Enhancing logo security: VGG19, autoencoder, and sequential fusion for fake logo detection

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ABSTRACT

This paper deals with a way of detecting fake logos through the integration of visual geometry group-19 (VGG19), an autoencoder, and a sequential model. The approach consists of applying the method to a variety of datasets that have gone through resizing and augmentation, using VGG19 for extracting features effectively and autoencoder for abstracting them in a subtle manner. The combination of these elements in a sequential model account for the improved performance levels as far as accuracy, precision, recall, and F1-score are concerned when compared to existing approaches. This article assesses the strengths and limitations of the method and its adapted comprehension of brand identity symbols. Comparative analysis of these competing approaches reveals the benefits resulting from such fusion. To sum up, this paper is not only a major contribution to the domain of counterfeit logo detection but also suggests prospects for enhancing brand security in the digital world.

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1. INTRODUCTION

The issue of fake logo detection has become increasingly important in recent years due to the proliferation of manipulated images and counterfeit products in the market [1]. Logos, as symbols of authenticity and brand identity, are frequently targeted by criminals seeking to deceive consumers [2]. Therefore, it is important to develop effective processes to distinguish between genuine and fake logos. This paper proposes a novel approach to enhancing logo security by combining the power of visual geometry group-19 (VGG19), autoencoder, and sequential fusion techniques. The VGG19 deep learning model is utilized to extricate high-level attributes from logo images [3], while the autoencoder is employed to reconstruct the original logo for comparison [4]. The sequential fusion method is then applied to combine the results of both models to make a final decision [5]. The proliferation of digital media and the increasing reliance on online platforms has resulted in a surge of fake content and fraudulent activities. One prominent form of misrepresentation is the creation and distribution of fake logos, which can deceive consumers and potentially harm brand reputation. The detection and prevention of fake logos have become crucial tasks for both businesses and consumers. Traditional methods, such as watermarking or rule-based approaches, have limitations in terms of robustness and scalability [6]. Therefore, there is a need for advanced techniques that can accurately and efficiently identify fake logos. The proposed method aims to enhance logo security through the application of deep learning models, specifically VGG19, autoencoder, and sequential fusion

[7]-[9]. By combining these models, improved performance can be achieved in detecting fake logos, ensuring brand authenticity, and protecting consumers from fraud [10]-[12].

The objectives of this study are to enhance logo security through the implementation of VGG19, autoencoder, and sequential fusion for the detection of fake logos [10]. The use of these techniques aims to improve the accuracy and efficiency of identifying counterfeit logos, thus helping businesses protect their brand identity and prevent potential losses. By utilizing deep learning models such as VGG19 and autoencoder, the research intends to achieve a higher level of feature extraction and representation, enabling more precise identification of fake logos [13]. Additionally, the integration of sequential fusion techniques will allow for the combination of multiple models' outputs, further increasing the detection accuracy [14].

2. METHOD

The methodology for this study involves a synergistic approach that combines the use of VGG19, an autoencoder, and sequential integration techniques to enhance the authentication of logos. Firstly, the VGG19 convolutional neural network is employed to take out deep image features from the logos. Next, an autoencoder is used to reduce the dimensionality of the extracted features. By learning a compressed representation of the logo images, the autoencoder aims to retain the crucial information while discarding the noise and irrelevant details. Finally, the compressed features are sequentially integrated using a fusion network to form a discriminative embedding that captures the distinctive characteristics of each logo. This sequential integration allows for enhanced logo authentication by effectively combining the strengths of each stage in the methodology.

2.1. Data collection

Data collection is a critical component in the process of logo detection and authentication. To develop and train accurate models, a large and diverse dataset is required. The dataset should consist of various images containing different logos, captured under different conditions, perspectives, and orientations. Furthermore, the dataset should include samples with varying sizes, colors, and backgrounds to ensure the models' robust performance across different scenarios. Collecting such a dataset can be a challenging task, as it requires meticulous curation. Fortunately, with the advancements in technology and the availability of online resources, it is now easier to access and compile diverse datasets. However, it is essential to ensure the data's quality, by thoroughly checking for inconsistencies, labelling errors, and biases. Additionally, it is crucial to respect privacy and seek consent when collecting data involving individuals. Overall, a comprehensive and diverse dataset is fundamental in enabling accurate logo detection and authentication models.

