Webology (ISSN: 1735-188X)
Volume 18, Number 6, 2021

Robust Image Forgery Detection Methodology Based On Glow-Worm Optimization And Support Vector Machine

Bokefode Shudhodhan Balbhim[1] , Harsh Mathur[2]

[1,2]Department of Computer Science & Engineering Madhyanchal Professional University, Bhopal, India.

Abstract

The authentication of digital images is a significant challenge over the internet. First, the image editing software changes the original images into multiple images. Then, it is published over the internet—the printed images damage the identity and reputation of a person and things. Image forgery detection plays a vital role in detecting the original image and forged image over the internet. The incremental approach of various authors proposed algorithms and models for detecting forgery. This paper proposed a feature optimization-based image forgery detection method. The proposed method optimized the features using a glowworm optimization algorithm and support vector machine. The glowworm optimization algorithm optimized the lower content of features such as the texture of images and improved detection ratio. The proposed algorithm has been simulated in MATLAB tools and tested with reputed copy-move database comofod_samll. The evaluation results of the proposed algorithm suggest that the proposed algorithm is efficient instead of SVM and CNN algorithms.

Keywords: - image Forgery, Detection, Machine Learning, DWT, GSO

Introduction

In the current decade, a flood of digital technology enforced the authentication and validity of content is the question mark. The digital image content is straightforward to tampered with online and offline editing software such as Photoshop and some geometrical application-based software. Copy move is the primary method of image tampering and forgery[1,2,3]. The processing of copy-move is an effortless way to change the content of the digital image. In recent years image forgery has defamed the reputation of various public identity persons and organizations. The process of image forgery also promotes fake currency in the market. Therefore, accurate image forgery detection is a significant issue in current research trends. The contribution of machine learning and the feature-based detection process enhances image forgery detection accuracy. The copy-move forgery detection (CMFD) has been quickly implemented in various real-time applications, indicating that the method could be helpful in security-related authentication. Many detection techniques have been presented to ensure authentication [4, 5, 6,7]. Currently, the technique delivers a satisfactory improvement in the authentication process and is rapidly growing in popularity. Tampering is defined as a method of importing objects onto a corresponding image to morph the image's features that are prone to destroying the actual content on the perspective image [8]. Finding the occurrence of picture tampering is a strenuous endeavour, to the point where the process may totally modify the image's features and thus gain access to the original image to generate a converted copy of the same [9, 10]. By reducing the computing complexity utilizing dimensionality reduction, the method may rapidly increase the operation of the stated issue [12,12,13]. The feature-based image forgery detection is the new direction of accuracy and simplicity of forgery detection of digital images. The feature-based forgery detection (FBFD) checks the lower content of digital images such as colour, texture, shape, and size. The shape and size of digital images remain the same in the case of image forgery—the alteration of lower feature content such as colour and texture. Most of the authors applied the texture feature-based image forgery detection methods. The texture feature is a prominent dominant feature of digital images. The extraction of texture features uses transform-based functions such as discrete wavelet transform, SIFT and variants of the wavelet transform. The machine learning-based algorithms enhance the performance of image forgery detection. Recently most authors applied the machine learning algorithms such as decision tree, ML, ELM, and many more derived machine learning algorithms[14,15]. The primary issue forms the machine learning algorithms is a selection of features data and training errors. To minimize selection problems and training, error applied the swarm intelligence-based feature optimization algorithms such as particle swarm optimization, ant colony optimization and many more algorithms. This paper focuses on the lower content feature optimization-based algorithm for image forgery detection. The lower content of digital image features faces a problem of feature selection and optimization. This paper proposed feature optimization-based image forgery detection. The proposed forgery detection algorithms apply glow-worm swarm optimization (GSO) with a support vector machine. The GSO algorithm optimized the lower content of digital images and inputted the support vector machine to detect forged areas of digital images. The rest of paper explain as in section II. Related work, in section II describes the proposed methodology for the image forgery detection, in section IV describes experimental analysis and conclude in section V.

II Related Work

Image forgery detection methods increase the trustworthy of digital image for the process of authentication and authorization. The incremental approach of transform methods and machine learning based algorithms increases the detection ratio. Some contribution of authors describes here. In this [1] author propose a comprehensive report on the numerous steganalysis methods for digital images discussed Choosing which method is more efficient in any domain it is a difficult task. The author assumes that in the vast majority of cases, where only the STEGO object is known, statistical steganalysis techniques are more robust and effective than signature steganalysis. In this [2] author propose the development of an MLF area proposal system and the summation fusion strategy for integrating the two convolution Smart video surveillance is a hot area of computer science vision and artificial intelligence techniques right now. Deep semantic networks were used in one of the systems because of their superior efficiency and quick completion at exam time. In this [3] author perform an end-to-end FCDNN design is discussed for the iris segmentation task on lower-quality iris images. When compared to state-of-the-art techniques applied to the same lower quality datasets, the optimization Deep Neural

