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Transfer Learning to Detect Age From Handwriting

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Abstract

Handwriting analysis is the science of determining an individual's personality from his or her handwriting by assessing features such as slant, pen pressure, word spacing, and other factors. Handwriting analysis has a wide range of uses and applications, including dating and socialising, roommates and landlords, business and professional, employee hiring, and human resources. This study used the ResNet and GoogleNet CNN architectures as fixed feature extractors from handwriting samples. SVM was used to classify the writer's gender and age based on the extracted features. We built an Arabic dataset named FSHS to analyse and test the proposed system. In the gender detection system, applying the automatic feature extraction method to the FSHS dataset produced accuracy rates of 84.9% and 82.2% using ResNet and GoogleNet, respectively. While the age detection system using the automatic feature extraction method achieved accuracy rates of 69.7% and 61.1% using ResNet and GoogleNet, respectively.

Keywords: Transfer learning, Handwritten analysis, Gender detection, Age detection.

1. INTRODUCTION

Handwriting is a mirror that reflects the writer's personality traits and demographic characteristics. As a result, handwriting analysis is now used in a wide range of fields, including medicine, socialisation, and security. The identification of a person's biometric information from handwriting has recently been a significant topic in research. As a consequence, we decided to focus our efforts on determining gender and age from handwriting, as the former is important in psychology, document analysis, paleography, graphology, and forensic investigation. On the other hand, the latter is crucial in medical diagnosis and forensic analysis.

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The manual method of handwriting analysis has a number of drawbacks, including the fact that the correctness of the analysis is largely dependent on the graphologist's skills, as well as the fact that it is time-consuming and exhausting. Furthermore, the graphologists' analysis may be influenced by the content of the handwriting. These flaws provide an impetus to develop an automatic tool that extracts features and analyses writer behaviour using a computer rather than requiring human contact [1]. Our research focuses on automatically detecting biographic features, such as the gender and age of the writer of a handwritten document, using the knowledge of two CNN architectures: ResNet and GoogleNet.

To conduct the aforementioned experiment, we created a new dataset of Arabic handwriting for various human interaction research purposes, such as handwriting recognition, gender classification, and age classification.

2. RELATED WORKS

Several databases have been used to research handwriting analysis and recognition such as IFN/ENIT [2], AHDB [3], MADCAT [4], QUWI [5], ICDAR2013 [6], LAMIS-MSHD [7], KHATT [8], ALTID [9] and AWIC2011 [10]. However, The language utilised, the number of writers, the amount of documents, and the method of collecting samples (online or offline) all differ amongst these databases.

Many researchers used these datasets to deduce gender and age from handwritten papers. Deep learning has recently become a popular method for image classification and feature extraction. Illouz et al. [11] used a convolution neural network (CNN) to extract features from 405 participants' Hebrew and English handwriting samples and classify the writer's gender. The system was trained on Hebrew samples before being tested on English samples, resulting in a classification accuracy of 75.65%. They scored 85.29% after training the system on English samples and tested it on Hebrew samples. Morera et al. [12] used the IAM and KHATT datasets to train and validate their deep learning approach for gender detection. They achieved 80.72% and 68.90% accuracy, respectively. While Rabaeve et al. applied their system to ICDAR2013 to detect the gender of writers and they got 67% and 50% accuracy rates when applied to the English and Arabic subsets, respectively. Xue et al. [13] used attention-based two-pathway Densely Connected Convolutional Networks (ATP-DenseNet) to detect the gender of writer. They extracted the handwriting features in two pathways. First, the ATP-DenseNet, which extracts hierarchical page features. Second, attention-based DenseNet (A-DenseNet) extracts the word features. Their work produced classification rates of 65.2%, 77.6% and 74.1% when applied on ICDAR2013, IAM and Khatt datasets, respectively.

