PREDICTION OF GENDER AND HANDEDNESS FROM OFFLINE HANDWRITING USING CONVOLUTIONAL NEURAL NETWORK WITH CANNY EDGE DETECTION

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ABSTRACT

Handwriting classification based on a writer's demographics, such as gender and handedness, has been an essential discipline in forensic science and biometric security. Although there are already experts in forensic science called Forensics Document Examiners, their work can be affected due to a lack of efficiency and the risk of human errors. As there are only limited studies on handwriter demographics problems using Convolutional Neural Networks (CNN), this research implemented a system that predicts the gender, handedness, and combined gender-and-handedness of offline handwritten images from the IAM Handwriting iDatabase 3.0 using 2-Layer and 3-Layer CNN with Canny Edge Detection (CED). The researchers found that the base model 2L-CNN without CED had the best performance in the binary classes, gender, and handedness, with an overall accuracy of 68.5% and 89.75%, respectively. On the other hand, 3L-CNN without CED had the best average accuracy of 51.36% in the combined gender-and-handedness class. It was observed that Canny Edge Detection is not an effective preprocessing technique in handwriting classification as it worsened its counterpart's performance, without CED, in most of the models.

KEYWORDS

Neural Networks, Edge Detection, Offline Handwriting, Machine Learning, Deep Learning, Preprocessing

1. INTRODUCTION

Handwriting identification and analysis has been an essential discipline of forensic science, as it can serve as crucial evidence in court testimonies in certain situations. Experts in the field are called Forensic Document Examiners (FDE), and they aid in criminal investigations by identifying the authenticity of documents in cases such as fraud, forgeries, theft, etc. Through forensic handwriting analysis, helpful information can be gathered just by examining the handwritten texts, which could reveal the demographics of the writer, such as gender and handedness, which can significantly help identify possible suspects. The process requires many

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steps that an FDE must follow to arrive at a conclusion that is as accurate as possible. However, forensics experts can still be prone to misinterpretations despite thorough examinations due to human error. This is the primary motivation behind the creation of automated systems, as they can reduce humans' subjectivity regarding sufficiency determination, quality decisions, feature selection and extraction, feature matching, and interpretation [1].

Nonetheless, despite many studies and enhancements regarding handwriting automated systems, they still have a long way to go before reaching the analysis capabilities of humans [2]. Further development is still needed before they can be used in forensic document examination, as they still have more potential for improving performance in terms of the computational speed and accuracy of the algorithms. That is why it is essential to continue advancing on the subject to supplement FDEs with their work and evaluation eventually.

Optical Character Recognition (OCR) is a field of study in pattern recognition, computer vision, and artificial intelligence that is tasked with accurately differentiating and recognizing printed text divided into two forms: online text and offline text [3]. Online text must be identified while written, whereas offline text merely needs a static representation that can be typed or handwritten. Numerous methods for recognizing handwriting include Convolutional Neural Networks (CNN), Incremental Recognition Methods, Line and Word Segmentation Methods, Zoning Methods, etc. Convolutional neural network (CNN) technology has been one of the most popular approaches that has been demonstrated to have a high accuracy rate and be effective in various handwriting recognition systems [4].

Edge detection is another fundamental technique used in image processing. Many edge detection algorithms have been developed that enhanced their abilities to evaluate effective edges to restrict false detection of edges, edge localization, and computational time [5]. Using edge detection, the object limits considered are instrumental during the stages of detection and segmentation [3]. Standard edge detection techniques include Prewitt Edge Detection, Sobel Edge Detection, Kirsch Edge Detection, Laplacian Edge Detection, and Canny Edge Detection.

One of the most popular edge detection methods is Canny Edge Detection (CED), which offers a better solution with a faster processing time thanks to its straightforward calculation process, better detection results compared to other methods of detection [6, 5], and the ability to retain important information filtered from the original image [7].

The main objective of this research paper is to develop a system that predicts the gender and handedness from offline handwritten images using 2-layer and 3-layer Convolutional Neural Networks with Canny Edge Detection. Meanwhile, the specific objectives of the study are the following: to determine the accuracy of 2-layer and 3-layer CNN when implemented with and without CED in predicting (a) gender, (b) handedness, and (c) combined gender-and-handedness in offline handwriting, and to test if there is a significant improvement in the performance of the system in terms of accuracy when the following was implemented: 2-layer CNN with and without CED, and 3-layer CNN with and without CED.

