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NP-PHOG: An Automated Gender Classification Model based on Nested Patch-based Prymadial Histogram-Oriented Gradients Feature Extraction using Shadow Images

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Abstract – Gender classification is a fundamental area of research in machine learning, and numerous types of data, such as gaits, faces, and speeches, have been utilized for gender classification. In this research, we introduce a novel data type, namely shadow images, for detecting gender.
We collected a shadow image dataset comprising two classes, namely (1) female and (2) male. To propose an automated shadow gender classification model, we developed a pyramidal histogram-oriented gradient (PHOG) based model. Our model consists of three primary phases, including (i) feature extraction using nested patches and PHOG, (ii) neighborhood component analysis (NCA) based feature selection, and (iii) classification with support vector machine (SVM) classifier. Therefore, we have named our model nested patches (NP) based PHOG – NP-PHOG–.
The proposed NP-PHOG model was applied to the collected shadow image dataset, and it achieved a classification accuracy of 99.69%. This result provides strong evidence that machine learning models can accurately detect gender using shadows, and new image forensic tools can be developed using this approach.

Keywords – Shadow Gender Classification, Shadow Images, Nested Patches, PHOG, Digital Forensics

I. INTRODUCTION

Acquiring accurate and comprehensive information is crucial in digital forensics [1, 2]. Traditional digital forensics techniques are effective for many applications, but they encounter various challenges in complex and multidimensional scenarios [3]. Machine learning techniques have been employed in recent years due to the desire to address these challenges and evaluate multiple parameters simultaneously [4]. Machine learning techniques are widely used in the field of data analysis because they offer experts fast and automated solutions [5-7]. Additionally, machine learning techniques can process multiple different parameters together [8]. For example, object recognition is used to identify evidence in a video, while gender recognition from shadows in the same video can provide significant clues to experts. Evaluating different parameters together in an automatic manner supports a faster resolution of the incident [9].

In this study, a machine learning-based method is proposed for gender recognition from shadows. As far as we know, there is no paper on shadow gender recognition in the literature. Some recent studies on gender recognition are presented below.

Kumar et al. [10] presented a multi-feature approach based on machine-learning techniques for gender detection. They used SCIEN, Live images, and FEI datasets for experiments. They attained accuracies of 91.00%, 94.00%, and 98.00% for SCIEN, Live images, and FEI datasets. Park and Woo [11] proposed a gender classification method using deep learning algorithms. They used data from HealthBoard.com and achieved an accuracy rate of 90.00% with the SVM classifier. Basit et al. [12] introduced a gender classification method using smartphone sensors. Their method was based on the Monte Carlo method. They obtained a balanced accuracy of 90.60%. Kumar et al. [13] developed a gender and age detection method with Convolution Neural Network (CNN). Their method was based on sentiment analysis. Their method calculated accuracies as 80.00% and 78.00% for gender and age classification. Santosh et al. [14] developed an age and gender identificaiton approach using dental x-ray images. They used 1142 teeth images (80 training, 20 testing) and obtained an accuracy of 95.83%. Aggarwal and Vig [15] explored an acoustic methodology for emotion and gender classification. They analyzed acoustic features and attained an accuracy rate of 70.00% with the SVM classifier. Safara et al. [16] presented a gender detection method with whale optimization techniques. They used Enron dataset for this aim. Their study obtained an accuracy value of 98.00% with an artificial neural network classifier.

A. *Motivation and Our Model*

Digital forensics is a crucial research area for gathering evidence in the cyber world [17, 18]. To automatically acquire informative evidence, digital forensics researchers must employ machine learning and deep learning models. In digital forensics, shadow images play a vital role as evidence, and information must be extracted from these images [19, 20]. Therefore, we present a novel image classification model for classifying genders using shadow silhouette images.

To classify genders, we propose a simple feature engineering model inspired by patch-based computer vision models such as vision transformers [21] and MLP-mixer [22]. We introduce a nested patch-based model, generating nested patches and applying a pyramidal histogram-oriented gradients (PHOG) feature extractor to each patch. In this research, we create 16 patches, generating 16 feature vectors. We concatenate these vectors to create a final feature vector. In the feature selection phase, neighborhood component analysis (NCA) [23] selects the most informative features, which are then fed to an SVM [24] classifier to obtain classification results.