Few researchers in the literature have studied the problem of automatic age detection from handwriting. These studies vary in age groups to be detected and the extracted features proposed to detect age. Basavaraja et al. [14] proposed a new method to estimate age from handwriting based on extracting disconnectedness features using Hu invariant. The two public datasets, IAM [2] and Khatt [8], were divided into two classes. As a result, an accuracy rates of 66.25% has been achieved using the IAM dataset and 64.44% using the Khatt dataset. Marzinotta et al. [15] provided a method to classify age and gender from online handwriting features available in the IRONOFF [16], dataset in French and English languages. Their work is a two-layer schema. Bouadjenek et al. [17] introduced two gradient features to classify the writer's age, gender and handedness: the histogram of oriented gradients and gradient local binary patterns. They used the Support Vector Machine (SVM) [18], method to classify the documents. IAM and Khatt datasets were used to evaluate the system. They got a 70% accuracy rate when using the IAM dataset and a 55% accuracy rate when using Khatt dataset. Almaadeed and Hassaine [19] developed a handwriting analysis method to classify people by their age, gender, and nationality. They used random forests and kernel discriminant analysis to extract a set of geometrical features. The OUWI [5] dataset was used to test their approach, and the accuracy rates were 55.7% and 60.62%, respectively. for age detection when all writers produced the same handwritten text and when each writer produced different handwritten texts, respectively. Marzinottto et al. [20] proposed an online age classification system based on a two-level clustering scheme. Supervised learning then is used to categorise the handwritten documents in terms of age. A dataset sample acquired from Broca Hospital in Paris was used to conduct the experiments. The writer ages range between 60 and 85 years old. Their approach came out with the following findings: first, people above 65 years old present three handwritten patterns regarding the dynamic features, pen pressure and time on air. Second, people aged above 80 years have almost the same unique style with lower speed.

3. DATASET PREPARATION AND IMAGE ACQUISITION

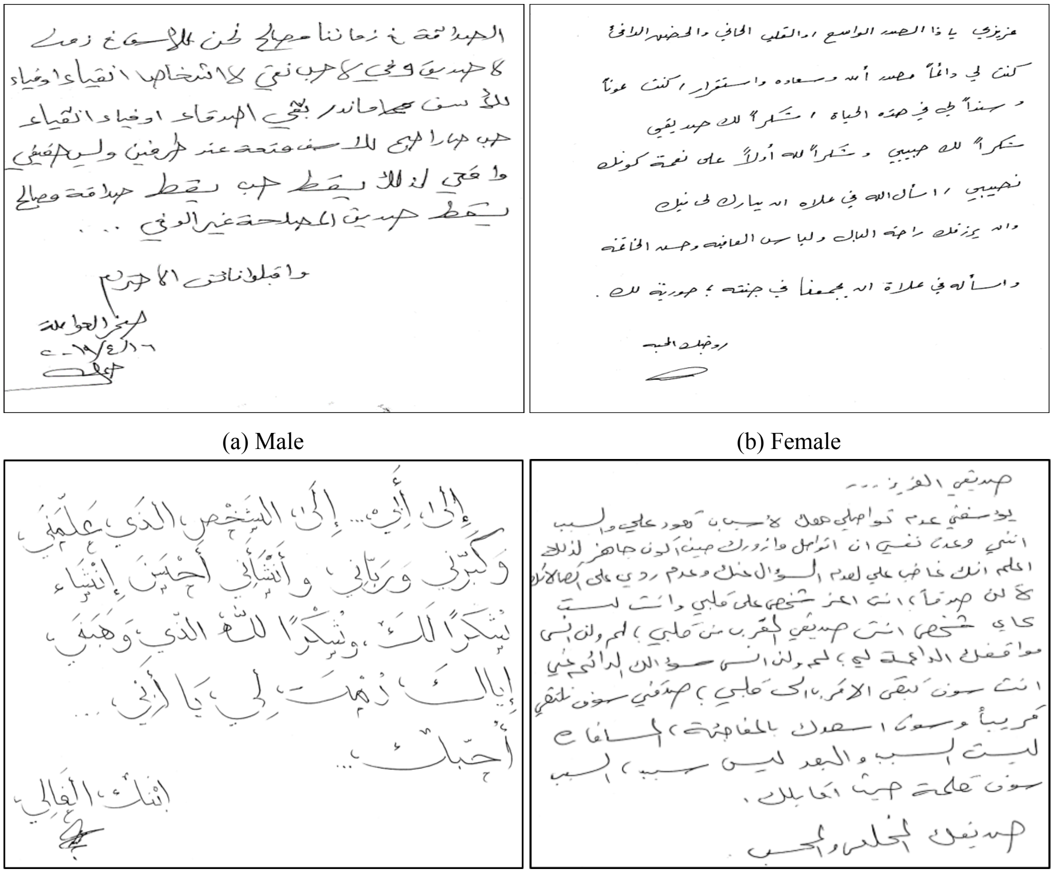
Handwriting analysis and recognition research has been conducted using a variety of databases. The language utilised, the number of writers, and the amount of documents in these databases, however, varied. To train and test the proposed approach, we generated an Arabic handwritten dataset. It was gathered in Jordan's capital city, Amman. The Free-Style Handwritten Samples was the name we gave to it (FSHS) [21].

