CSE 4238 Group 4

by Fatema Tuj Johora Faria

Automatic Profiling of Gender, Age, and Handedness from Offline Bangla Handwritten Document Images

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***Abstract*—Tackling the complex problem of demographic characteristics identification is a continuous endeavor. Previously, handwriting analysis was used to predict factors such as gender, age, handedness, ethnicity, nation, and behavior. The automated assessment of handwritten samples is important in many domains, including psychology, historical document interpretation, and forensics. However, determining gender, age, and handedness from offline handwriting poses difficulties, as seen by cutting-edge approaches usually achieving poor outcomes. Despite broad interest, current efforts are mostly focused on English and Arabic, and frequently rely on manual feature selection. In this study, we examine Bangla document images as a new line of investigation. We employed Convolutional Neural Networks (CNNs) intended for efficient feature extraction, utilizing ImageNet pretraining cross-domain transfer learning. We achieved remarkable gender detection accuracy of 0.9352 with MobileNetV3, whereas DenseNet121 achieved 0.8046 for age detection and MobileNetV3 achieved 0.7622 for handedness. Our findings suggest that these CNNs outperform standard models and open the way to automated classification, hence advancing the field of handwriting-based characteristic prediction.**

***Index Terms*—Deep Learning, Handwriting Analysis, Gender prediction, Handedness classification, Demographic characteristics , Convolutional Neural Networks**

I. Introduction

Handwriting analysis, also known as graphology, involves the examination and interpretation of an individual's handwriting to gather insights into their personality traits, behaviors, and psychological characteristics [1]. While it lacks scientific validation as a dependable means of assessing personality, handwriting analysis has found applications in diverse areas such as digital forensic investigations [2], the authenticity of historical handwriting documents [3], offline signature verification [4], handwriting recognition systems [5], and demographic prediction tasks including identifying gender, handedness, age range, and nationality [6]. These tasks can be formulated as supervised learning problems involving binary or multiclass classification. Male handwriting often exhibits angular and disorderly characteristics, whereas female handwriting tends to be more rounded and organized [7]. Handwriting recognition can be categorized into two types: offline and online recognition [8]. The process of turning spoken word or audio material into written text is called transcribing. It involves listening to audio files or speech and precisely copying the words and phrases. Offline handwriting recognition comprises inspecting and transcribing handwritten text that has already been inscribed on paper and then digitized or scanned for analysis. It focuses on recognizing the shapes and structures of individual characters, words, and sentences in static images [9]. On the other hand, online handwriting recognition focuses on recognizing text written using electronic digitizer devices, which capture various dynamic measures associated with the writing process, such as writing pressure, pen altitude, and azimuth [10]. Even though technology has advanced, there are presently no algorithms that can assist a computer in understanding and writing down the text of difficult handwritten documents, such as old historical records. Handwriting recognition is a challenging topic in general because people's writing styles differ, handwriting often flows together, different types of pens are used, and the paper might include distracting patterns or markings. [11]. In this research paper, we focus on automatically establishing a person's gender, age, and whether they are left-handed or right-handed by looking at their handwritten bangla documents. This is becoming more relevant and interesting to investigate. By utilizing digital image processing and computer vision techniques, we aim to extract valuable demographic information from handwritten documents. In summary, the key contributions we made in our research are as follows:

- We present the innovative Bangla Handwritten Document Profiling Dataset (BHDPD), containing diverse offline handwritten documents from schools, colleges, and universities. BHDPD includes gender, age, and handedness profiles, serving as a valuable asset for advancing Bangla handwriting analysis research.
- We extensively compare different CNN architectures for profiling gender, age, and handedness from Bangla handwritten documents. Our study evaluates ResNet-152, DenseNet-121, VGG19, MobileNetV3,

and ShuffleNet V2, shedding light on their performance and suitability for precise profiling.
- We present evaluation using measures such as accuracy, precision, recall, and F1 score, with a focus on gender, age, and handedness profile. This method promotes improved comprehension and increases trust in the outcomes provided by our models.

The remaining portion of the paper is structured as follows: Section (III) shows some of the prior works that are related. Section (IV) describes the corpus creation method in detail. Section (V) discusses briefly some key background research on image processing, CNN architectures, and performance evaluation criteria. Section (VI) explains the recommended approach, while Section (VII) explains and analyzes the experimental results. Finally, in section (VIII), the study closes with a concluding note.