Networks design performs extremely well. In this [4] author propose a new method for exposing fake face videos generated by neural networks. Their method relies on detecting eye blinking in videos, which is a physiological signal that is poorly represented in the fabricated fake videos. Their method has been tested on eye-blinking detection dataset benchmarks and shows promising performance in detecting Deep Fake videos. In this [5] author propose a novel CNN architecture for CMI, with a focus on the pre-processing task, which is thought to be inevitable for removing the image content that heavily obscures the camera model fingerprints. Outcomes show that 19 camera models have 99 percent accuracy, with an overall accuracy of 98.23 percent on test images from unseen devices. In this [6] author used Steganography, cryptography, and neural networks in tandem to conceal an image within another container image of greater or equal size. Although the cryptographic technique used is simple, it is effective when combined with deep neural networks. Other steganography techniques involve efficiently concealing data in a uniform pattern, which makes it less secure. In this [7] author propose a new high-capacity image steganography method based on deep learning to improve the anti-detection property of the obtained image the secret image is transformed using DCT. The outcomes of the experiments show that the method can effectively allocate each pixel in the image, likely to outcome in a steganography relative capacity of one. In this [8] author providing a strong framework for extracting highly discriminative speaker-specific features from speech recordings VOCALISE maintains support for both legacy and cutting-edge speaker modelling algorithms. Users present the x-vector framework and its implementation in VOCALISE, as well as demonstrate its powerful performance capabilities on forensically relevant data. In this [9] author investigate how strong color casts caused by inaccurately applied computational color constancy known in photography as WB degrade the performance of DNNs aimed at image segmentation and classification. Author also discuss how existing image augmentation methods for improving DNN robustness are unsuitable for modelling WB errors. In this [10] author examines a novel technique for identifying GAN generated fake images that combines co-occurrence matrices and deep learning. Experiments on two diverse and difficult GAN datasets with over 56,000 images based on unpaired image-to-image translations cycle GAN and facial attributes/expressions Star GAN show that their approach is promising, achieving more than 99 percent classification accuracy in both datasets. In this [11] author propose a blind method for detecting local mosaic inconsistencies that can train directly on unlabelled and potentially forged images. they created a CNN structure based on demos icing algorithms and aimed at classifying image blocks based on their position in the image modulo. They investigate the efficiency of the method and its ability to adapt quickly to any new data by creating a diverse benchmark database using various demos icing methods. In this [12] author Global fuzzy segmentation, a projection-based feature transform, and a deep convolutional neural networks (DCNNs) model were all used. According to the study's findings, the method can classify images with high accuracy, allowing for automated age estimation. In this [13] author propose a fast image processing method for detecting plant diseases in this study. The innovative outcomes showed that the Rider-CSA-DBN outperformed other existing methods, with a maximum accuracy of 0.987, sensitivity of 0.654, and specificity of 0.547. In this [14] author demonstrate how the frequency representation can be used to detect deep fake images automatically, outperforming state-of-the-art methods The limitation and its outcome demonstrate that GAN-generated images have severe artefacts in frequency space that are easily identified. In this [15] author propose a deep neural network that can tell the difference between PI and CG. Existing approaches to image feature classification are computationally intensive and do not support real-time analysis. Experiment outcomes show that this method can effectively identify PI and CG with an average detection accuracy of 97 percent. In this [16] author propose a new forensic technique based on deep learning that employs a convolutional neural network (CNN) to learn hierarchical representations from input images. The outcomes of experiments on several publicly available datasets show that the discussed CNN-based model outperforms some state-of-the-art methods. In this [17] author assist academic and industry researchers in identifying research gaps in order to develop more robust digital image forgery detection techniques to counter anti-forensics attacks A bibliographic analysis of cutting-edge publications in a variety of venues is also included in this work. In this [18] author proposed an algorithm based on deep learning and wavelet transform is discussed to detect the spliced image. Their outcomes show that the discussed algorithm is efficient and performs well when detecting the spliced image. In this [19] author proposed a novel method for detecting deblocking that can learn feature representations automatically using a deep learning framework They first train a supervised convolutional neural network (CNN) with labelled patches from the training datasets to learn the hierarchical features of deblocking operations. The experimental outcomes on several public datasets show that the discussed scheme is superior. In this [20] author propose a deep learning–based passive Copy Move Forgery Detection algorithm that uses a novel dual branch convolutional neural network to classify images as original or forged. Extensive outcomes analysis and comparison show that the discussed architecture increases the existing architecture in terms of performance scores, computation time, and complexity. In this [21] author proposed a new deep convolutional neural network based on statistical histogram features from each block and a vectorized quantization table for double JPEG detection. The discussed method was experimentally validated to produce cutting-edge performance in detecting various image manipulations. In this [22] author propose a detection algorithm for splicing, one of the most common types of digital image forgery The algorithm employs the VGG-16 convolutional neural network. the obtained output shows high classification accuracy 96.8 percent accuracy for the fine-tuned model and 97.4 percent accuracy for the zero-stage trained. In this [23] author created a modular CGI–PI discriminator using a customized VGG-19 network as the feature extractor, statistical convolutional neural networks as the feature transformers, and a discriminator, leveraging recent advances in deep convolutional networks. In addition, to deal with high-resolution images, they devised a probabilistic patch aggregation strategy. This method outperformed a state-of-the-art method and achieved accuracy of up to 100%. In this [24] author used multiple models to maximize the probability of different target classes in order to create such examples. author used MNIST datasets and the TensorFlow library in their experiment. The experimental outcomes showed that the discussed scheme for generating a multi-targeted adversarial example outcomes in a 100% attack success rate. In this [25] author given a number of watermark-based DNN ownership verification methods in the face of ambiguity attacks that forge counterfeit watermarks to cast doubt on ownership verification. Extensive experimental output confirms the effectiveness of the previously discussed passportbased DNN ownership verification schemes. In this [26] author proposed Deep learning methods, as defined by the DIF, primarily employ convolutional neural networks (CNN) in conjunction with significant pre-processing modules. As a output, the primary goal of this article is to examine the pre-processing modules associated with CNN models. In this [27] author proposed an order forensics framework based on convolutional neural network (CNN) is presented for detecting image operator chain. The outcomes of the experiments show that not only does the discussed framework achieve significant detection performance, but it also distinguishes the order in some cases that previous works were unable to identify. In this [29] author proposed a novel neural network and deep learning-based scheme focusing on the CNN architecture approach to improve copy-move forgery detection to achieve satisfactory outcomes, the discussed approach employs a CNN architecture with pre-processing layers. The experiments show that with a set iteration limit, the overall validation accuracy is 90%. In this [30] author compared to five machine learning algorithms that were recently used in speaker recognition, DNN produced better classification outcomes. The experimental output revealed that two-level classification outperformed one-level classification. The features and classification model for identifying a speaker discussed here can be widely applied to various types of speaker datasets.