The researchers followed the study of (1) Morera et al. (2018) [8], which made use of use bilinear interpolation in resizing images, while this study utilized padded resizing, and (2) Ahlawat et al. (2020) [9], which used different multi-layered CNN architectures, and focused ondeepening their studies by researching and applying the Canny Edge Detection algorithm as a preprocessing technique.

2. RELATED WORKS

The following are the reviews of related works in predicting gender and handedness using the Canny Edge Detection and Convolutional Neural Networks.

2.1. Canny Edge Detection

Canny edge detection is an algorithm that can detect noise-suppressed edges in an image and was proposed by John F. Canny in 1986 [10]. In this technique, the image is smoothed using a Gaussian filter. Then, it determines the image's intensity gradient, including its edge magnitude and direction. The canny edge determines edge points by applying non-maximal suppression to the gradient magnitude. The non-maximal suppression post-processing method is used to soften the edges of an image. Once prospective edges have been identified, a double threshold is used to finalize them by suppressing weak edges and leaving only the strong ones (Liu & Mao, 2018; Rabby et al., 2018) [6, 7]. The Gaussian filter's principle of smoothing makes error detection effective. The presence of the non-maximal suppression also brings out the advantage of improving the signal with respect to the noise ratio. Its thresholding mechanism allows Canny Edge to detect edges when noise is present. The lengthy computation of the Canny edge is due to its complex computation, as explained by Shah et al. (2020) [10].

Like other edge detection algorithms discussed, Canny Edge has various computer vision, medical imaging, and handwriting recognition applications. Kanagarathinam et al. (2019)[11] used Canny edge detection as one of its feature extraction algorithms for their research on the steps involved in text recognition and research on Optical Character Recognition (OCR). The research methodology is as follows: preprocessing, feature extraction, recognition, and post-processing. For the preprocessing, the initial step was to adjust the contrast and eliminate the noise from the image. The next step was thresholding to remove the noise if present, followed by page segmentation for separating graphics from the text. The next step is text segmentation to separate individual characters, followed by morphological processing or image enhancement. After the preprocessing, the researchers continued by applying spatial image filters or edge detection algorithms to eliminate high and low frequencies to enhance the edges of the image further. Text recognition was performed after these techniques and segmenting the characters from the original image. The proposed algorithm was then compared on the CVSLD, CPAR, and Chars74k Latin script database. The recognition rate for multilingual characters yielded 97.33%, 98.26%, and 97.10% respectively. Premananada et al. (2020) [12] also made use of Canny edge detection in their proposed study on the design and implementation of automated handwriting sentence recognition using hybrid techniques on a Field-programmable gate array (FPGA).

The research methodology used Canny Edge to improve the quality of the image by removing the pixels or noise terms in an image. According to the researchers, the study aims to formulate a real-time application that deals with handwritten identification, enabling a comprehensive computerized system to recognize handwritten data, which is more efficient and free from noise. Aside from the Canny edge detection algorithm, the filters used are based on Probabilistic Patch (PPB) identification. After the handwritten recognition with the help of the edge detection algorithm, the text is then classified by the database.

2.2. Convolutional Neural Network

Convolutional Neural Network (CNN) is a neural network with a deep structure where multiple layers are trained robustly and is widely used in computer vision [13]. It is a prominent topic regarding image recognition and classification [13, 14], but deep learning, in general, is still an active field in research [15, 14]. The core structure of a CNN includes (1) the convolutional layer, (2) the pooling layer, and (3) the fully connected layer. The convolutional layer isolates small areas of the image to determine their eigenvalues. However, if the convolutional kernel (weight filter) is bigger, image classification will be effective. To reduce the data dimension and prevent overfitting, the pooling layer downsampled the small regions of the images. Depending on the CNN architecture being used, this could be repeated. Still, after the characteristic data has been extracted, it will be sent to the following layer to create a fully connected layer that will be used to categorize and provide the result. The error of each layer is calculated to update the weight of each layer for the backpropagation training using the output result and the expected outcome. These repeated processes train the CNN to obtain suitable parameters to recognize images correctly [16, 14, 17]. With this core structure in mind, various research studies considered different CNN architectures to improve previous studies.