Our proposed model shows promising results in classifying genders using shadow silhouette images, demonstrating the potential of using machine learning and deep learning in digital forensics to extract informative evidence automatically.

B. *Contributions*

This paper proposes a new gender classification model based on shadow images. To the best of our knowledge, there is no publicly available shadow image dataset for gender classification in the literature. Therefore, we collected a new shadow image dataset and presented a new computer vision model, NP-PHOG, to detect genders. The novelties and contributions of the presented NP-PHOG model are listed below.

Novelties:

- A new shadow image dataset has been gathered.
- We propose an innovative feature engineering model, NP-PHOG.

Contributions:

- We are the first team to propose a shadow image-based gender classification model using a patch-based feature engineering model in the literature.
- Our presented NP-PHOG model is highly accurate, achieving over 99% classification accuracies for the gathered dataset.
- Our proposed model demonstrates the potential of using shadow images for gender classification and opens up a new research direction in digital forensics. Moreover, the proposed NP-PHOG model can be applied to other research areas beyond gender classification, providing a framework for further exploration of shadow images.

II. MATERIALS AND METHOD

A. *Material*

We gathered a total of 641 shadow images from the internet, which are categorized into two classes: female and male. The dataset consists of 272 female and 369 male shadow images. The images were saved in the JPG file format and have varying sizes. Additionally, all images are 24-bit images. We provide a visual representation of the dataset in Figure 1, which displays sample images from each class.

(a) Female

(b) Male

Fig. 1 Sample images of the collected shadow images per the categories

B. *The Proposed NP-PHOG*

In this study, we proposed the NP-PHOG feature engineering model to classify the collected shadow images. Our main objective was to achieve high classification accuracy while maintaining low computational complexity. To accomplish this, we developed a lightweight feature engineering model. Figure 2 presents a block diagram of our proposed model, providing a clear overview of its design and functionality.

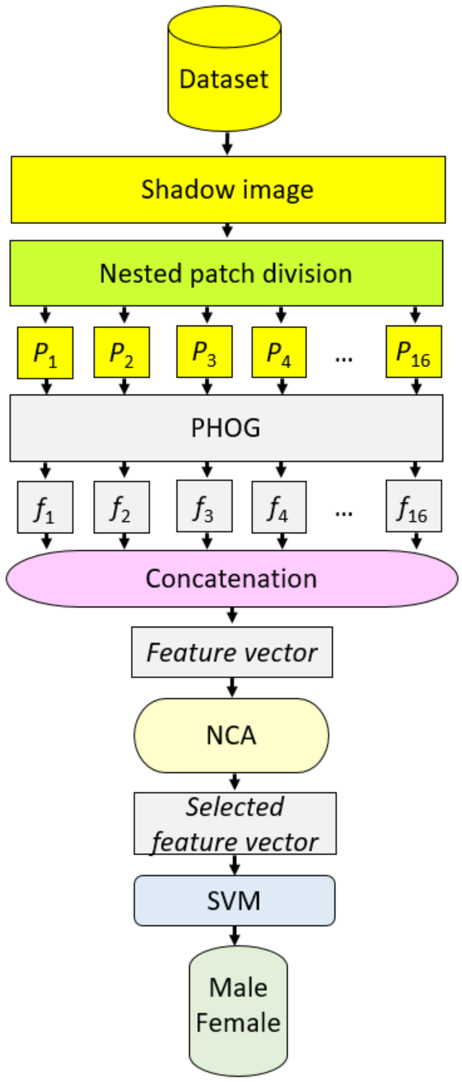


Fig. 2 Schematically explanation of the proposed NP-PHOG model. Herein, P: patches, f: feature vectors.

To provide a better understanding of our proposed NP-PHOG image classification model, we outline the steps below:

Step 1: Read each shadow image from the collected shadow image dataset.