II. Related Works

Morera et al. [3] investigates a unique deep neural network approach for demographic prediction in gender and handedness classification. According to the findings, the suggested combined multiclass technique exceeds the typical separate handling of binary issues, obtaining considerably better accuracy rates (83.19%) than the joint average accuracy (73.21%). The improved accuracy, along with the economy in training times, demonstrates the effectiveness of the multiclass approach over hierarchical classification. This finding is consistent for both the IAM and KHATT databases, with the combined multiclass system yielding 70.84% accuracy, a notable 29.26% improvement over separate binary classification. Rahmanian et al. [1] explored the application of advanced CNNs such as DenseNet201, InceptionV3, and Xception in automatic gender and handedness classification based on handwriting data from IAM (English texts) and KHATT (Arabic texts) databases. The results demonstrate the effectiveness of the proposed CNN architectures, achieving notable improvements in classification accuracy. Specifically, an 84% accuracy (1.27% improvement) is obtained for gender classification using the IAM database, and a remarkable 99.14% accuracy (28.23% improvement) is achieved for handedness classification using the KHATT database. Bouadjenek et al. [12] worked on a problem where they tried to determine a person's gender using certain features extracted from handwritten text, like patterns in the writing and they used a method involving features from something called "Histogram of Oriented Gradients" and a special classifier called "SVM". They checked their method using two databases with handwritten English and Arabic documents, called IAM and KHATT. They found that their method was about 75.45% accurate for IAM and 68.89% accurate for KHATT, on average.The co-training strategy for age range prediction from handwriting analysis was examined by Zouaoui et al. [13]. The authors suggested various descriptors of features and used an SVM predictor for classification.Agarwal et al. [14] compared supervised machine learning algorithms (SVM, KNN, RFC, Naive Bayes) for gender and handedness prediction using IAM and Real-time datasets. Naive Bayes and SVM achieved higher accuracy scores than KNN and RFC in gender prediction (68.82%, 68.65% IAM; 68.32%, 68.45% Real-time) and handedness prediction (68.82%, 68.65% IAM; 71.54%, 71.35% Real-time). In combined prediction, SVM consistently scored highest (75.65% IAM, 72.09% Real-time), followed by Naive Bayes. These results highlight Naive Bayes and SVM effectiveness for both individual and combined gender and handedness prediction.

III. Corpus Creation

A. Data Collection

The BHDPD dataset used in this study consists of 1,800 samples collected from 90 participants, including 30 each from school, college, and university students. Each participant contributed 20 Bangla handwritten documents to ensure diverse demographic representation. We aimed to cover gender, age, and handedness variations. The dataset's creation involved participants from different educational levels to capture distinct writing styles influenced by educational backgrounds. We provided materials and instructions for writing 20 documents, maintaining consistency with 5 identical documents and 15 varying ones. This dataset serves as a valuable resource for advancing Bangla handwriting analysis research.

B. Bangla Handwritten Document Annotation Process

The annotation process involved labeling each document with the corresponding age, gender, and handedness information. An Excel sheet was used to store these labels in a structured manner. The labels were assigned based on the information provided by the participants during data collection.

C. Bangla Handwritten Document Annotation Guideline

The BHDPD dataset's annotation process ensured accurate gender detection. Participants' info from schools, colleges, and universities was used to label handwritten images. The dataset was thoughtfully compiled, with 15 males and 15 females from each level contributing 20 handwritten texts. Language cues and distinctive handwriting styles aided gender determination. Age was inferred by analyzing writing maturity, habits, and speed. Handedness was identified through stroke analysis, providing insights into handwriting style variations for gender detection research.

D. Bangla Handwritten Document Annotator Identity

To ensure unbiased and reliable annotation, the identities of the annotators were kept anonymous. This measure aimed to eliminate any potential personal biases or preconceptions that could influence the labeling process. The anonymity of the annotators helped maintain objectivity and consistency throughout the annotation process.

E. Bangla Handwritten Document Annotation Quality

Our Bangla handwritten document annotation's quality is vital for successful natural language processing and document analysis tasks. Addressing challenges like writing style variations and noise, we prioritize high annotation accuracy. With expert annotators and clear guidelines, our rigorous quality assurance process maintains consistency and minimizes errors. We emphasize tackling challenges and promoting high-quality Bangla handwritten document annotation to enhance downstream task performance and application effectiveness.