The study of Husnain et al. (2019) [18] proposed an architecture of a 2-layered CNN that uses the nonlinear rectification units (ReLu) function as the activation function. Their study focusedon Urdu Handwritten Numerals recognition with a result of 98.3% and Urdu handwritten character recognition with 96.04% accuracy, which overall showed that the proposed CNN model produced better accuracy compared to previous studies that used other classification models in predicting Urdu handwritten numerals and characters. Similarly, Morera et al. (2018)[8] used a CNN architecture with two layers. However, their study is regarding gender and handedness prediction. Specifically, Morera et al.'s (2018) [8] architecture has two stacks of convolutional and pooling layers and two final dense layers without padding to preserve spatial size. Moreover, all hidden layers have the ReLu function, and the output layer utilizes the SoftMax activation function. An important thing to note is that the binary class classification, namely "gender" and "handedness," was trained with Stochastic Gradient Descent. Still, the multiclass "gender-and-handedness" was trained with the Adam optimization algorithm. As aforementioned, their study achieved 68.90% accuracy in gender prediction, 70.91% in handedness prediction, and 70.84% in combined gender-and-handedness prediction using the KHATT Database, while with the IAM Database, 80.72% accuracy was achieved in gender prediction, 90.70% in handedness prediction, and 83.19% in combined gender-and-handedness prediction.

3. METHODOLOGY

This section discusses the methodology used in this research.

3.1. Data Gathering and Preparation

The English offline-handwritten text dataset, the IAM database, that Morera et al. (2018) used was also used in this study. The database contains XML files as metadata for the writers, and with this, information regarding the writers' gender and handedness was extracted from the file and used to label the images of handwritten texts appropriately. The database includes both an online and an offline version, but the researchers used the offline version, as pertained in the study's title.

3.2. System Architecture

The system architecture shown in Fig. 1 displays the different processes implemented in creating the Gender and Handedness Prediction System for Offline Handwriting. There are three phases contained in the system architecture: (1) Data Preparation, (2) Preprocessing, and (3) Classification.

The input section includes the Data Preparation phase. The original line images were split into a train and test set, after which word segmentation was performed. Data augmentation, which consists of scaling, rotation, dilation, and erosion, was applied to the train set images, which increased their amount and were split again into training and validation sets. Meanwhile, the testing dataset remained as is. All input images were resized by adding paddings with a uniform size of 30h × 100w resolution. Regarding the training and validation dataset, for both gender and handedness, 100,000-word images that have already gone through data augmentation (synthetic images) were used for training. Moreover, 20,000 and 25,000 synthetic images were used for validation datasets of gender and handedness, respectively. For the combined gender and handedness problem, 130,000 synthetic images were used as the training dataset, and 20,000 images were used for the validation dataset. The next phase is the Preprocessing phase, which includes Thresholding, Canny Edge Detection, and Normalization of the prepared images. Implementation-wise, the thresholding step is already built-in within the Canny Edge Detection function in the sklearn Library.

Table 1. Total Produce Trained CNN Models

12 Produced Models	
4 Architectural Models	**3 Classes**
*2L_CNN without CED	(1) For gender (2) For handedness (3) For gender-and-handedness
**2L_CNN with CED	
**3L_CNN without CED	
**3L_CNN with CED	

