nonetheless, Qian Net's average pooling idea inspired further research to use average pooling with the aim of protecting the stego signal in the image that may be lost when using max pooling, but not lost when using average pooling. Research continued to improve existing binary steganalysis CNNs, including Xu-Net [5] which uses batch normalization (BN) and TanH activation function to avoid overfitting in the first two layers of feature extraction, while subsequent layers use BN and ReLU activation function. Xu Net outperformed the performance of SRM and ensemble classifier for the first time, with an accuracy of 67.5%. In 2017 Ye Net [6] for binary steganalysis used 30 SRM filters adapted from feature extraction in machine learning, namely Spatial Rich Model, the value of SRM is used to initiate the filter in the pre-processing stage. The TLU activation function is used in his research to improve the Peak Signal to Noise Ratio (PSNR) because the steganography algorithm requires a minimum PSNR value. Ye Net also adds transfer learning from a network trained with a high payload dataset to a dataset with a low payload, this is because the high payload makes it easier for the classifier to classify stego and cover images because the patterns are easier to read. Ye Net's accuracy result is 66.9%.

Furthermore, in 2018 Yedroudj Net [7] improved the performance of binary steganalysis on the previous CNN by combining the advantages of Xu Net and Ye Net, including using a preprocessing module with 30 SRM filters and batch normalization like Xu Net. Then the TLU activation function in the first two layers are adapted from Ye Net. Ye Net and Yedrouj Net research uses the TLU (Truncated Linear Unit) activation function. In addition to adapting the architecture of Xu Net and Ye Net, Yedrouj Net research also uses average pooling, which was previously used in Qian Net. The accuracy result of Yedroudj Net is 72.3%. In the same year, binary steganalysis research developed using SR Net [8] with an accuracy of 75.5%. The difference between SR Net and CNN research for binary steganalysis before is in the preprocessing module, SR Net does not use a fixed value filter in the preprocessing module, such as 30 SRM filters on Ye Net and Yedroudj Net, but SRnet uses 30 SRM filters as an initial weight that will learn from the initial weight (trainable). This aims to clarify the stego signal, but makes the architecture less efficient in terms of computation. The next binary steganalysis research is Zhu Net [9] with an accuracy of 76.9%, Zhu Net reduces the size of the convolution filter to reduce the number of parameters and uses spatial pyramid pooling (SPP). SR Net has 1 fully connected layer before the softmax function in the classification module, while Zhu Net has 2 fully connected layers, which causes overfitting so that in the next binary steganalysis research this is fixed, namely in GBRAS Net [10].

GBRAS Net research for binary steganalysis has superior performance to the previously discussed CNN, which is an accuracy of 80.3%. In simple terms, this GBRAS Net network has a special block for preprocessing, using the SRM filter in the first convolution in the preprocessing stage. This filter is a fixed filter whose value has been determined (non-trainable), the contents are 30 SRM (Spatial Rich Model) filters that aim to clarify the stego signal. This network has a convolution module for feature extraction with depthwise and separable convolutional layers and 2 skip connections. The activation function used is Exponential Linear Unit (ELU). Then for the classification module, it is directly connected to softmax, without a fully connected layer. Recent research on binary steganalysis [11] improved CNN architecture from previous research, such as the use of 2D depthwise separable convolution to prevent overfitting due to fewer parameters than other types of convolution layers. The activation function used is Leaky Rectified Linear Unit (Leaky RELU) so that the network can converge faster and the pooling used is multiscale pooling to protect spatial information related to features. The accuracy test result for Ntivuguruzwa Net is 90.2%.

The optimization strategies used in the study [12] include the use of Spatial Rich Model (SRM Filter), Spatial Dropout, Batch Normalization, and 3 Fully Connected Layer before softmax which has shown improved accuracy on three binary CNN steganalysis namely Xu Net, Ye Net and Yedroudj Net, as well as two CNNs for image classification (VGG-16 and VGG-19), but which computational elements are relevant to the accuracy of binary steganalysis CNNs remains unknown [12]. Moreover, this strategy has not been tested on other CNNs, such as the GBRAS Net and the Ntivuguruzwa Net. Therefore, in this study, the effects of adding SRM filter, spatial dropout, batch normalization, and 3 fully connected layers will be investigated to get the factors that affect the accuracy of binary steganalysis CNN.

This research consists of five sections, namely the first section of the introduction, followed by literature review in section two and research methodology containing CNN comparison scenarios in section three. Results and analysis are given in section four and closed with conclusions and further research in the last section.