Step 2: Resize each image to 256 × 256 and convert them to grayscale images to facilitate feature extraction using the PHOG feature extraction model. The PHOG feature extraction function is an improved version of the HOG feature selector, using multi-resolution images to obtain comprehensive features. This feature extractor uses the angles of the gradients, similar to HOG, and is a directional feature extractor.

Step 3: Create 16 nested patches, with size ranges from 16 × 16 to 256 × 256. This patch division methodology extracts both local and global features. The sizes of the extracted patches are 16 × 16, 32 ×

32, 48 × 48, …, 256 × 256. Refer to Figure 3 for an illustration of this patch division process.

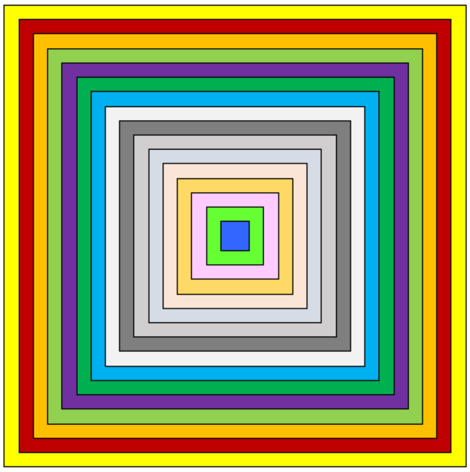


Fig. 3. The used nested patch division. Herein, there are 16 nested patches.

Step 4: Extract features using the PHOG feature extraction model from the created patches.

$$f_k = \rho(P_k), k \in \{1,2, \dots ,16\} \quad (1)$$

Herein, f is the feature vector with a length of 168, P defines the nested patches and $\rho(.)$ is the PHOG feature extraction function.

Step 5: Merge/concatenate the 16 feature vectors generated for creating the final feature vector.

$$F\big(j + 168 \times (k - 1)\big) = f_k(j), \quad j \in \{1,2, \dots ,168\} \quad (2)$$

where F is the final feature vector with a length of 2688 (=16×168).

Step 6: The top 168 most informative features were selected using the NCA feature selector from the 2688 generated features. NCA is a feature selection version of the k-nearest neighbors (k-NN) proposed by Hinton's team. It generates positive weights (feature ranking) for each feature, and the top features were selected using the generated feature ranking by generating NCA feature selector.

Step 7: The selected features were fed into an SVM classifier, which is a commonly used shallow classifier with various kernels. In this research, the cubic kernel was used, and the SVM classifier was named Cubic SVM classifier [25]. 10-fold cross-validation, which is a frequently used validation technique in the literature, was also employed.

The above seven steps have defined the proposed NP-PHOG feature engineering model.

III. RESULTS

We implemented the proposed NP-PHOG image classification model in MATLAB programming environment, using a simple configured personal computer due to the lightweight nature of our proposal. To calculate the time complexity of the proposed NP-PHOG, we used big O notation. The computational complexity of each phase is explained below:

- *Feature extraction:* We utilized PHOG and nested patches to obtain features. The complexity of PHOG is $O(n)$, where n is the size of the used patches. Moreover, we used m to denote the number of patches. Therefore, the time complexity of this phase is $O(mn)$.
- *Feature selection:* We employed NCA to select the most informative features. The computational complexity of NCA is $O(s)$, where s is the feature selection coefficient.
- *Classification:* We used the Cubic SVM classifier, and the time complexity coefficient of this phase is defined as c. Therefore, the computational complexity of this phase is $O(c)$.

Thus, the time complexity of the proposed NP-PHOG model is $O(mn + s + c)$. This result shows that the proposed NP-PHOG has a linear time complexity.

To demonstrate the classification performance of the proposed NP-PHOG model, we depicted the confusion matrix in Figure 4.