F. Dataset Statistics

The BHDPD dataset used in this study comprises a rich and diverse collection of handwritten texts contributed by 90 participants. It is divided into three educational levels: school students, college students, and university students, with each group consisting of 15 males and 15 females.

Table I
DISTRIBUTION OF SAMPLES BY AGE AND GENDER

Age Range	**Male (samples)**	**Female (samples)**	**Source**
11-15	300	300	School students
16-20	300	300	College students
21-25	300	300	University students
Total samples	**900**	**900**	

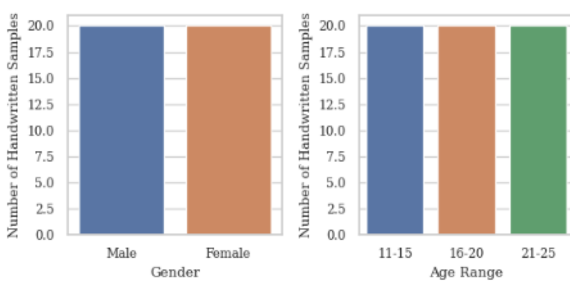


Figure 1. Handwritten Samples of Each Person by Gender and Age

IV. BACKGROUND STUDY

A. Digital Image Processing

The research paper presents five essential image processing techniques for computer vision. Canny edge detection [18] identifies object boundaries using Gaussian smoothing, gradient calculation, non-maximum suppression, and double thresholding. Inverse binarization [19] highlights dark objects against a light background by reversing pixel values. Contrast Limited Adaptive Histogram Equalization (CLAHE) [20] enhances local contrast, preserving details and avoiding noise. Erosion [21] shrinks objects in binary images through kernel scanning. MedianBlur [22] efficiently removes noise while retaining edges by using neighboring pixel medians.

B. Convolutional Neural Network

ResNet-152, introduced by He et al. [15] in 2015, overcomes vanishing gradients with 152 layers, utilizing convolutional layers, batch normalization, ReLU activation, and shortcut connections for effective training. DenseNet-121, proposed by Huang et al. [16] in 2016, maximizes feature reuse through dense connectivity, addressing vanishing gradients. VGG19, an extension of VGG16 [23], uses 3x3 convolutional filters and ReLU activation for complex feature learning. MobileNetV3 [24], optimized for mobile devices, achieves high accuracy with minimal size and complexity. ShuffleNet V2 [25], an advanced CNN by Ma et al. in 2018, excels in efficiency and accuracy through channel shuffling for improved information exchange.

C. Evaluation Metrics

Table II
EVALUATION METRICS FOR GENDER, AGE, AND HANDEDNESS DETECTION

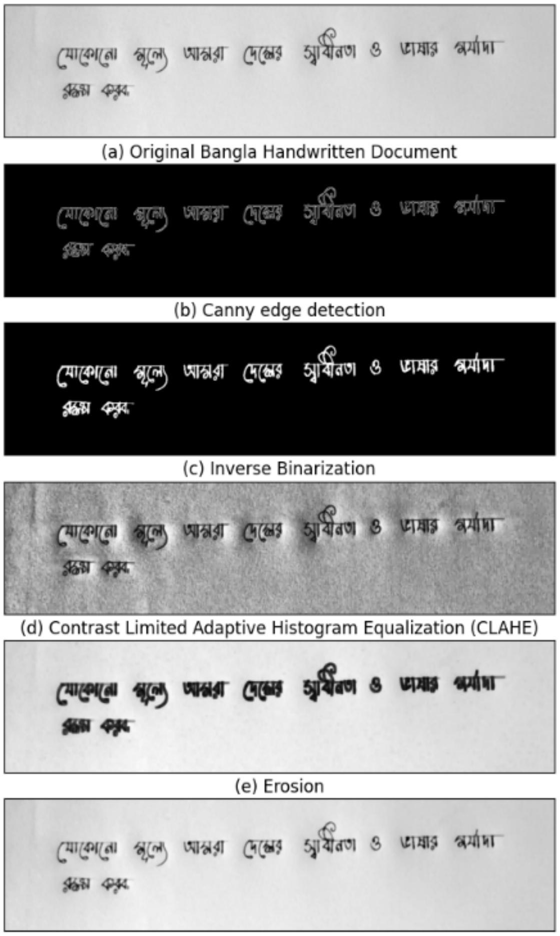
Metric	**Equation**
Accuracy	$\frac{TP_{GAH}+TN_{GAH}}{TP_{GAH}+TN_{GAH}+FP_{GAH}+FN_{GAH}}$
Precision	$\frac{TP_{GAH}}{TP_{GAH}+FP_{GAH}}$
Recall	$\frac{TP_{GAH}}{TP_{GAH}+FN_{GAH}}$
F1 Score	$\frac{2\cdot \text{Precision}_{GAH}\cdot \text{Recall}_{GAH}}{\text{Precision}_{GAH}+\text{Recall}_{GAH}}$