II. Literature Review

A. Steganalysis

Steganalysis is the process of detecting secret messages in digital media, such as images. Binary steganalysis aims to predict whether an image is a cover image (does not contain a secret message) or a stego image (contains a secret message). Fig. 1 is an illustration that provides an explanation between steganography and steganalysis. The discussion begins with a fictional character in steganography, Alice, who wants to hide a secret message (M) into an empty medium (without the secret message), which in steganography is called a cover object (C). If the cover object is inserted with a secret message with a stego key (K), it is called a stego object (S). Thus, the stego object (S) contains the secret message (M) and the cover object (C). This process is called embedding, which is the core sequence in steganography [13].

Steganalysis is the study of detecting secret messages hidden with steganography algorithms. The main goal of steganalysis is a binary classification that determines whether a media suspect is a cover object (does not contain a secret message) or a stego object (contains a secret message). In addition to the main objective above, there are several advanced steganalysis studies [1], including:

- determining the message length.
- determining the type of insertion algorithm.
- the key used.
- the secret message, if possible.

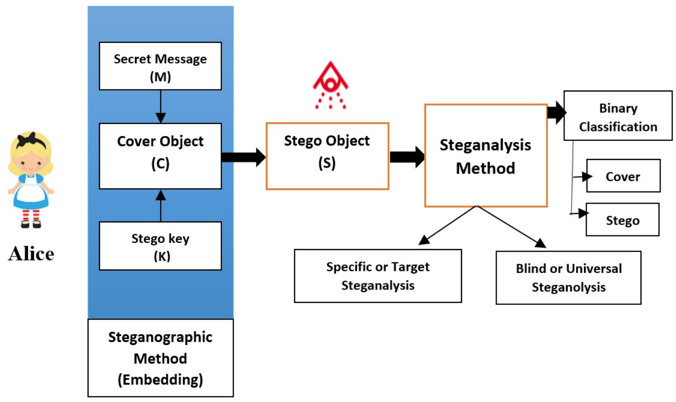

Fig. 1. Steganography and Steganalysis [14]

B. Deep Learning

Convolutional neural network (CNN) uses convolution as the basis for building a neural network. Convolution is described in Fig. 2, an image with a certain pixel value multiplied by the value of a filter will produce a feature map [15].

Stride is the displacement step of the filter or kernel during the convolution process. The stride value determines how much the filter shifts after the convolution operation is performed. If stride is 1, the filter will shift one pixel at each step. If stride is 2, the filter will shift two pixels. Padding is used to add extra values at the edges of the input image so that the size of the convolution layer output remains the same as the input or larger than the size without padding. Padding is important to preserve the edge information of the image. Same padding means adding padding so that the output has the same size as the input, while valid padding means no padding is added so that the output size is smaller than the input [16].

C. Binary Steganalysis Success Measures

CNN performance will be evaluated using accuracy, precision, recall, and F_1score testing. Tests generally use accuracy testing by comparing the number of images that are correctly classified with the total number of test images. The expected result in steganalysis research on digital images is to find pattern data to detect whether there is a secret message hidden in a digital image. Accuracy is the ratio of true predictions (positive and negative) to the overall data [17], can be calculated by (1), where *TP* is true positive which means a stego image is correctly detected as stego and *TN* is true negative which means a cover image is correctly detected as cover, while *FP* is false positive and *FN* is false negative. Precision is the ratio of true positive predictions compared to the overall positive predicted results, can be calculated by (2) and recall which is the ratio of true positive predictions compared to the overall true positive data can be calculated by (3). In addition to accuracy testing, there are several other tests to measure the success of steganalysis, such as F_1 score and Area Under ROC Curve (*AUC*). F_1 score is the harmonic mean of the precision and recall values which can be calculated with (4).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

The ROC curve describes the relationship between the true positive ratio and the false positive ratio, while the AUC or Area Under the ROC Curve is a value that summarizes the performance of the classifier. The higher the AUC, the better the model is at predicting class 0 as 0 and class 1 as 1.