IV Proposed Methodology

The robust image forgery detection is based on discrete wavelet transform and support vector machine. The GSO (glowworm swarm optimization) algorithm reduces the irrelevant feature coefficients of wavelet transform and increases the performance of forged images. The process of the proposed algorithm describes in three sections; in 1st section describes the feature extraction, in 2nd section describe the support vector machine and GSO algorithm, and finally in 3rd section describes the proposed algorithm of forgery detection.

1st section

Feature extraction is primary phase of image forgery detection. The multimedia image data is rich dominated texture features, hence discrete wavelet transform methods apply for the extraction of features. The discrete wavelet transform is deriving form mother wavelet transform and overcome the limitation of other coefficient-based transform methods. the applied transform decomposes the raw images in multiple forms of LF HF horizontal, vertical and diagonal. The decompose layers estimate the value of features in terms of energy entropy [14].

Let $L(x) \in L^2(I)$ is corelated function $\psi(x)$and scaling function $\phi(x)$, the formulation of transform as

$$W_{\phi}(j0,k) = \frac{1}{\sqrt{M}} \sum_{x} L(x)\phi_{j0,k}(x) \dots\dots\dots\dots\dots\dots\dots\dots.(1)$$

$$W_{\psi}(J,K) = \frac{2}{\sqrt{M}} \sum_{X} L(x)\psi_{j,k}(x) \dots\dots\dots\dots\dots\dots\dots\dots\dots(2)$$

The coefficient of feature of images as

$$F(L) = \frac{1}{M}\sum_{K} W_{\phi}\,(j0,k)\phi_{j0,k}(x) + \frac{1}{\sqrt{M}}\sum_{J=J0}^{J-1}\sum_{K} W_{\psi(J,K)}\,\psi_{J,K}(X) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

The above derivates of function estimates the feature of raw image in terms of source image and symbol image. The estimated features

F(L)={f1,f,2,f3,……………………..,fn}…………………………………………(4)

2nd Section

Glow-worm swarm optimization (GSO)

Process of GSO algorithm

1. Luciferin update: - the value of luciferin update depends on fitness value and pervious value of luciferin [15,16]

$$l_i(t+1) = (1-\rho)l_i(t) + \gamma \text{fitness}(xi(t+1)$$

$$\text{here li(t) denotes the luciferin value of glowworm i at time t}$$

2. Neighborhood selection
   The selection of neighborhood Ni(t) as

$$N_i(t) = \{\, J: d_{ij}(t) < r_d^i(t); l_i(t) < l_j(t)\}$$

$$\text{here dij(t)euclidean distance between glowworm i and j at time t}$$

3. Compute probability
   Glowworm applied function of probability to measure the movements of glowworm

$$P_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k\in Ni(t)} l_k(t) - l_i(t)}$$

4. Movement process

$$x_i(t+1) = x_i(t) + s(\frac{x_j(t) - x_i(t)}{|\quad x_j(t) - x_i(t)|})$$

5. Decision rule update

$$r_d^i(t+1) = \min\{r_{s,max}\{0, r_d^i(t) + \beta(n_t - |N_i(t)| \quad)\}\}$$

Here β is constant, $r_{s,}$ shows radius of glowworm

Support Vector Machine (SVM)