"GAH" represents "Gender, Age, Handedness." The overall accuracy of predictions is indicated by accuracy. Precision refers to the correctness of positive predictions.The ability to correctly recognize actual positives is measured by recall.The F1 Score strikes a balance between accuracy and recall for a thorough evaluation [17].

V. PROPOSED METHODOLOGY

This section presents the proposed methodology for Profiling of Gender, Age, and Handedness from Offline Bangla Handwritten Document Images which is divided into six major steps.In the proposed methodology, a single input image attains two different pre-trained CNN architectures.Furthermore,through several performance metrics we evaluate the detection of all the candidate CNN architectures against the actual ground truth . The primary stages of the proposed method for profiling, considering a Bengali document "একদিন একটা শিয়াল খাবারের সন্ধানে বনে

ঘুরছিল।" (English translation: "One day a fox was roaming in the forest in search of food.") as an example are summarized in Figure 3. and are further detailed below.



(a) Original Bangla Handwritten Document

(b) Canny edge detection

(c) Inverse Binarization

(d) Contrast Limited Adaptive Histogram Equalization (CLAHE)

(e) Erosion

(f) MedianBlur

Figure 2. Images of a bangla handwritten document after applying image processing techniques.

A. Input Image:

The process begins by obtaining an input image of a Bangla handwritten document. The image size is 200 x 1100 pixels, and it contains handwritten text that we want to profile for gender, age, and handedness information.

B. Image Preprocessing:

We preprocess the handwritten document images using digital image processing techniques. Perform operations such as image resizing, grayscale conversion, noise removal, and contrast enhancement to standardize and improve the quality of the images. A bangla handwritten document "যেকোনো মূল্যে আমরা দেশের স্বাধীনতা ও ভাষার মর্যাদা রক্ষা করব।" (English translation: "We will protect the freedom of the country and the dignity of the language at any cost.") in Figure 2. as an example that has undergone various image processing techniques.

C. Image Transformations:

In our research, we applied diverse image transformations to BHDPD dataset, training CNNs."Random Horizontal Flip" and "Random Vertical Flip" introduce orientation and positional variety."Random Rotation" adds controlled rotations, valuable for handling various object orientations. "Color Jitter" adjusts brightness, contrast, and saturation, enhancing adaptability. "Normalization" scales pixel values for stable training and improved convergence.

D. Feature Extraction:

After preprocessing, important characteristics from images are retrieved using sophisticated pre-trained CNN architectures: ResNet-152, DenseNet-121, VGG-19, MobileNet-V3, and ShuffleNet-V2. These CNNs, trained on a variety of datasets, recognize handwriting patterns such as stroke direction, curvature, slant, spacing, and pressure changes. Using CNNs as feature extractors, high-level handwriting representations are captured, which is important for profiling. Passing photos through CNNs and extracting feature vectors from Bangla handwritten documents delivers accurate gender, age, and handedness characterization.

E. Flatten and Classification:

We flatten the extracted feature vector to a 1D array and pass it through a fully connected layer. This layer performs classification by mapping the features to the corresponding class probabilities.

F. Training the Classifier:

We train the classifier using the extracted features and the ground truth labels from the training set. Use a loss function such as cross-entropy to measure the difference between predicted and actual class probabilities. Optimize the model using an optimization algorithm like Adam.

G. Model Evaluation:

We afterwards analyze the trained model using the testing dataset in order to assess its overall performance. This involves calculating essential metrics like as accuracy, precision, recall, and F1-score. These measures allow us to statistically examine the classifier's ability to correctly predict the appropriate classes.