** base models; ** tuned models*

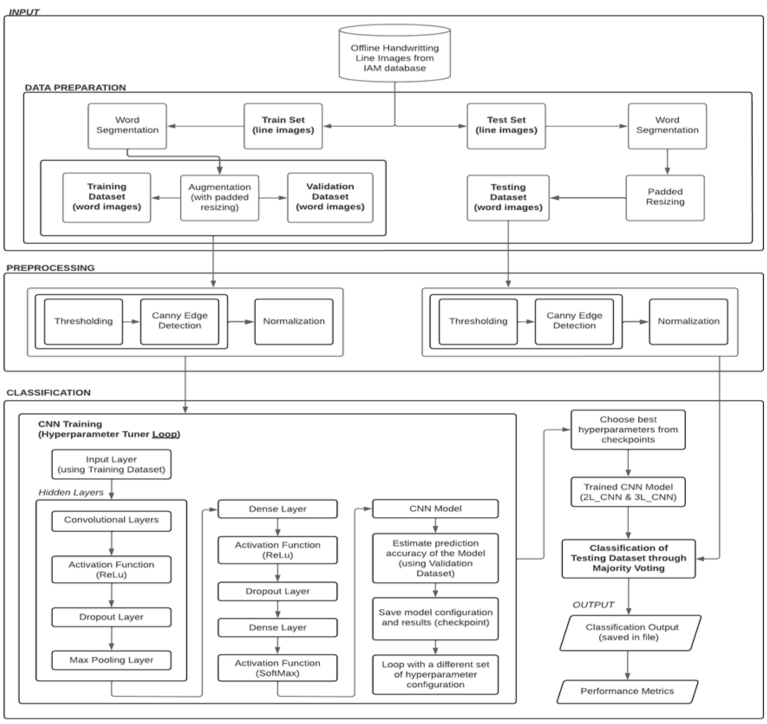

Figure 1. System Architecture

The classification phase used the preprocessed training and validation images as input for CNN training with hyperparameter tuning. Then, the preprocessed testing images were used to test the models with the trained CNN model. A majority voting scheme is done to finalize the prediction per test line image. The predicted subclass, e.g., male or female, with the majority of the votes, is chosen to be the subclass of the whole line image. The hidden layers in the systemarchitecture correspond to the number of CNN layers in which two hidden layers correspond to 2-layered CNN (2L-CNN) while three hidden layers correspond to 3-layered CNN (3L-CNN). Each of the four architectural models will have a corresponding classification model for each class, as shown in Table 1.

For each produced model, the input shape is a constant 30 height × 100 width resolution. All the convolutional layers used zero padding to preserve their size. The ReLU activation function was also used. A dropout layer and a max pooling layer followed the activation function. A flattened layer was applied after the last convolutional layer, followed by the first dense layer. Finally, the kernel size is 5 × 5, the max-pooling size is 2 × 2, and the number of units/filters for the dense layer, right before the output layer, is 512. For the base models, the first hidden layer used 128, 64, and 32 filters for gender, handedness, and gender-and-handedness, respectively, which doubled every hidden layer, e.g., 128 and 256 for the 2nd and 3rd layers of the handedness models. The dropout has a value of 0.25 for each hidden layer, and the first dense layer has a dropout value of 0.5. The optimizer functions utilized a 0.001 learning rate and $1x10^{-7}$ weight decay. For the tuned models, Bayesian Optimization was used to get the best hyperparameters, and similarly to the base model, zero-padding was also used. Only the first hidden layer filter was tuned, doubling the following hidden layers.

3.3. Hypotheses and Assumptions

This study aimed to compare the performance of gender and handedness prediction from offline handwritten images through the application of Convolutional Neural Networks based on the approaches of previous studies by Morera et al. (2018) and Ahlawat et al. (2020), with the addition of Canny Edge Detection. Thus, the following hypotheses were derived:

3.3.1. H_o : There is no significant improvement in the performance of the 2L-CNN model when implemented with CED*
H_a: There is a significant improvement in the performance of the 2L-CNN model when implemented with CED*

3.3.2. H_o : There is no significant improvement in the performance of the 3L-CNN model when implemented with CED*
H_a: There is a significant improvement in the performance of the 3L-CNN model when implemented with CED*

3.3.3. H_o : There is no significant improvement in the performance of 2L-CNN with CED when 3-layer was implemented*
H_a : There is a significant improvement in the performance of 2L-CNN with CED when 3-layer was implemented*

**in predicting (a) gender, (b) handedness, and (c) combined gender and handedness in offline handwriting.*

3.4. Statistical Treatment of Data

Slovin's formula, shown in equation (1), was used to reduce significantly the number of inputs utilized for the hyperparameter tuning process to increase time efficiency. This is used in determining the sample size of a population in which nothing is known. To determine the sample size, it was computed with an error tolerance of 0.01, where N is the population of the synthetic images per class and e is the error tolerance.

$$n = \frac{N_c}{1+N_c e^2} \quad (1)$$

In testing, the statistical treatment of data used is standard classification metrics such as overall accuracy, average accuracy, precision, recall, and F1-score, which were used to measure the system's effectiveness and draw the appropriate conclusions. Equations (2), (3), (4), and (5) show the formulas for the metrics mentioned earlier.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1\text{-}score = \frac{2(Precision)(Recall)}{Precision+Recall} \quad (4)$$

$$Overall_{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

Following Morera et al.'s (2018) study, precision and recall equations (6) and (7) are used to calculate the F1-score for the multiclass gender-and-handedness, where l = 4, representing the four subclasses of the multiclass.