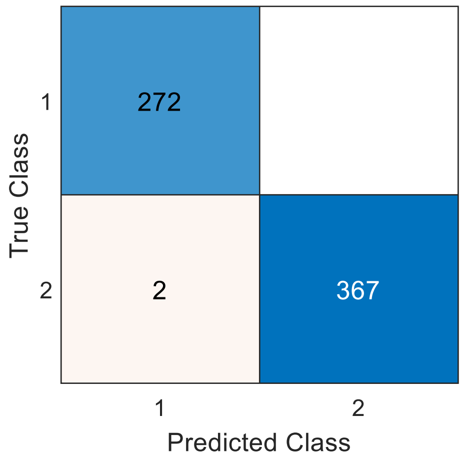


Fig. 4. The calculated confusion matrix. Herein, 1: female, 2: male.

To evaluate the classification performance of the proposed NP-PHOG model, we present the confusion matrix in Figure 4, where the model achieved 99.69% accuracy, 100% sensitivity, 99.49% specificity, and 99.73% geometric mean.

Since the dataset is new and shadow image-based gender classification is a new area, we cannot compare our model to previously presented models. To address this, we conducted ablation studies and defined eight cases to obtain ablation results, as described below:

Case 1: NP-PHOG-based feature extraction + NCA feature selection + kNN classification [26].

Case 2: NP-PHOG-based feature extraction + Chi2 feature selection [27] + kNN classification.

Case 3: NP-PHOG-based feature extraction + minimum redundancy maximum relevancy (mRMR) [28] feature selection + kNN classification.

Case 4: NP-PHOG-based feature extraction + ReliefF feature selection + kNN classification.

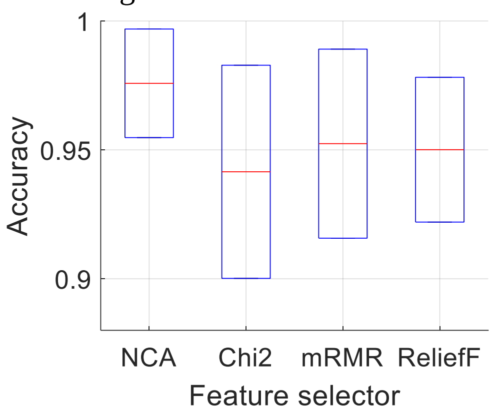
Case 5: NP-PHOG-based feature extraction + NCA feature selection + SVM classification. This case defines our proposed gender classification model.

Case 6: NP-PHOG-based feature extraction + Chi2 feature selection + SVM classification.

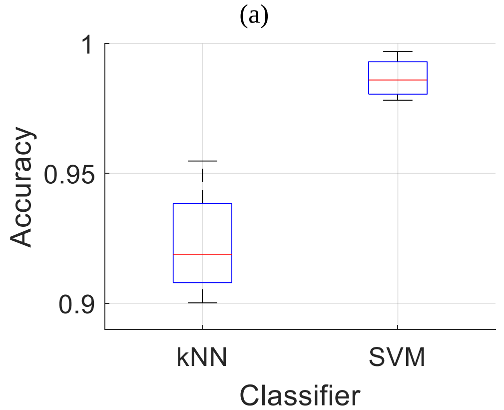
Case 7: NP-PHOG-based feature extraction + mRMR feature selection + SVM classification.

Case 8: NP-PHOG-based feature extraction + ReliefF feature selection [29] + SVM classification.

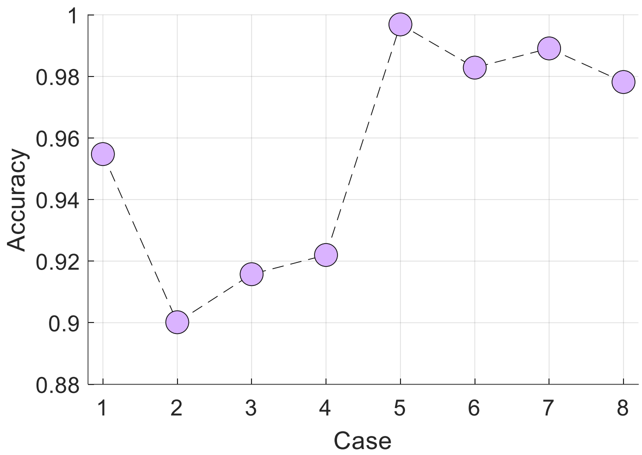
The classification accuracies of these cases are illustrated in Figure 5.