VI. Experimental Results

A. Experimental Setup:

We conducted experiments in a Jupyter Notebook using PyTorch (v1.13.1) as our primary deep learning framework. Our setup included an NVIDIA GeForce RTX 3050 GPU with compute capability 8.6, greatly speeding up

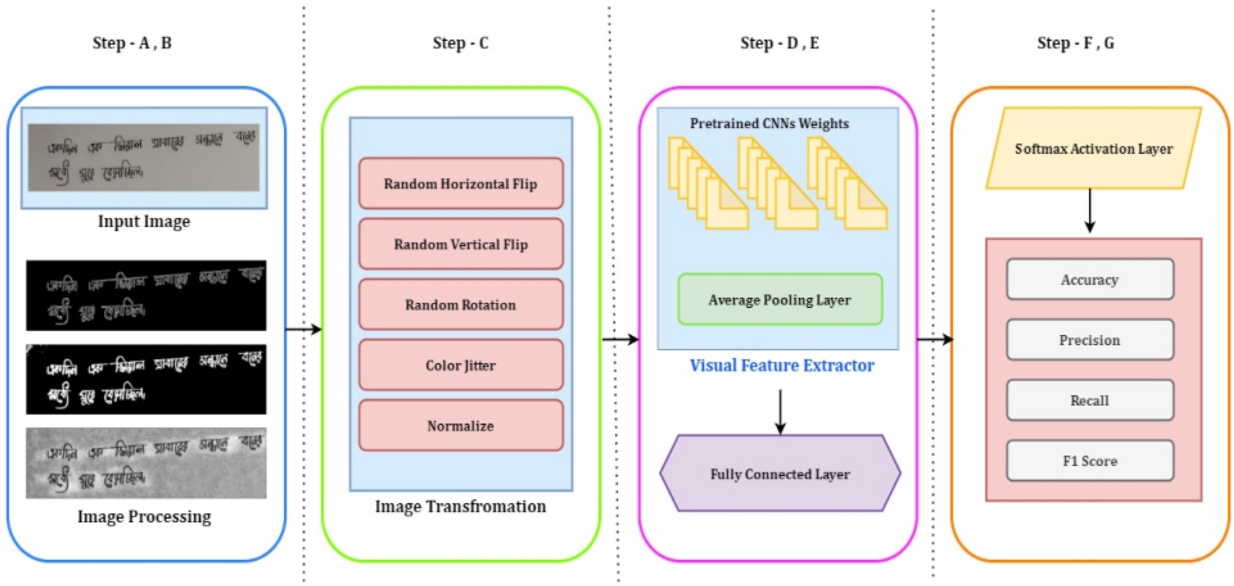


Figure 3. Suggested methodology using a sample data as input image and detect Gender, Age, and Handedness as the output for different pre-trained CNNs architecture from Offline Bangla Handwritten Document Images.

training for complex neural networks. PyTorch's user-friendliness and broad neural network support enabled us to design and train advanced CNN models for gender detection on the BHDPD dataset.

B. Result Analysis:

We split the BHDPD dataset into training, validation, and test sets with 70%, 20%, and 10%, respectively, in our studies. The method we used was trained using the training set, optimized using the validation set, and tested using the test set. The results, as shown in Table III, give an in-depth evaluation of the efficacy of our approach.

Table III
Evaluating the Potential of Pre-trained CNNs Architecture with Adam Optimizer on Test Dataset

Gender Detection

Pre-trained CNNs	Accuracy	Precision	Recall	F1 Score
ResNet152	0.8300	0.8311	0.8300	0.8298
DenseNet121	0.7756	0.7756	0.7756	0.7756
VGG19	0.8381	0.8384	0.8381	0.8381
MobileNetV3	0.9352	0.9354	0.9352	0.9352
ShuffleNetV2	0.7957	0.7978	0.7957	0.7954

Age Detection

Pre-trained CNNs	Accuracy	Precision	Recall	F1 Score
ResNet152	0.7020	0.7061	0.7020	0.7003
DenseNet121	0.8046	0.8099	0.8046	0.8037
VGG19	0.6529	0.6532	0.6529	0.6525
MobileNetV3	0.7343	0.7645	0.7343	0.7262
ShuffleNetV2	0.7220	0.7380	0.7220	0.7171