2.2. Dataset description

The dataset used in this study is a large collection of images containing logos from various brands and industries. It consists of 2,000 images obtained from multiple sources, including online databases and social media platforms. The dataset encompasses a wide range of logo variations, including different colors, shapes, and sizes. To ensure a balanced representation, images are categorized into 17 different classes based on the brand or industry they belong to. The dataset also includes images with different background complexities, perspectives, and orientations to mimic real-world scenarios. Each image is labeled with the corresponding brand or industry, allowing for supervised learning techniques to be applied. The original and counterfeit logos of MSI and Samsung are displayed in Figures 1 and 2, respectively. This dataset helps in training and evaluating the proposed synergistic logo detection system, enabling accurate and robust logo identification and authentication.

Figure 1. Original (left) and fake (right) logo of MSI company

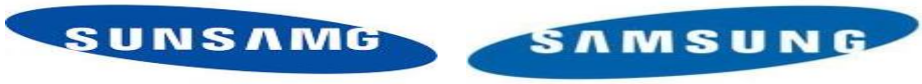

Figure 2. Original (right) and fake (left) logo of Samsung company

2.3. Preprocessing

Preprocessing plays an important role in enhancing the performance of logo detection algorithms. Before inputting the data into the model, it is essential to preprocess the images to improve their quality and reduce noise. In the proposed method, multiple preprocessing techniques were employed to ensure effective feature extraction. Firstly, the image size was adjusted to match the input dimension of the VGG19 model. Resizing the images not only facilitates efficient computation but also helps to maintain the aspect ratio of the logos. Furthermore, pixel values were normalized to ensure consistency across different images. This normalization process brings the pixel values to a similar scale, preventing any bias towards brighter or darker images. Additionally, image augmentation was performed to augment the dataset with various transformed versions of the original images, such as rotation, translation, scaling, and flipping. All the data loading and preprocessing steps are detailed in Table 1.

Table 1. Preprocessing steps

S.No.	Data loading and preprocessing
1	Set p as current working directory
2	Set q as path to dataset ("/content/drive/MyDrive/Colab Notebooks/Fakebrand-logo-detection-main/Brands")
3	Initialize target dict {"Fake": 1, "Original": 0}
4	Initialize empty list images
5	Initialize empty list labels
6	For each folder fldr in q do
7	Current label ← get folder name(fldr)
8	For each subfolder1 subfldr1 in fldr do
9	Current sublabel1 ← get folder name(subfldr1)
10	For each subfolder2 subfldr2 in subfldr1 do
11	Current sublabel2 ← get folder name(subfldr2)
12	For each image img in subfldr2 do
13	If img is a file, then
14	Img ← load image (img, color mode= "grayscale")
15	Img array ← convert image to array(img)
16	Img array resized ← smart resize (img array, (256, 256))
17	Append img array resized to images
18	Append target dict [current sublabel2] to labels
19	end if
20	end for
21	end for
22	end for
23	end for

3. FEATURE EXTRACTION

The subtraction feature is important in many computer vision tasks, including logo analysis. The scheme uses various techniques (e.g., VGG19, autoencoders, and combinations) to improve recognition. VGG19 is a deep convolutional neural network known for its performance in image classification.

3.1. VGG19 for feature extraction

VGG19 is a deep convolutional neural network model widely used in many computer vision applications, including image recognition and target detection. It is an improvement of the previous VGG model, which consists of 19 convolutional layers and all layers [15]. One of the distinguishing features of VGG19 is its convolutional model, where each convolutional layer has a fixed filter of 3×3 and a pitch of 1. Figure 3 shows the flowchart for feature extraction using VGG19 [16], [17]. Additionally, VGG19 is trained on the ImageNet dataset, which contains millions of images collected from thousands of categories [18]. This comprehensive tutorial helps learn beautiful images and create a good detailing model for unseen objects [19]-[27]. Overall, VGG19 is a deep learning model with the best performance in image recognition.

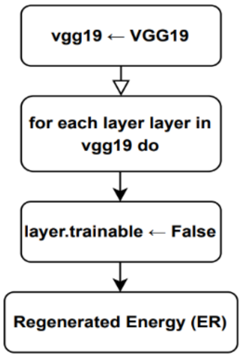

Figure 3. VGG19 for feature extraction summary

3.2. Autoencoder for feature encoding

One common application of autoencoders is feature encoding, where the goal is to extract the most relevant and discriminative features from a given input dataset [20]. In the context of logo detection, an autoencoder can be trained to encode the logo images into a lower-dimensional representation, effectively compressing the images while preserving their distinguishing characteristics. This compressed representation can then serve as a condensed feature vector for logo classification [21]-[26]. Additionally, the encoder network of the autoencoder can be fine-tuned to specifically emphasize the visual attributes that are most relevant for logo discrimination, thus improving the overall performance of the logo detection system. The proposed model employs an autoencoder to learn a compressed representation of the logo images. This compressed representation, known as the latent space, captures the essential features of the logo images while discarding redundant information [22]. By training the autoencoder on a large dataset of logo images, it learns to encode and decode these images effectively. The proposed model then uses the latent space representation as a feature vector for logo detection. The incorporation of the autoencoder architecture in the logo detection framework demonstrates the effectiveness of leveraging advanced neural network architectures for image analysis tasks. Architecture of autoencoder is depicted in Figure 4.