SVM (Support vector machine) is machine learning algorithm derived by Vipin in 1990[17,18]. The support vector machine applied in various filed of image classification and pattern recognition. The nature of support vector machine is linear, non-linear and sigmoid. The non-linear support vector machine mapping the feature data with respect to one plane to another plan. The separation of data plan is non-linear and decision factor correlate with margin function of support vector[18,19]. The hyperplane of equation is derived as

$$\mathrm{WD.xi} + \mathrm{b} \geq 1 \text{ if } \mathrm{yi} = 1 \qquad (1)$$

$$\mathrm{WD.xi} + \mathrm{b} \leq -1 \text{ if } \mathrm{yi} = -1$$

Here W is weight vector, x is input vector yi label o class and b is bias.

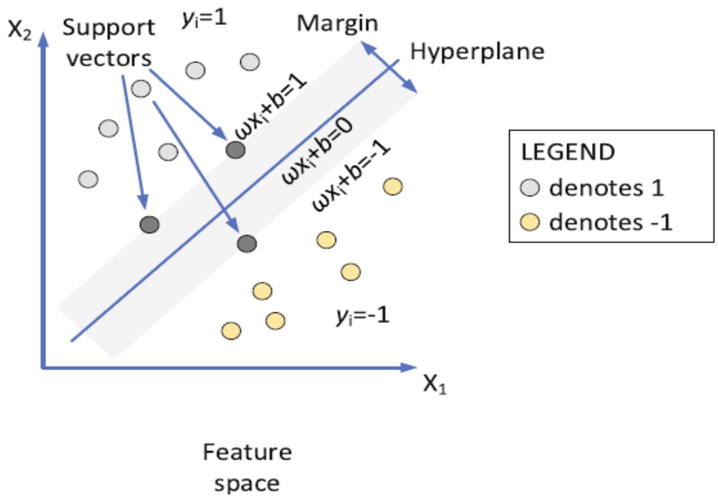

Figure 1 process block diagram of support vector machine.

The minimization formulation of support vector

$$\text{Minimize } \frac{1}{2}||\mathrm{w}||2 + \mathrm{C}\sum_{\mathrm{i}=1}^{\mathrm{n}} \varepsilon\mathrm{i}\,,\mathrm{i} = 1,2, \dots \dots, \mathrm{n}$$

$$\text{subject to } \mathrm{y_i}(\mathrm{w^T D.x1} + \mathrm{b}) \geq 1 - \varepsilon 1$$

$$\varepsilon_{\mathrm{i}} \geq 0 \ \mathrm{i} = 1,2, \dots \dots, \mathrm{n} \dots \dots \dots \dots \dots \dots \dots \dots . (2)$$

Here C is constant, n is number of observation and ε1 is slack variable.

The rule of decision function is

$$\mathrm{f(x)} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{yi}\alpha\mathrm{iK(xi,xj)} + \mathrm{b} \dots \dots \dots \dots \dots \dots . (3)$$

Proposed algorithm

The proposed algorithm focusses on feature optimization of forged image data for accurate detection of forged area in image. The processing of algorithm encapsulates feature extraction method, GSO and support vector machine. The support vector machine performs the process of training of extracted features for the detection of forged area in image data. The processing of algorithm describes here.

1. Input: a DWT features(f1,f2,....,fn), SVM, GSO
2. Output: Detection of forged image
3. Compute $D_{(P_t,k)}$ and $k - \text{disimarilty}(p_t)$
4. for all $DP \in SVM_{(f_t,k)}$ do
5. estimate local features$-Lp(f_t, DP)$
6. end for
7. $W_{update} \leftarrow GSO$ {the set of glows}
8. for all $DP \in W_{update}$ and $FP \in M_{(DG,K)}$ do
9. Update $k - \text{disimarilty}(DP)$ and $\text{cluester} - \text{ds}(GSO, DP)$
10. if $DP_{(FP,k)}$ then
11. $W_{update} \leftarrow W_{update} \cup \{DP\}$
12. end if
13. end for
14. for all $DP \in W_{update}$ do
15. Update $FD(DP)$ and $FD(\{GSO_{o,k}\})$
16. end for
17. return FD(forged detection)
18. measure person coefficient for both pattern p1………….pn, s1……………..sn
19. if value of difference is near about zero.
20. The process of forgery detection
21. Measure value of parameters