Handedness Detection

Pre-trained CNNs	Accuracy	Precision	Recall	F1 Score
ResNet152	0.7566	0.7567	0.7566	0.7566
DenseNet121	0.7209	0.7232	0.7209	0.7203
VGG19	0.6875	0.6891	0.6875	0.6866
MobileNetV3	0.7622	0.7622	0.7622	0.7622
ShuffleNetV2	0.7187	0.7435	0.7187	0.7110

VII. Conclusion

In the end, this research effectively demonstrates the great potential of sophisticated deep learning algorithms for automating the recognition of Gender, Age, and Handedness from Offline Bangla Handwritten Document Images. Our study achieves impressive levels of accuracy by using a broad dataset and employing a range of pre-trained CNN architectures. Going ahead, we intend to improve the openness and dependability of our models by including Explainable AI approaches. These techniques will give vital insights into our models' decision-making processes, enabling increased understanding and user confidence.

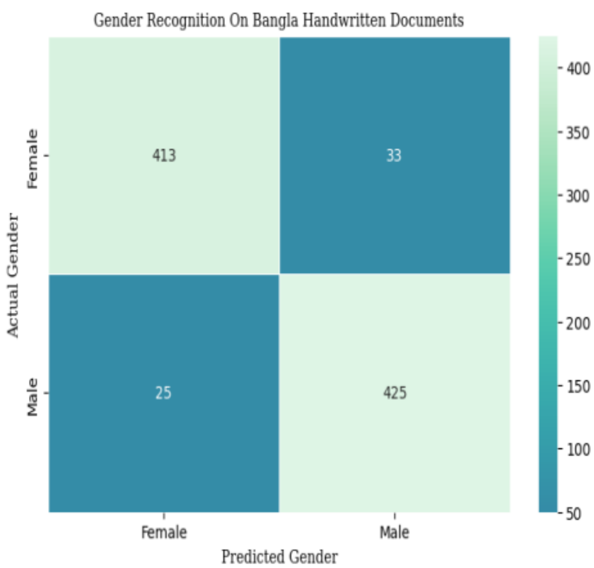


Figure 4. Confusion matrix of the Pre-trained MobileNetV3 architecture trained on BHDPD dataset.

Furthermore, we recognize the need of developing strong domain adaptation techniques, which is a critical step in ensuring consistent performance across varying data distributions, particularly in real-world applications. Extending our research to include multi-language attribute identification is an interesting potential in the future. This project requires managing the deep minutiae of several languages, scripts, and linguistic variations. We foresee the advancement in automatic attribute recognition by tackling these challenges, generating models that excel not only in accuracy but also in flexibility and accessibility in a wide range of real-world circumstances.

References

[1] Rahmanian, Mina & Shayegan, Mohammad. (2021). Handwriting-based gender and handedness classification using convolutional neural networks. Multimedia Tools and Applications. 80. 10.1007/s11042-020-10170-7.

[2] Shaik, Bushra & Katikireddy, Jyothi & Kambham, Vamsidhar & Sravani, K.. (2023). Offline Signature Verification Using Image Processing. E3S Web of Conferences. 391. 10.1051/e3sconf/202339101074.

[3] Morera, Angel & Sánchez, Ángel & Vélez, José & Moreno, A.B.. (2018). Gender and Handedness Prediction from Offline Handwriting Using Convolutional Neural Networks. Complexity. 2018. 1-14. 10.1155/2018/3891624.

[4] Engin, Deniz & Kantarcı, Alperen & Arslan, Secil & Ekenel, Hazım. (2020). Offline Signature Verification on Real-World Documents.

[5] Hamdan, Yasir & Ammayappan, Sathesh. (2021). Deep Learning based Handwriting Recognition with Adversarial Feature Deformation and Regularization. Journal of Innovative Image Processing. 3. 367-376. 10.36548/jiip.2021.4.008.

[6] Al-ma'adeed, Somaya & Hassaïne, Abdelâali. (2014). Automatic prediction of age, gender, and nationality in offline handwriting. EURASIP Journal on Image and Video Processing. 10. 10.1186/1687-5281-2014-10. https://www.sciencedirect.com/science/article/pii/S0306457320306002

[7] Nader, Lamis & Mohamed, Arafa & Nazir, Muhammad & Awadalla, Mohamed. (2018). Identification of Writers Gender using Handwriting Analysis. International Journal of Scientific and Research Publications (IJSRP). 8. 10.29322/IJSRP.8.10.2018.p8288.