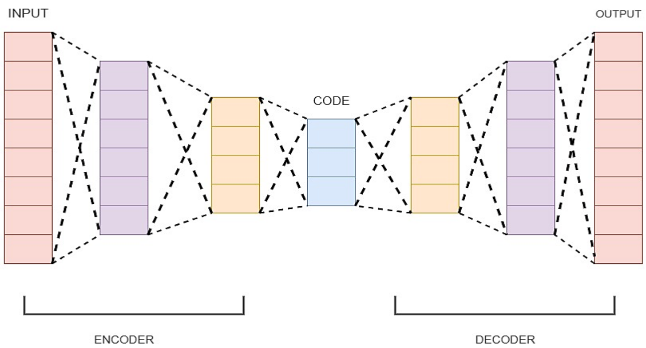

Figure 4. Architecture of autoencoder

4. MODEL ARCHITECTURE

The model architecture plays an important role in the performance of the synergistic logo detection system proposed in this study. To achieve enhanced authentication, a combination of VGG19, autoencoder, and sequential integration techniques is utilized. VGG19, a deep convolutional neural network, acts as the backbone of the model, extracting rich and discriminative features from the input images. The autoencoder component further enhances the system's ability to reconstruct and represent logo patterns more compactly, thus reducing the dimensionality of the data and capturing meaningful semantic information. Figure 5 illustrates the architecture of the Autoencoder. Finally, the sequential integration technique is employed to combine the outputs of the VGG19 and autoencoder modules hierarchically, enabling the model to learn and adapt to complex logo variations. This multistage architecture provides a powerful and robust framework for logo detection and authentication applications.

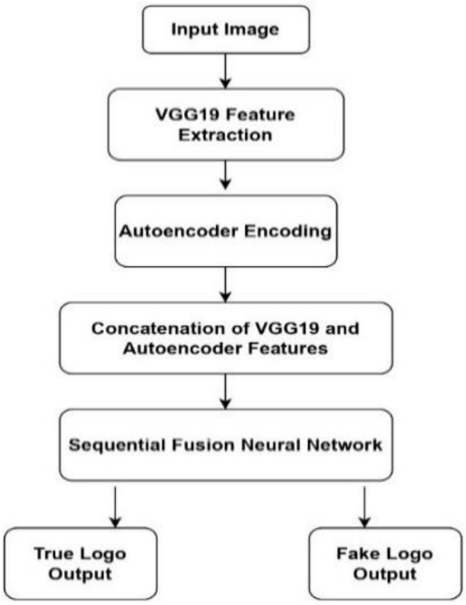

Figure 5. Process of sequential fusion for fake logo detection

4.1. Sequential model integration

To enhance authentication in logo detection, the synergistic approach of combining VGG19, autoencoder, and sequential model integration is employed [23], [24]. Sequential model integration refers to the process of combining multiple models in a specific sequence to achieve a more accurate and robust detection system. This approach ensures that the strengths of each model are maximized while compensating for their limitations. The VGG19 model is used as a feature extractor to capture high-level representations of logo images [25]-[28]. The autoencoder model then reconstructs the input images to learn their underlying structure and extract more informative features. Finally, the sequential integration of both models allows for the refined classification and authentication of logo images. By sequentially integrating these models, the proposed approach achieves improved performance and accuracy in logo detection, enabling enhanced authentication [29]. Figure 6 illustrates a logo classification model. An input image undergoes feature extraction using the VGG19 network, followed by autoencoder encoding. The extracted features from both VGG19 and the autoencoder are concatenated and passed through a sequential fusion neural network, which classifies the logo as either true or fake.