A total of 2,000 volunteers were asked to write a letter to someone they care about that was large enough to include all of the diverse handwriting styles. Some volunteers were also requested to copy a few paragraphs. There were no restrictions on the type of writing equipment used to accommodate the writers' comfort. However, a white sheet of paper was provided on which to write their letter. Although the majority of the documents in the collection are text-independent, roughly 500 of them are text-dependent samples. Some text-independent specimens about gender and age are shown in FIGURE 1.

The ages of the writers span from 15 to 75. To collect the dataset from the educational institution (schools and universities), we had to get a permission from the head of each department to arrange the time slot and the place for collecting the samples. Then, twenty to thirty minutes were given to the volunteers to complete the form and write their letters. Volunteers were invited to fill up a questionnaire about their gender, age, handedness and work position. FIGURE 2 shows the information page used to collect the writer information for labelling purposes.

The process of labelling the handwritten documents was as follows. First, each sample was given a unique identifier in an Excel sheet ($Doc_1, Doc_2, Doc_3, ...Doc_n$). Second, the writers' information was then extracted from the information page and saved for each document, like in TABLE 1, which shows the labelling of five different handwritten specimens.

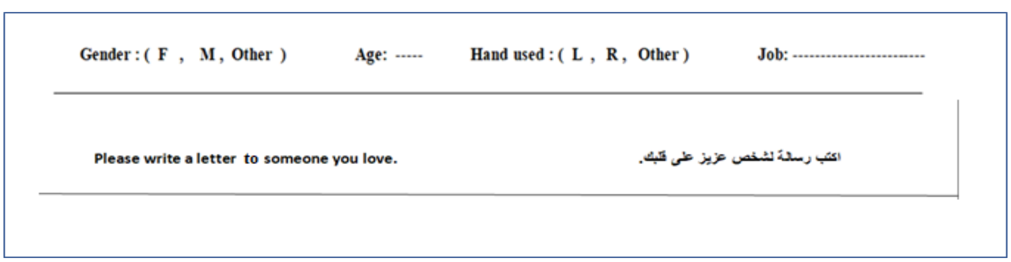
We have carried a comprehensive manual cleaning process for all the dataset documents. As a result, we excluded the empty samples, files with no information about the writer, and documents with less



(a) Male (b) Female

(c) Youth (d) Adult

Figure 1: Samples of the dataset (FSHS) in terms of gender and age.


Gender : (F , M , Other) Age: ----- Hand used : (L , R , Other) Job: -----------------------

Please write a letter to someone you love. اكتب رسالة لشخص عزيز على قلبك.

Figure 2: Information page of samples in the dataset.

than five text lines. For example, some of the writers draw ruled lines on the white papers, which do not concern our work. The total number of the excluded samples is 272.