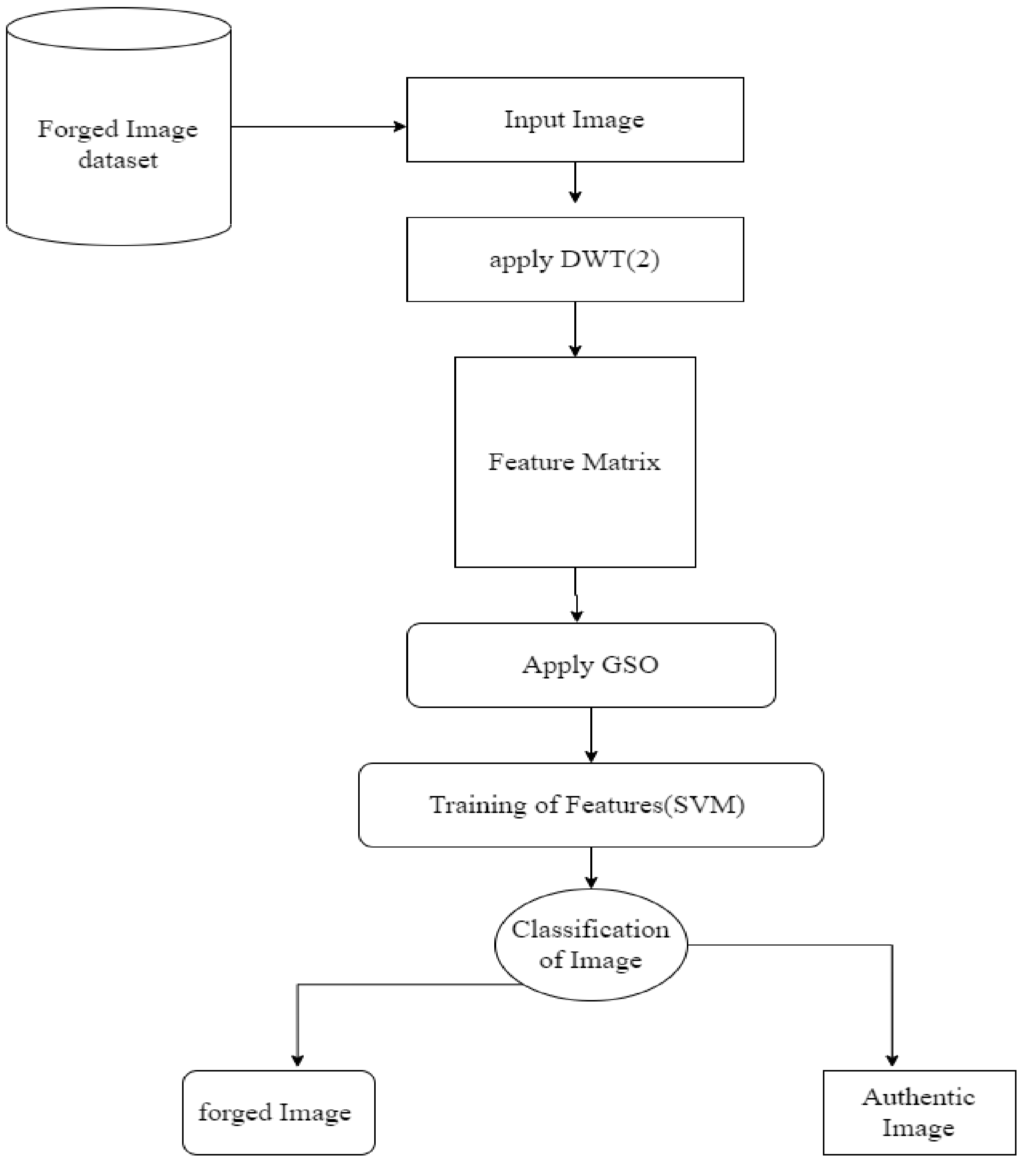

Figure 2 Proposed Model of image forgery Detection using SVM and GSO

V Experimental Analysis

To validate the proposed SVM based forgery detection performance has been evaluated and compared with existing SVM [10] and CNN [16]. The processing of forged database images are trained and then tested. In training process, 250 authentic images and 250 forged images are used for proposed model and the images are selected as randomly. In testing, the whole 500 images are divided into 5 sets of images and each set consists of 100 images. Each and every set is trained and tested with SVM. The performance is evaluated in terms of False negative and false positive. The all-simulation process done in MATLAB environments with windows operating system and I7 processors.

Table:1 Shows that the performance evaluation using CNN, SVM and proposed methods.

Types of Images	Method Name	FN	FP
Image-1	CNN	38.56	53.47

	SVM	26.58	49.32
	PROPOSED	23.46	35.24
Image-2	CNN	21.54	33.56
	SVM	15.64	31.89
	PROPOSED	13.96	27.32
Image-3	CNN	25.65	41.25
	SVM	21.87	36.78
	PROPOSED	18.32	25.64