$$Precision_C = \frac{cell_{C,C}}{\sum_{i=1}^{l} cell_{i,C}} \quad (6)$$

$$Recall_C = \frac{cell_{C,C}}{\sum_{j=1}^{l} cell_{C,j}} \quad (7)$$

Equations (8), (9), (10), and (11) can then be calculated for True Positive (TP), True Negative (TN), False Negative (FN), and False Positive (FP), respectively, where l = 4 also.

$$TP_C = cell_{C,C} \quad (8)$$

$$TN_C = \sum_{i=1}^{l} \sum_{j=1}^{l} cell_{i,j}, \text{ where } i, j \neq C \quad (9)$$

$$FN_C = \sum_{j=1}^{l} cell_{C,j} - cell_{C,C} \quad (10)$$

$$FP_C = \sum_{i=1}^{l} cell_{i,C} - cell_{C,C} \quad (11)$$

To compute the accuracy of each model for the multiclass gender-and-handedness using the equations (8), (9), (10), and (11), equation (12) was utilized for the average accuracy, where l = 4 as well.

$$Average_{Accuracy} = \sum_{c=1}^{l} \frac{TP_c+TN_c}{TP_c+TN_c+FP_c+FN_c} \div l \quad (12)$$

For the statistical analysis of the results, the Wilcoxon Signed-Rank Test, a non-parametric test, is used since the datasets have non-normal distribution due to the majority voting scheme. Since the objective is to know whether there is an improvement between the models being compared, a one-tailed test with a 0.05 significance level (α=0.05) is required, wherein if the p-value is less than the significance level (p<0.05). the null hypothesis is rejected. The formula for getting the p-value of the Wilcoxon Signed-Rank Test is shown in equation (13), where W+ is the positive rank sum of the positive differences of the paired accuracies from the compared models, and n is the number of handwriting input images.

$$Z = \frac{(W+ \; - \; n(n+1))}{4n(n+1)(2n+1)24} \tag{13}$$

With the aforementioned statistical metrics and methods above, a comparison was made between the different models and determined which model produced the best accuracy in predicting gender, handedness, and gender-and-handedness.

4. Results and Discussion

The actual training of the models was preceded by the hyperparameter tuning, where Slovin's formula was used, and then, the testing was done to determine the accuracy of the models.

Table 2. Standard hyperparameters of the Base Models, the Best Hyperparametrs of Tuned Models, and the Maximum Number of Epochs During the Training Process

Base Models						
Model	**f**	**dl**	**dd**	**lr**	**wd**	**epochs**
G-2L-NC	128	0.25	0.5	0.001	1e-7	194
G-2L-NC	64	0.25	0.5	0.001	1e-7	411
GH-2L-NC	32	0.25	0.5	0.001	1e-7	122
Tuned Models						
Model	**f**	**dl**	**dd**	**lr**	**wd**	**epochs**
G-2L-WC	32	1e-4	0.5	0.01	2.32e-7	84
G-2L-WC	128	0.5	1e-4	0.01	1e-8	79
GH-2L-WC	96	0.5	0.5	1e-4	1e-8	78
G-3L-NC	128	1e-4	0.5	0.01	1e-8	190
G-3L-NC	128	0.5	0.5	0.01	1e-06	177
GH-3L-NC	32	0.5	0.5	1e-4	1e-6	148
G-3L-WC	128	1e-4	1e-4	0.01	1e-8	94
G-3L-WC	128	1e-4	0.5	0.01	1e-6	64
GH-3L-WC	32	0.5	0.5	1e-4	1.91e-8	197

The hyperparameters that were tuned are filters (f), dropout regularization for all convolutional layers (dl), dropout regularization for the dense layer before the output layer (dd), and the learning rate (lr), as well as the weight decay (wd), for the optimizer function. The tuning is done for all models of each class, which are gender (G), handedness (H), and combined gender-and-handedness (GH), on 2-layered (2L) and 3-layered (3L) CNN, With (WC) andWithout

(NC) CED, except for the base models (2L-CNN without CED). Table II shows the best hyperparameters found by the Bayesian Optimization tuning technique for each of the nine tuned models, as well as the standard hyperparameters of the base models for comparison, together with the maximum number of epochs during training after the Early Stopping was called.