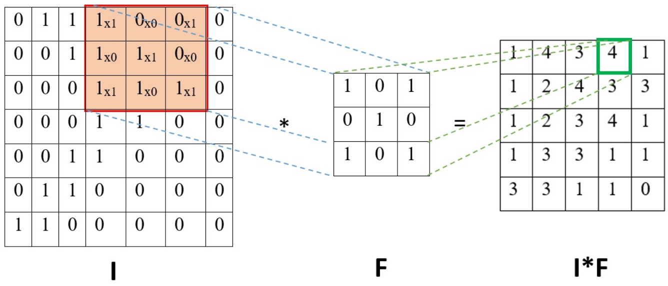

Fig. 2. Convolution [15]

D. GBRAS Net

GBRAS Net is a binary steganalysis CNN that aims to predict whether an image is a stego or cover image. The input image has a dimension of 256*256. The GBRAS Net network [10] has a special block for preprocessing, which contains 30 SRM (Spatial Rich Model) filters and has a convolution module with depthwise separable convolutional layers and 2 skip connections. Each convolutional layer is followed by Batch Normalization as in Fig. 3, which helps keep the input distribution of each layer stable during training. In the GBRAS Net convolution module, the average pooling layer after batch normalization aims to reduce the spatial dimension of the data, and at the end of the network, GlobalAveragePooling2D is used to average all features before the classification layer. GBRAS Net has 8 convolution layers and 4 depthwise separable convolutions. The last block of the convolution module is connected to the classification module. GBRAS Net. does not have a fully connected layer but directly uses the softmax function. The final result of GBRAS Net is the probability of an image belonging to the first class (cover image class) or the second class (stego image class). The classification decision is obtained by selecting the class with the highest probability value.

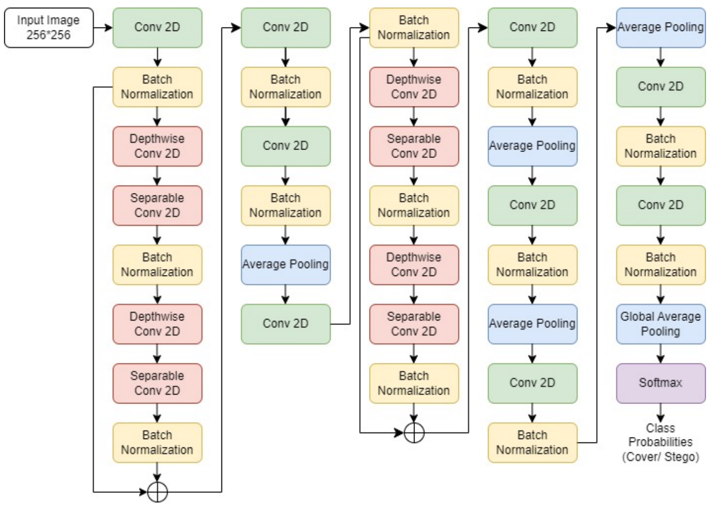

Fig. 3. GBRAS Net [10]

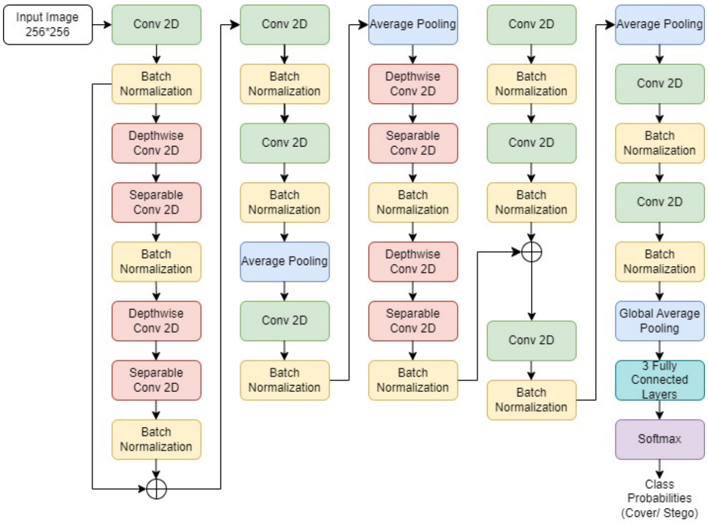

Fig. 4. Ntivuguruzwa Net [11]

Fig. 5. Bossbase 1.01

E. Ntivuguruzwa Net

Ntivuguruzwa Net [11] improved the previous CNN with several improvements, such as the improvement of the convolution layer and the addition of a fully connected layer before softmax, as shown in Fig. 4. The input image is 256*256 grayscale image given pre-processing using 30 SRM (Spatial Rich Model) kernels. There are 8 regular convolution modules and 4 depthwise separable convolution modules. The activation function used is Leaky RELU, which is an improvement of ReLU, where negative inputs do not immediately become zero, but instead are multiplied by a small value (usually 0.01). Each convolutional layer is followed by Batch Normalization, which helps keep the input distribution of each layer stable during training. The average pooling layer after batch normalization aims to reduce the spatial dimension of the data, with a pool size of (2,2) and stride of (2,2). Before heading to the Fully Connected Layer, Multiscale Average Pooling is given with three scales, namely (4,4), (2,2) and (1,1). There are three fully connected layers, each with ReLU activation except for the last layer which uses Softmax activation. Softmax is used in the output layer to generate class probability distributions (two output classes indicated by two neurons in the last layer), namely stego and cover classes.