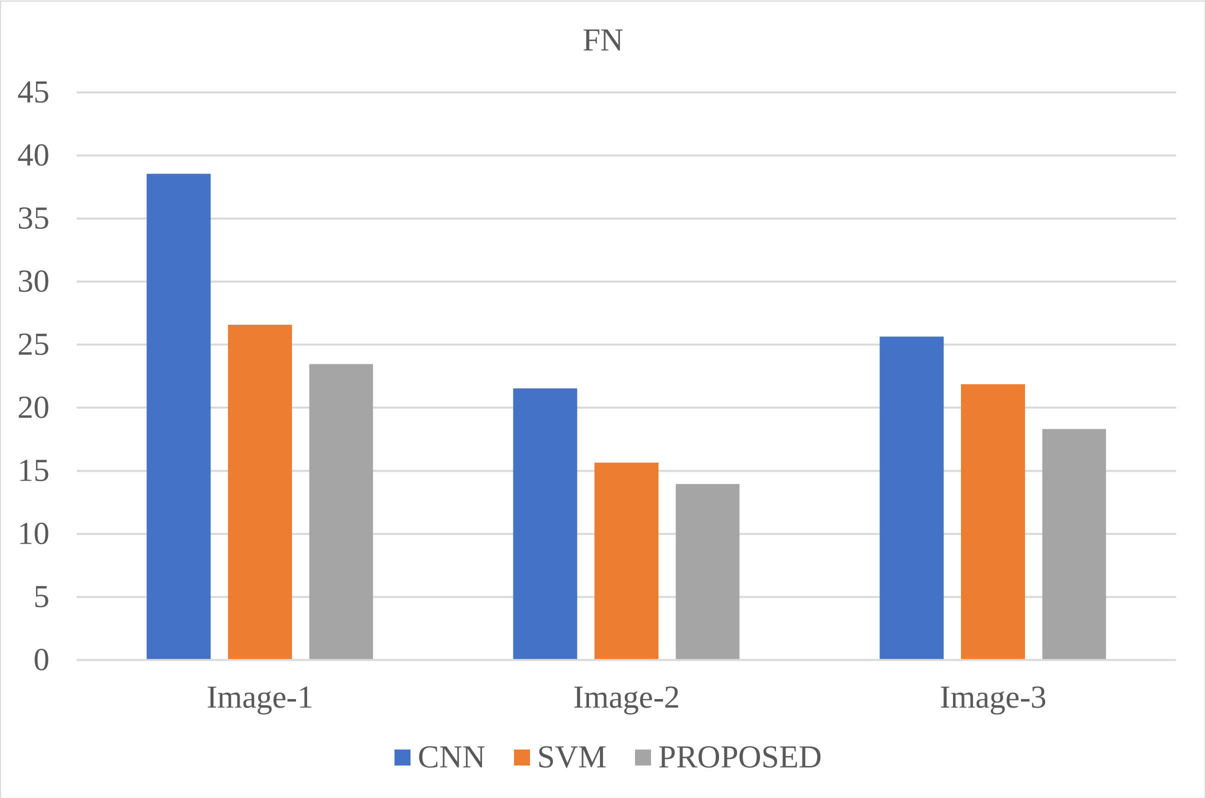

Figure: 3 Shows that the comparative performance evaluation graphs for FN with using CNN, SVM and Proposed methods with using image-1, image-2, image-3.

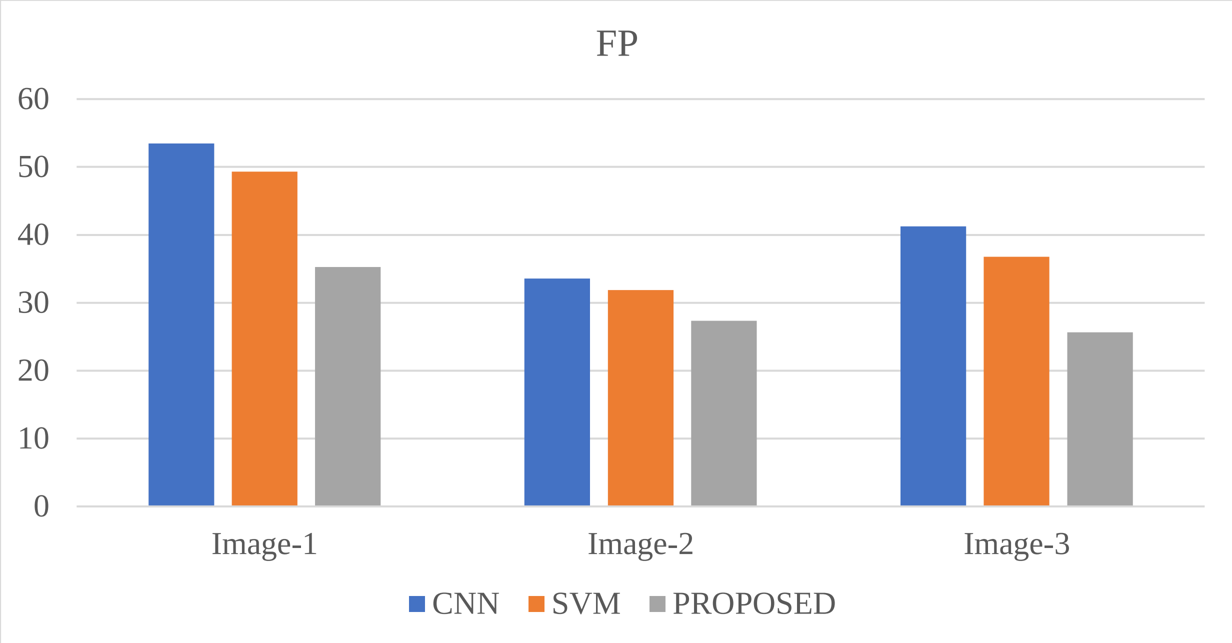

Figure 4: Shows that the comparative performance evaluation graphs for FP with using CNN, SVM and Proposed methods with using image-1, image-2, image-3.