The size of our dataset, as well as the number of authors, are noteworthy. The wide range of ages and the large number of authors were responsible for the wide range of handwriting styles. Although the majority of the documents in the dataset are written in Arabic, there are about 15 instances written in English. In total, the dataset contains 2428 digitized pages after cleaning. 43% of the samples were written by males, which equals to 1044 documents, and 57% were written by female writers,

Table 1: Example of labelling five handwritten documents of the FSHS dataset.

	Gender	Age	Handedness	Position	Label
Doc1	Female (F)	16	Right (R)	School Student (SS)	F_15_R_SS
Doc2	Male (M)	20	Left (L)	University Student (US)	M_20_L_US
Doc3	Male (M)	30	Right (R)	Public Job (PJ)	M_30_R_PJ
Doc4	Female (F)	35	Right (R)	Private Job (PRJ)	F_35_R_PRJ
Doc5	Female (F)	45	Right (R)	No Job (NJ)	F_45_R_NJ

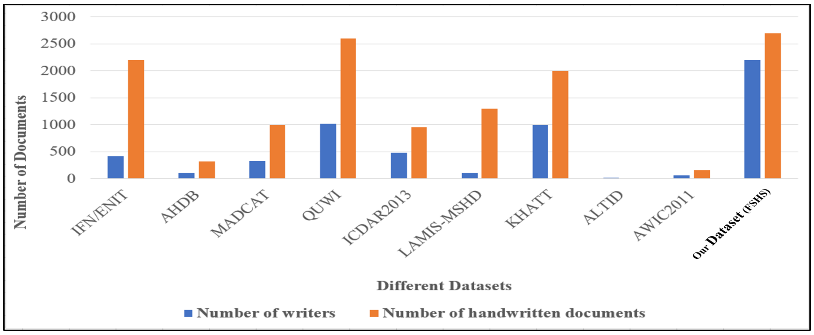
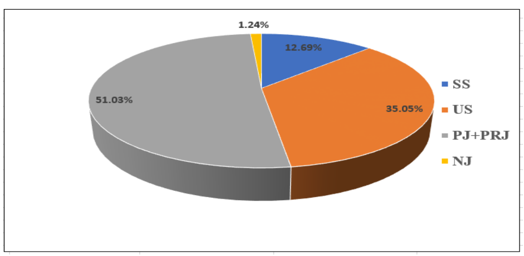
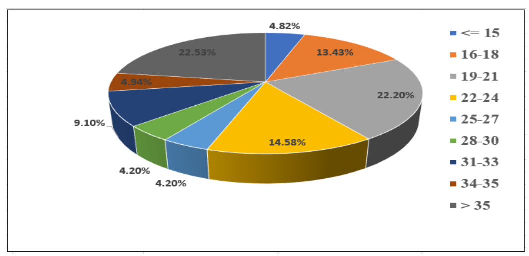


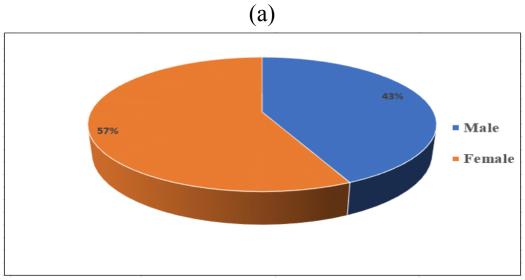
Figure 3: Comparison between our dataset and other datasets.



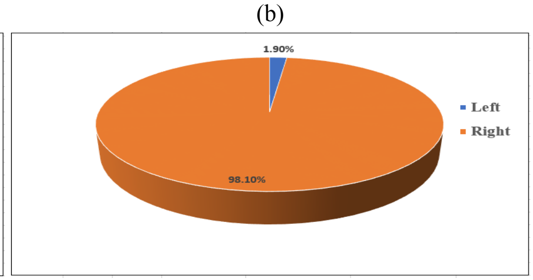
(a)



(b)



(c)



(d)

Figure 4: Distribution of writers with respect to (a) Occupation, (b) Age, (c) Gender and (d) Handedness.

which equals to 1383 documents. Each page includes a minimum of five lines with 12140 lines for the whole dataset. Each text line contains approximately ten words yielding 121400 words for the entire dataset.