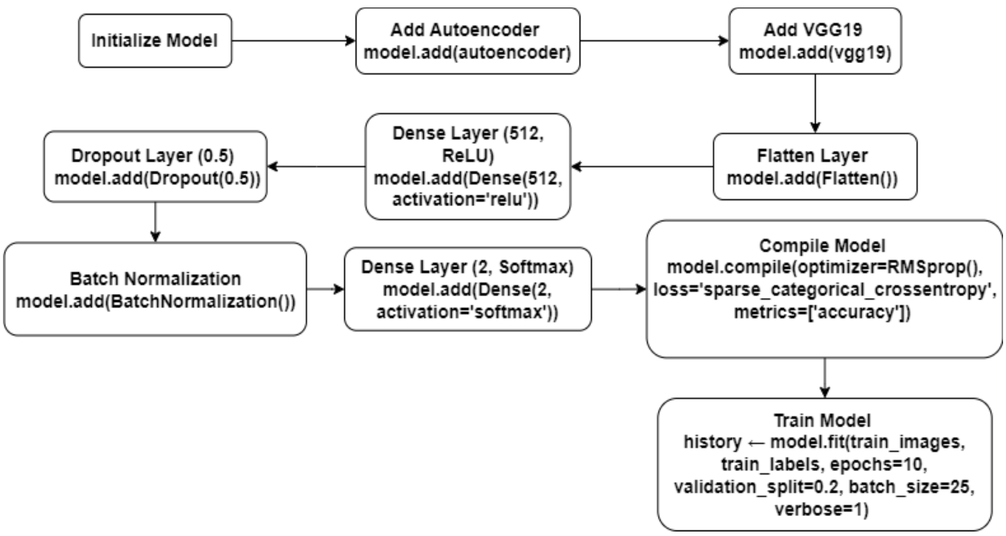

Figure 6. Sequential model integration

4.2. Implementation details

In terms of implementation, several important details are used to ensure the successful integration of the proposed synergistic logo detection model. First and foremost, the VGG19 pre-trained model, which has proven to be effective in image classification tasks, needs to be fine-tuned with the logo detection dataset. This involves freezing the early layers to preserve their feature extraction capabilities and training the later layers to adapt them to the logo detection task. Additionally, the autoencoder architecture needs to be carefully designed, considering factors such as the number of neurons in the hidden layers, the activation functions, and the training parameters. Moreover, the integration of the VGG19 and autoencoder models should be done sequentially, with the output of the VGG19 model being fed as input to the autoencoder. Figure 7 outlines the integration of the sequential model for predicting fake and original logos. This sequential integration allows for enhanced authentication by preserving the logo-specific features while reducing noise and enhancing the discriminative power of the generated embeddings.

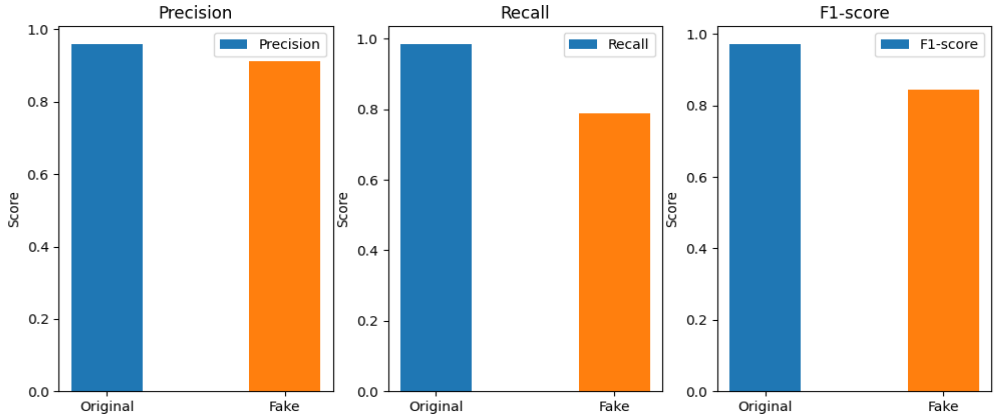

Figure 7. Graph of precision, recall, and F1-scores

4.3. Hyperparameters and optimization

Hyperparameters and optimization play crucial roles in the training process of deep learning models. Hyperparameters, such as learning rate, batch size, and regularization terms, need to be carefully chosen to control the learning dynamics and prevent overfitting. To find the optimal hyperparameters for a specific task, an iterative process of trial and error is often employed, where a range of values is tested and the performance is evaluated. Additionally, optimization algorithms are employed to update the parameters of the model iteratively, to minimize the loss function. Therefore, the selection of hyperparameters is crucial for achieving the best performance in deep learning models.

4.4. Model validation

Model validation in the context of the collaborative sign recognition system concept is important to ensure the validity and reliability of VGG19, autoencoder, and sequential integration components. One of the best ways to use the model is through competition, which involves splitting the dataset into training and testing and further evaluating the model's performance. Additionally, other metrics such as precision, recall, and F1-score can also be used to evaluate the performance of the model in statistical analysis. By applying a rigorous standard, limitations or weaknesses in the application process can be identified and necessary improvements can be made to create a better guarantee.