III. Research Method

This research is experimental research. The dataset used in this study, namely Bossbase 1.01 with the S-Uniward 0.4 bpp steganography algorithm. CNN implementation for binary steganalysis in this study uses Python 3.8.5 and Tensorflow 2.5.0 on the windows operating system. The Google Colabolatory used is Tesla T4 (16GB) GPU. The Bossbase 1.01 dataset [18] has 10,000 images in PGM format, each measuring 512*512 pixels as in Fig. 5. This dataset is a cover image (without a secret message). The cover image is then inserted with a secret message using a steganography algorithm.

This research uses the BOSSbase 1.01 dataset which is inserted with a secret message using the Spatial-Universal Wavelet Relative Distortion or S-Uniward steganography algorithm [19] with a message length of 0.4 bits per pixel (bpp). The binary steganalysis dataset is available and publicly accessible via [10]. This dataset consists of 10,000 cover images and 10,000 stego images divided into 4000 pairs for training data, 1000 pairs for validation data, and 5000 pairs for testing data. The characteristics of the dataset can be explained as follows:

- The size of the whole image is changed from 512*512 to 256*256.
- Dividing the image into cover and stego with a proportion of 50:50.
- Perform insertion with the S-Uniward algorithm with a random message that has a message length of 0.4 bpp.
- The author changes the format to NumPy array to improve the reading time by the system..

Partitioning of training, testing, and validation data is as follows:

- Images from index 0 to 3999 (4000 cover data) and from index 10000 to 13999 (4000 stego data). So, there is a total of 8000 data for training.
- Images from index 4000 to 4999 (1000 cover data) and from index 14000 to 14999 (1000 stego data). So, there is a total of 2000 data for validation.
- Images from index 5000 to 9999 (5000 cover data) and from index 15000 to 19999 (5000 stego data). So, there is a total of 10000 data for testing.

The CNNs studied in this research are GBRAS Net and Ntivuguruzwa Net. The success measures used in this study are accuracy, precission, recall, AUC and F_1 score.

IV. Results and Analysis

The test results for accuracy, precision, recall, F_1 score and AUC for GBRAS Net and Ntivuguruzwa Net are shown in Table I. It shows that the GBRAS Net model with no dropouts

TABLE I
CNN TEST RESULTS

No.	CNN	Description	Accuracy (%)	Precision (%)	Recall (%)	F_1-score (%)	AUC (%)
1	GBRAS_net	Without SRM dan BN	50.08	50.13	50.08	45.04	50
2		Original	87.16	87.31	87.16	87.15	96
3		Add dropout	75.49	76.79	75.49	75.19	86
4		Add 3 FC layer	78.48	79.39	78.48	78.31	89
5	Ntivuguruzwa net	Without SRM dan BN	50	25	50	33.33	50
6		Original, Batch size=64	81.13	81.19	81.13	81.12	91
7		Batch size=32	82.58	82.79	82.58	82.55	93
8		Batch size=32 + dropout	80.26	80.51	80.26	80.22	91
9		Without 3 FC layer	70.66	71.33	70.66	70.43	79

and 3 FC layers has the best performance for the model across all metrics with accuracy, precision, recall, AUC and F_1-score above 87% and the Ntivuguruzwa Net model with batches of 32 gives the highest performance for the model, with results over 82% across all metrics.

CNN-based deep learning for binary steganalysis gives the best results when using Spatial Rich Model (SRM) filter and batch normalization after convolution layer. This applies to GBRAS Net and Ntivuguruzwa Net. Ntivuguruzwa Net without SRM and batch normalization produces an accuracy of 50%, while after using SRM and batch normalization it increases to 81.13%. GBRAS Net without SRM and batch normalization produces an accuracy of 50.08%, while after using SRM and batch normalization it increases to 87.16%. Spatial Rich Model (SRM) filter for the pre-processing stage of binary steganalysis contains 30 filters that are adapted from the best feature extraction in machine learning, namely Spatial Rich Model. Batch normalization normalizes the distribution of each feature in the feature map so as to improve accuracy by making learning in CNN less sensitive to poor parameters initialization.