(a)



(b)



(c)

Fig. 5. The calculated accuracies to get comparative results. (a) comparison of the feature selectors, (b) comparisons of the used classifiers, (c) ablation results.

As evident from Figure 5, we have compared the results obtained from the eight defined cases. According to the results, the NCA feature selection function (Figure 5a) has shown the best performance, whereas the SVM classifier (Figure 5b) has yielded the highest accuracy. Moreover, the maximum accuracy has been obtained by Case 5 (Figure 5c), our proposed NP-PHOG model. These outcomes strongly support the superiority of our proposed model as it utilizes the best feature selection function and classifier combination.

IV. CONCLUSION

In this study, we aimed to explore the gender classification ability of a feature engineering model based on shadow images. To accomplish this, we collected a new dataset of shadow images and proposed a novel feature engineering model called NP-PHOG. We leverage nested patches and PHOG features in our proposed model for effective feature extraction. In addition, we employ NCA feature selection to refine our feature set and utilize an SVM classifier for accurate classification. The experimental results revealed that the proposed model achieved high accuracy, demonstrating its effectiveness for shadow detection tasks.

Furthermore, we performed an ablation study to compare the performance of various feature selection and classification methods. Our findings indicated that NCA feature selection and SVM classification are the optimal choices for this task. Furthermore, the proposed NP-PHOG model (Case 5) achieved the highest accuracy among all the tested cases. The results of our research also showcased the potential of computer vision models for detecting genders using shadow images.

Overall, our proposed NP-PHOG model holds promise as a novel approach that can be further developed and adapted for similar tasks. Nonetheless, additional experiments and evaluations are required to assess the model's robustness and generalization capabilities to different datasets and scenarios.

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Data availability: The authors are committed to making the data available if requested by the journal

Declarations

Conflict of interest: The authors declare that they have no conflict of interest.

Ethical approval: Ethics approval was not required for this research.

REFERENCES

[1] I. Yaqoob, I. A. T. Hashem, A. Ahmed, S. A. Kazmi, and C. S. Hong, "Internet of things forensics: Recent advances, taxonomy, requirements, and open challenges," *Future Generation Computer Systems*, vol. 92, pp. 265-275, 2019.

[2] N. Koroniotis, N. Moustafa, E. Sitnikova, and B. Turnbull, "Towards the development of realistic botnet dataset in the internet of things for network forensic analytics: Bot-iot dataset," *Future Generation Computer Systems*, vol. 100, pp. 779-796, 2019.

[3] Z. Tian, M. Li, M. Qiu, Y. Sun, and S. Su, "Block-DEF: A secure digital evidence framework using blockchain," *Information Sciences*, vol. 491, pp. 151-165, 2019.

[4] A. M. Qadir and A. Varol, "The role of machine learning in digital forensics," in *2020 8th International Symposium on Digital Forensics and Security (ISDFS)*, 2020: IEEE, pp. 1-5.

[5] F. Hutter, L. Kotthoff, and J. Vanschoren, *Automated machine learning: methods, systems, challenges*. Springer Nature, 2019.

[6] S. Berg *et al.*, "Ilastik: interactive machine learning for (bio) image analysis," *Nature methods*, vol. 16, no. 12, pp. 1226-1232, 2019.

[7] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *SN computer science*, vol. 2, no. 3, p. 160, 2021.

[8] S. A. Friedler, C. Scheidegger, S. Venkatasubramanian, S. Choudhary, E. P. Hamilton, and D. Roth, "A comparative study of fairness-enhancing interventions in machine learning," in *Proceedings of the conference on fairness, accountability, and transparency*, 2019, pp. 329-338.

[9] M. Groh, Z. Epstein, C. Firestone, and R. Picard, "Deepfake detection by human crowds, machines, and machine-informed crowds," *Proceedings of the National Academy of Sciences*, vol. 119, no. 1, p. e2110013119, 2022.