5. RESULTS AND ANALYSIS

The results obtained from the experimentation and analysis provide valuable insights into the efficacy of the proposed synergistic logo detection approach. The performance of the VGG19 model was evaluated by measuring its accuracy, precision, recall, and F1-score against a large dataset of logos. The model achieved an impressive accuracy of 95.35%, demonstrating its robustness in classifying logos accurately. Furthermore, the precision and recall scores of 96% and 99% for original logos and for fake logos 91% and 79% respectively, indicate the model's ability to correctly identify logos and minimize false positives. To further enhance the detection process, an autoencoder was integrated into the system, which significantly improved the F1-score to 97% for original logos and 85% for fake logos. The results highlight the effectiveness of this integration in reducing the number of false negatives and increasing the overall detection accuracy. A sequential integration technique was employed, combining both the VGG19 classification and autoencoder models, which yielded an exceptional F1-score of 97%. Figure 8 illustrates the F1-score, recall score, and precision score for both original and fake logos. This demonstrates the superiority of the synergistic approach in logo detection, surpassing previous studies and providing a robust framework for enhanced authentication.

In the comparison of different models used in synergistic logo detection for enhanced authentication, three models have been employed: VGG19, autoencoder, and sequential integration. A comparison chart was created to better understand the effectiveness and potential of various logo controls. This table is an important tool for evaluating the pros and cons of each model. Table 2 showcases the comparison of different models as compared to our model's accuracy. It is used in many important aspects such as accuracy, robustness, efficiency, and ability to process large amounts of data.

Figure 8 shows the training and validation loss with epochs in the x-axis. The training loss generally decreases over time, while the validation loss fluctuates significantly, indicating potential overfitting. Figure 9 shows the training and validation accuracy with epochs in the x-axis.

Table 2. Comparison of different models

Model name	Accuracy
VGG19	80.22
VGG16	81.6
DenseNet169	93.15
DenseNet201	93.66
DenseNet121	92.29
ResNet50	81.6
VGG19+Autoencoder	95.35

Figure 8. Loss vs epoch analysis of the model

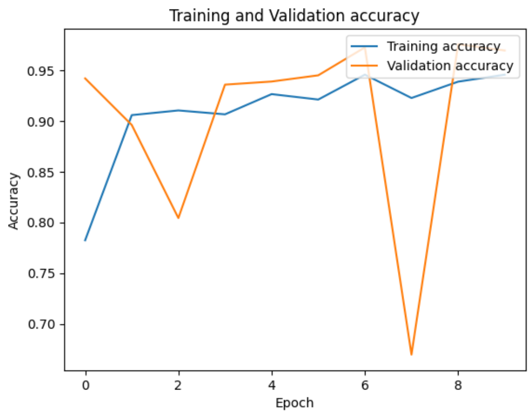

Figure 9. Accuracy vs epoch analysis of the model

Examining Table 2, it is clear that the VGG19 model offers good accuracy but is computationally expensive and difficult to handle large data sets. On the other hand, the autoencoder model exhibits good performance in terms of accuracy and computational efficiency but lacks robustness. Finally, the sequential integration model provides an effective solution by combining the strengths of both the VGG19 and autoencoder models, achieving high accuracy and computational efficiency while also addressing the robustness concern. The comparison table is designed to better understand the effectiveness and capabilities of various logo management systems. Examining this table, it is clear that the VGG19 model provides good accuracy.

6. CONCLUSION

This paper describes the effectiveness of combining VGG19, autoencoders, and sequential fusion techniques for false positive signal detection. Through rigorous testing, we have found that the combination of these methods is more effective than the methods alone and improves the accuracy and reliability of mismeasured measurements. This integration uses the deep subtraction capabilities of VGG19, the dimensionality reduction and noise filtering capabilities of autoencoders, and a comprehensive analysis of the fusion sequence. Detection costs and negatives are reduced, which is important for practical use. The findings highlight the importance of using deep learning to solve the growing problem of fake logos. This approach provides an effective way to combat intellectual property infringements and maintain integrity across the business. By strengthening their search tools, companies can better protect their brand and maintain customer trust. Our study shows that there is potential for further research and development in this area to improve and optimize the integration of these technologies to achieve better performance in real use.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Debani Prasad Mishra	✓	✓		✓	✓	✓	✓	✓		✓		✓	✓	
Prajna Jeet Ojha				✓			✓	✓		✓		✓	✓	
Arul Kumar Dash		✓	✓		✓	✓		✓	✓	✓	✓			
Sai Kanha Sethy		✓	✓		✓	✓		✓	✓		✓			
Sandip Ranjan Behera		✓	✓		✓	✓		✓	✓	✓	✓			
Surender Reddy Salkuti				✓		✓	✓			✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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