[8] Alheraki, Mais & Al-Matham, Rawan & Al-Khalifa, Hend. (2022). Handwritten Arabic Character Recognition for Children Writing Using Convolutional Neural Network and Stroke Identification. Human-Centric Intelligent Systems. 3. 10.1007/s44230-023-00024-4.

[9] Sueiras, Jorge. (2021). Continuous Offline Handwriting Recognition using Deep Learning Models.

[10] Faundez-Zanuy, Marcos & Mekyska, Jiri & Impedovo, Donato. (2021). Online Handwriting, Signature and Touch Dynamics: Tasks and Potential Applications in the Field of Security and Health. Cognitive Computation. 13. 10.1007/s12559-021-09938-2.

[11] Plamondon, Réjean. (2000). On-line and off-line handwriting recognition: a comprehensive survey. IEEE Trans Pattern Anal Mach Intell (T-PAMI). IEEE Trans. Pattern Anal. Mach. Intell.. 22. 63-84. 10.1109/34.824821.

[12] Bouadjenek, Nesrine & Nemmour, Hassiba & Chibani, Youcef. (2015). Histogram of Oriented Gradients for writer's gender, handedness and age prediction. 10.1109/INISTA.2015.7276752.

[13] Zouaoui, Fatima & Bouadjenek, Nesrine & Nemmour, Hassiba & Chibani, Youcef. (2017). Co-training approach for improving age range prediction from handwritten text. 1-5. 10.1109/ICEE-B.2017.8192233.

[14] Agarwal, Ayushi & Saraswat, Mala. (2023). Analyzing Various Handwriting Recognition Phenomenon for Predicting Gender, Age and Handedness. 10.1007/978-3-031-23724-9_21.

[15] He, Kaiming & Zhang, Xiangyu & Ren, Shaoqing & Sun, Jian. (2016). Deep Residual Learning for Image Recognition. 770-778. 10.1109/CVPR.2016.90.

[16] Huang, Gao & Liu, Zhuang & van der Maaten, Laurens & Weinberger, Kilian. (2017). Densely Connected Convolutional Networks. 10.1109/CVPR.2017.243.

[17] Hossin, Mohammad & M.N, Sulaiman. (2015). A Review on Evaluation Metrics for Data Classification Evaluations. International Journal of Data Mining & Knowledge Management Process. 5. 01-11. 10.5121/ijdkp.2015.5201.

[18] Akbari Sekehravani, Ehsan & Babulak, Eduard & Masoodi, Mehdi. (2020). Implementing canny edge detection algorithm for noisy image. Bulletin of Electrical Engineering and Informatics. 9. 1404-1410. 10.11591/eei.v9i4.1837.

[19] Chaki, Sudipto & Shila, Dipu & Jahan, Nafsin. (2019). Automation of water meter billing process based on digital image processing approach. Journal of Advances in Technology and Engineering Research. 5. 207-218. 10.20474/jater-5.5.3.

[20] Musa, Purnawarman & Rafi, Farid & Lamsani, Missa. (2018). A Review: Contrast-Limited Adaptive Histogram Equalization (CLAHE) methods to help the application of face recognition. 1-6. 10.1109/IAC.2018.8780492.

[21] Said, K & Jambek, Asral. (2021). Analysis of Image Processing Using Morphological Erosion and Dilation. Journal of Physics: Conference Series. 2071. 012033. 10.1088/1742-6596/2071/1/012033.

[22] Mustafa, Suleiman & oyeniran, kola. (2017). Comparing Median and Gaussian Blurring for GrabCut Segmentation of Melanoma.

[23] Simonyan, Karen & Zisserman, Andrew. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv 1409.1556.

[24] Howard, Andrew & Sandler, Mark & Chu, Grace & Chen, Liang-Chieh & Chen, Bo & Tan, Mingxing & Wang, Weijun & Zhu, Yukun & Pang, Ruoming & Vasudevan, Vijay & Le, Quoc & Adam, Hartwig. (2019). Searching for MobileNetV3.

[25] Ma, Ningning & Zhang, Xiangyu & Zheng, Hai-Tao & Sun, Jian. (2018). ShuffleNet V2: Practical Guidelines for Efficient CNN Architecture Design.

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