[10] S. Kumar, S. Singh, and J. Kumar, "Gender classification using machine learning with multi-feature method," in *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, 2019: IEEE, pp. 0648-0653.

[11] S. Park and J. Woo, "Gender classification using sentiment analysis and deep learning in a health web forum," *Applied Sciences*, vol. 9, no. 6, p. 1249, 2019.

[12] A. Basit, M. Y. Khan, S. S. Ali, M. Suffian, A. Wajid, and S. Khan, "Gender Classification Using Smartphone Sensors and Machine Learning Approaches," in *2022 Mohammad Ali Jinnah University International Conference on Computing (MAJICC)*, 2022: IEEE, pp. 1-6.

[13] S. Kumar, M. Gahalawat, P. P. Roy, D. P. Dogra, and B.-G. Kim, "Exploring impact of age and gender on sentiment analysis using machine learning," *Electronics*, vol. 9, no. 2, p. 374, 2020.

[14] K. Santosh *et al.*, "Machine learning techniques for human age and gender identification based on teeth X-ray images," *Journal of Healthcare Engineering*, vol. 2022, 2022.

[15] G. Aggarwal and R. Vig, "Acoustic methodologies for classifying gender and emotions using machine learning algorithms," in *2019 Amity International Conference on Artificial Intelligence (AICAI)*, 2019: IEEE, pp. 672-677.

[16] F. Safara *et al.*, "An author gender detection method using whale optimization algorithm and artificial neural network," *IEEE Access*, vol. 8, pp. 48428-48437, 2020.

[17] R. Montasari and R. Hill, "Next-generation digital forensics: Challenges and future paradigms," in *2019 IEEE 12th International conference on global security, safety and sustainability (ICGS3)*, 2019: IEEE, pp. 205-212.

[18] L. Caviglione, S. Wendzel, and W. Mazurczyk, "The future of digital forensics: Challenges and the road ahead," *IEEE Security & Privacy*, vol. 15, no. 6, pp. 12-17, 2017.

[19] S. Ferreira, M. Antunes, and M. E. Correia, "A dataset of photos and videos for digital forensics analysis using machine learning processing," *Data*, vol. 6, no. 8, p. 87, 2021.

[20] J. Atiyah, "Image forensic and analytics using machine learning," *International Journal of Computing and Business Research*, vol. 12, pp. 69-93, 2022.

[21] A. Dosovitskiy *et al.*, "An image is worth 16x16 words: Transformers for image recognition at scale," *arXiv preprint arXiv:2010.11929*, 2020.

[22] I. Tolstikhin *et al.*, "MLP-Mixer: An all-MLP Architecture for Vision," *arXiv preprint arXiv:2105.01601*, 2021.

[23] J. Goldberger, G. E. Hinton, S. Roweis, and R. R. Salakhutdinov, "Neighbourhood components analysis," *Advances in neural information processing systems,* vol. 17, pp. 513-520, 2004.

[24] V. Vapnik, "The support vector method of function estimation," in *Nonlinear Modeling*: Springer, 1998, pp. 55-85.

[25] U. Jain, K. Nathani, N. Ruban, A. N. J. Raj, Z. Zhuang, and V. G. Mahesh, "Cubic SVM classifier based feature extraction and emotion detection from speech signals," in *2018 international conference on sensor networks and signal processing (SNSP)*, 2018: IEEE, pp. 386-391.

[26] J. Maillo, S. Ramírez, I. Triguero, and F. Herrera, "kNN-IS: An Iterative Spark-based design of the k-Nearest Neighbors classifier for big data," *Knowledge-Based Systems,* vol. 117, pp. 3-15, 2017.

[27] H. Liu and R. Setiono, "Chi2: Feature selection and discretization of numeric attributes," in *Proceedings of 7th IEEE international conference on tools with artificial intelligence*, 1995: IEEE, pp. 388-391.

[28] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Transactions on pattern analysis and machine intelligence,* vol. 27, no. 8, pp. 1226-1238, 2005.

[29] I. Kononenko, "Estimating attributes: Analysis and extensions of RELIEF," in *European conference on machine learning*, 1994: Springer, pp. 171-182.