Table 3. Performance Results of 2L-CNN for Each Class

Subclass	Metrics	With CED %	Without CED %
GENDER			
M	F1-score	63.76	73.06
F		46.58	62.11
	Overall Accuracy	56.81	68.50
HANDEDNESS			
R	F1-score	85.85	94.35
L		22.77	45.25
	Overall Accuracy	76.08	89.75
COMBINED GENDER-AND-HANDEDNESS			
RM	F1-score	55.79	55.08
LM		19.69	15.13
RF		48.72	42.73
LF		24.72	21.11
	Average Accuracy	48.61	45.11

The testing results were based on the accuracy and F1-scores of all the models for each class, in which Tables 3 and 4 show the performances of 2L-CNN and 3L-CNN models, respectively.

For the statistical treatment, comparisons were made between 2L-CNN with and without CED and between 3L-CNN with and without CED to determine if there was a significant improvement when Canny Edge Detection was applied to the models. Additionally, 2L-CNN and 3L-CNN, both with CED, were also compared to identify if there was any significant improvement when an additional layer was implemented. The one-tailed Wilcoxon Signed-Rank Test was implemented with the scipy.stats module.

To find out if there is a significant improvement between the accuracies of the two 2L-CNN models, which are with and without CED, the hypotheses were:

- H_o : 2L-CNN without CED ≥ 2L-CNN with CED
- H_a : 2L-CNN without CED < 2L-CNN with CED

Table 4. Performance Results of 3L-CNN for Each Class

Subclass	Metrics	With CED %	Without CED %
GENDER			
M	F1-score	64.76	64.53
F		46.77	46.51
	Overall Accuracy	57.59	57.35
HANDEDNESS			
R	F1-score	84.74	91.53
L		24.89	38.83
	Overall Accuracy	74.63	85.12
COMBINED GENDER-AND-HANDEDNESS			
RM	F1-score	58.16	56.48
LM		25.26	28.41
RF		48.95	51.59
LF		20.22	31.07
	Average Accuracy	50.47	51.36

Regarding the significant improvement between the accuracies of the 3L-CNN, with and without CED, the hypotheses were:

- H_o : 3L-CNN without CED ≥ 3L-CNN with CED
- H_a : 3L-CNN without CED < 3L-CNN with CED

Table 5. One-Tailed Wilcoxon Signed-Rank Test Results Between the Accuracies of the Compared Models

Compared Models	Gender	Handedness	Gender-and-handedness
2L-CNN With versus Without CED	0.95096 > 0.05	1.0 > 0.05	0.00032 < 0.05
3L-CNN With versus Without CED	0.52402 > 0.05	1.0 > 0.05	0.98815 > 0.05
2L-CNN versus 3L-CNN, With CED	0.80659 > 0.05	0.99768 > 0.05	0.02633 < 0.05

Lastly, 2L-CNN and 3L-CNN, both with CED, were compared to determine if there was a significant improvement between the accuracies of the models. The hypotheses were as follows:

- H_o : 2L-CNN with CED ≥ 3L-CNN with CED
- H_a : 2L-CNN with CED < 3L-CNN with CED

And for all the hypotheses, the null hypothesis will be rejected if the p-value is less than the 0.05 significance level. Table 5 shows the results (p-value – alpha) of the Wilcoxon Signed-Rank Test computation.

It can be inferred that there was a significant improvement in the combined gender-and-handedness on 2L-CNN. However, the 3L-CNN did not improve at all when CED was applied. On the other hand, between the 2L-CNN and 3L-CNN (both with CED), there wasa significant improvement in adding another layer to the combined gender and handedness class. At the same time, there was no significant improvement for both the gender and handedness classes.

5. CONCLUSIONS

With the study of Morera et al. (2018) and their CNN architecture being utilized but with padded resizing instead, as well as the strategy of Ahlawat et al. (2020) on experimenting with different multi-layered CNN architectures, this study focused on 2L-CNN and 3L-CNN (multi-layered CNN), with binary (gender and handedness) and multiclass classifications (gender-handedness).

In terms of applying CED to the models, CED only significantly improved the 2L-CNN and 3L-CNN on multiclass classification.

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