V Conclusion & Future Work

The proposed algorithm is very efficient for the detection of image forgery detection. The process of feature optimization enhances the detection ratio and decrease the false positive ratio. CNN method of detecting copy–paste forgeries usually suffer from the problems of false positives and susceptibility to many image processing operations. In this work, we describe a new forgery detection method, which is based on support vector machine and GSO. With 500 experiments, we demonstrate the efficacy of the proposed approach. Experiment results show that if the forged image is rotated, scaled, or highly compressed, the proposed approach can achieve better detection results. We compared the robustness of our method to that of a previously proposed scheme that uses Zernike moments as features, and we demonstrated that our method is more robust to different types of processing. The proposed copy–move forgery detection approach has a higher computational complexity, which means it cannot be used effectively in real-time applications. In the future, we plan to use super pixel theory to eliminate these drawbacks.

References

[1]. Murthy, A. Sampath Dakshina, T. Karthikeyan, B. Omkar Lakshmi Jagan, and Ch Usha Kumari. "Novel deep neural network for individual re recognizing physically disabled individuals." Materials Today: Proceedings 33 (2020): 4323-4328.

[2]. Bazrafkan, Shabab, Shejin Thavalengal, and Peter Corcoran. "An end-to-end deep neural network for iris segmentation in unconstrained scenarios." Neural Networks 106 (2018): 79-95.

[3]. Li, Y., M. C. Chang, H. Farid, and S. Lyu. "In ictu oculi: Exposing AI generated fake face videos by detecting eye blinking. 2018." arXiv preprint arXiv:1806.02877 (1806).

[4]. Rafi, Abdul Muntakim, Thamidul Islam Tonmoy, Uday Kamal, QM Jonathan Wu, and Md Kamrul Hasan. "RemNet: remnant convolutional neural network for camera model identification." Neural Computing and Applications 33, no. 8 (2021): 3655-3670.
[5]. Sharma, Kartik, Ashutosh Aggarwal, Tanay Singhania, Deepak Gupta, and Ashish Khanna. "Hiding Data in Images Using Cryptography and Deep Neural Network." arXiv preprint arXiv:1912.10413 (2019).
[6]. Duan, Xintao, Daidou Guo, Nao Liu, Baoxia Li, Mengxiao Gou, and Chuan Qin. "A new high-capacity image steganography method combined with image elliptic curve cryptography and deep neural network." IEEE Access 8 (2020): 25777-25788.
[7]. Kelly, Finnian, Oscar Forth, Samuel Kent, Linda Gerlach, and Anil Alexander. "Deep neural network based forensic automatic speaker recognition in VOCALISE using x-vectors." In Audio Engineering Society Conference: 2019 AES International Conference on Audio Forensics. Audio Engineering Society, 2019.
[8]. Afifi, Mahmoud, and Michael S. Brown. "What else can fool deep learning? Addressing color constancy errors on deep neural network performance." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 243-252. 2019.
[9]. Nataraj, Lakshmanan, Tajuddin Manhar Mohammed, B. S. Manjunath, Shivkumar Chandrasekaran, Arjuna Flenner, Jawadul H. Bappy, and Amit K. Roy-Chowdhury. "Detecting GAN generated fake images using co-occurrence matrices." Electronic Imaging 2019, no. 5 (2019): 532-1.
[10]. Bammey, Quentin, Rafael Grompone von Gioi, and Jean-Michel Morel. "An adaptive neural network for unsupervised mosaic consistency analysis in image forensics." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 14194-14204. 2020.
[11]. Kahaki, Seyed MM, Md Jan Nordin, Nazatul S. Ahmad, Mahir Arzoky, and Waidah Ismail. "Deep convolutional neural network designed for age assessment based on orthopantomography data." Neural Computing and Applications 32, no. 13 (2020): 9357-9368.
[12]. Cristin, R., B. Santhosh Kumar, C. Priya, and K. Karthick. "Deep neural network-based Rider-Cuckoo Search Algorithm for plant disease detection." Artificial intelligence review 53, no. 7 (2020).
[13]. Frank, Joel, Thorsten Eisenhofer, Lea Schönherr, Asja Fischer, Dorothea Kolossa, and Thorsten Holz. "Leveraging frequency analysis for deep fake image recognition." In International Conference on Machine Learning, pp. 3247-3258. PMLR, 2020.
[14]. Cui, Qi, Suzanne McIntosh, and Huiyu Sun. "Identifying materials of photographic images and photorealistic computer-generated graphics based on deep CNNs." Comput. Mater. Continua 55, no. 2 (2018): 229-241.
[15]. Yang, Bin, Xingming Sun, Enguo Cao, Weifeng Hu, and Xianyi Chen. "Convolutional neural network for smooth filtering detection." IET Image Processing 12, no. 8 (2018): 1432-1438.
[16]. Qureshi, Muhammad Ali, and El-Sayed M. El-Alfy. "Bibliography of digital image anti-forensics and anti-anti-forensics techniques." IET Image Processing 13, no. 11 (2019): 1811-1823.