The addition of a spatial dropout layer did not improve accuracy in GBRAS Net and Ntivuguruzwa Net. GBRAS Net with dropout layer produces an accuracy of 75.49%, while without using dropout layer it increases to 87.16%. Ntivuguruzwa Net with dropout layer produces an accuracy of 80.26%, while without using dropout layer it increases to 81.13%. This could be due to two factors, steganalysis aims to detect very small changes in the image, often at the noise or residue level so Spatial Dropout, which turns off the entire feature map, can lead to the loss of important information relevant for steganalysis and CNN works by identifying spatial patterns through feature maps meaning that by turning off the entire feature map (spatial dropout), important structural information can be lost. If the CNN model is already optimized without spatial dropout, adding this layer provides no additional benefit. In this case, fine tuning other parameters such as batch size can be more effective than adding spatial dropout. For example, changing the batch size of Ntivuguruzwa Net from 64 to 32 can increase the accuracy from 81.13% to 82.58%.

Ntivuguruzwa Net with 3 fully connected layers produces an accuracy of 81.13%, while without using 3 fully connected layers it decreases to 70.66%. Therefore, the presence of 3 FC layers in Ntivuguruzwa Net are an influential factor for the increase in accuracy. The use of 3 Fully Connected Layer before softmax is a strategy to improve accuracy in binary steganalysis CNNs does not always provide increased accuracy for CNNs that were originally designed without using Fully Connected Layer before softmax, this happened to GBRAS Net. GBRAS Net without FC layer produces an accuracy of 87.16%, but the addition of Fully Connected Layer before softmax results in the decrease of accuracy (78.48%). The Fully Connected layer adds a large number of new parameters that need to be learned. If the amount of data is not large enough, adding parameters can cause overfitting of the training data. The model will tend to learn very specific patterns on the training data, but fail to generalize on the test data.

The ultimate goal of a binary steganalysis CNN is to predict whether an image is a cover or stego image. In this example, the binary steganalysis CNN used is GBRAS Net. The input image is a grayscale image with dimensions 256*256 taken from one of the images from the Bossbase 1.01 dataset as shown in Fig.6. The secret message is in the form of an image as shown in Fig.7. In addition to images, the secret message inserted can also be in the form of text. The result of inserting the secret message (Fig. 7) into the cover image produces a stego image as shown in Fig.8. There is no noticeable difference between the cover image in Figure 6 and the stego image in Fig.8. However, CNN steganalysis can detect that there is a secret message hidden in Fig.8.

Fig. 6. Cover Image

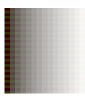

Fig. 7. Secret message

Fig. 8. Stego Image

Fig. 9. The Result of Binary Steganalysis

The detection results of GBRAS Net CNN steganalysis are in the form of binary classification, 0 or 1, where 0 states that an image is a cover image and 1 states that an image is a stego image, as shown in Fig.9. This prediction is the main purpose of steganalysis, which in future research can be used for research on message length estimation and the extraction of the secret message itself.

V. Conclusion and Future Works

Spatial Rich Model (SRM) filters can improve the performance of deep learning-based binary steganalysis on GBRAS Net and Ntivuguruzwa Net. Batch normalization normalizes the distribution of each feature in the feature map so that it can improve accuracy. Ntivuguruzwa Net without SRM and batch normalization produces an accuracy of 50%, while after using SRM and batch normalization it increases to 81.13%. The addition of a spatial dropout layer did not improve accuracy in GBRAS Net and Ntivuguruzwa Net. GBRAS Net with dropout layer produces an accuracy of 75.49%, while without using dropout layer it increases to 87.16%. The use of 3 Fully Connected Layers is a strategy that can improve the performance of Xu Net, Ye Net, Yedroudj Net and Ntivuguruzwa Net. However, 3 Fully Connected Layers do not always provide an increase in accuracy for CNNs which were originally designed without using Fully Connected Layers before softmax, this happens to GBRAS Net. GBRAS Net without Fully Connected Layer produces an accuracy of 87.16%, but the addition of 3 Fully Connected Layer before softmax results in the decreases of accuracy (78.48%).

The baseline of deep learning-based binary steganalysis model is the first step to conduct further research on steganalysis. The output of binary steganalysis is a reference for estimating message length (quantitative steganalysis), predicting steganography algorithm type, and extracting secret messages. So, further research can continue the binary steganalysis into research on secret message length estimation.

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