[17]. Abd El-Latif, Eman I., Ahmed Taha, and Hala H. Zayed. "A passive approach for detecting image splicing using deep learning and haar wavelet transform." International Journal of Computer Network and Information Security 11, no. 5 (2019): 28.

[18]. Liu, Xianjin, Wei Lu, Wanteng Liu, Shangjun Luo, Yaohua Liang, and Ming Li. "Image deblocking detection based on a convolutional neural network." IEEE Access 7 (2019): 26432-26439.

[19]. Goel, Nidhi, Samarjeet Kaur, and Ruchika Bala. "Dual branch convolutional neural network for copy move forgery detection." IET Image Processing (2021).

[20]. Park, Jinseok, Donghyeon Cho, Wonhyuk Ahn, and Heung-Kyu Lee. "Double JPEG detection in mixed JPEG quality factors using deep convolutional neural network." In Proceedings of the European conference on computer vision (ECCV), pp. 636-652. 2018.

[21]. Kuznetsov, A. "Digital image forgery detection using deep learning approach." In Journal of Physics: Conference Series, vol. 1368, no. 3, p. 032028. IOP Publishing, 2019.

[22]. Nguyen, Huy H., T. Ngoc-Dung Tieu, Hoang-Quoc Nguyen-Son, Vincent Nozick, Junichi Yamagishi, and Isao Echizen. "Modular convolutional neural network for discriminating between computer-generated images and photographic images." In Proceedings of the 13th international conference on availability, reliability and security, pp. 1-10. 2018.

[23]. Kwon, Hyun, Yongchul Kim, Ki-Woong Park, Hyunsoo Yoon, and Daeseon Choi. "Multi-targeted adversarial example in evasion attack on deep neural network." IEEE Access 6 (2018): 46084-46096.

[24]. Fan, Lixin, Kam Woh Ng, and Chee Seng Chan. "Rethinking deep neural network ownership verification: Embedding passports to defeat ambiguity attacks." (2019).

[25]. Berthet, Alexandre, and Jean-Luc Dugelay. "A review of data preprocessing modules in digital image forensics methods using deep learning." In 2020 IEEE International Conference on Visual Communications and Image Processing (VCIP), pp. 281-284. IEEE, 2020.

[26]. Wu, Yue, Wael Abd-Almageed, and Prem Natarajan. "Buster net: Detecting copy-move image forgery with source/target localization." In Proceedings of the European Conference on Computer Vision (ECCV), pp. 168-184. 2018.

[27]. Abdalla, Younis, M. Tariq Iqbal, and Mohamed Shehata. "Convolutional neural network for copy-move forgery detection." Symmetry 11, no. 10 (2019): 1280.

[28]. Jahangir, Rashid, Ying Wah Teh, Nisar Ahmed Memon, Ghulam Mujtaba, Mahdi Zareei, Uzair Ishtiaq, Muhammad Zaheer Akhtar, and Ihsan Ali. "Text-independent speaker identification through feature fusion and deep neural network." IEEE Access 8 (2020): 32187-32202.

[29]. Zhang, Jialong, Zhongshu Gu, Jiyong Jang, Hui Wu, Marc Ph Stoecklin, Heqing Huang, and Ian Molloy. "Protecting intellectual property of deep neural networks with watermarking." In Proceedings of the 2018 on Asia Conference on Computer and Communications Security, pp. 159-172. 2018.

[30]. Liao, Xin, Kaide Li, Xinshan Zhu, and KJ Ray Liu. "Robust detection of image operator chain with two-stream convolutional neural network." IEEE Journal of Selected Topics in Signal Processing 14, no. 5 (2020): 955-968.

[31]. Mahmood, Toqeer, Zahid Mehmood, Mohsin Shah, and Tanzila Saba. "A robust technique for copy-move forgery detection and localization in digital images via stationary wavelet and discrete cosine transform." Journal of Visual Communication and Image Representation 53 (2018): 202-214.

[32]. Yang, Bin, Xingming Sun, Honglei Guo, Zhihua Xia, and Xianyi Chen. "A copy-move forgery detection method based on CMFD-SIFT." Multimedia Tools and Applications 77, no. 1 (2018): 837-855.