FIGURE 3 shows a comparison between our dataset (FSHS) and state of the art Arabic datasets. It can be noticed that the FSHS dataset has the highest number of writers and documents among the other available datasets. FIGURE 4 shows the statistics of all writers' demographics information. As shown, most writers used the right hand to write, as their percentage was 98.1%. While the older subjects were divided into two age ranges: the first 19 and 21 range and the second is over 35 years old. Regarding the occupation, the highest percentage was workers. The FSHS dataset can be used in many research areas related to human interaction, such as handwriting recognition if appropriately labelled, gender, and age classification.

4. AUTOMATIC FEATURE EXTRACTION USING TRANSFER LEARNING

Transfer learning relies on utilizing the knowledge of a pre-trained networks. It helps to automatically extracts the features without the need of typical machine learning approaches. However, to get a decent results using transfer learning, the dataset must be sufficient [22, 23]. Thus to address this issue, the transfer-learning was evolved. In the transfer learning method, the learning process is faster, more precise, and needs fewer training samples as well as learning new task based on a pre-trained task. While on the other hand, in the traditional machine learning systems, each task is carried out separately, and no knowledge is transferred between tasks [24].

In our experiment, we used GoogleNet [25] and ResNet [26] architectures to automatically extract the features from the handwritten documents and fed them to an SVM classifier to detect gender and age of the writer. These CNN architectures have been trained over a million images from ImageNet, and they can classify images into 1000 categories. Training a network deeper makes the training processes very difficult. As the gradients become small, therefore, the weights become unchanged constant, leading to a halt in the network learning process, which affects the network ability to do well. The residual network is a powerful way to solve the vanishing gradient problem. ResNet has residual blocks (skip connections) to jump over layers. It speedup learning by using a fewer number of layers to propagate through [26]. On the other hand, GoogleNet is an inception network. It helps to reduce the computation cost by using 1x1 convolution layer(bottleneck), which is used as a non-linear dimension reduction module [25]. FIGURE 5 shows the structure of the automatic feature extraction.

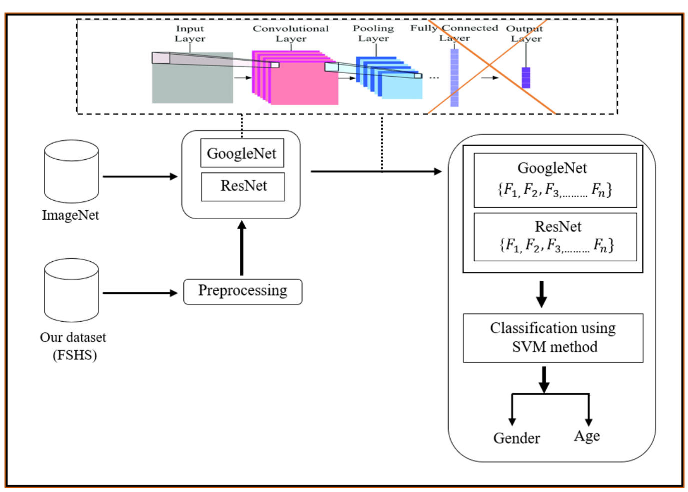


Figure 5: Structure of transfer learning method.

In their first convolutional layer, most convolutional neural networks learn to spot features like colour and edges. The network learns to detect more complex features as it progresses through the convolutional layers. The features of later layers are built up by merging the features of earlier ones. We applied the Stand-Alone Extractor approach, in which pre-trained layers are used to extract image features only once. The retrieved features would then be combined to generate a new dataset that does not require image processing.

In our proposed work, The architecture of the pre-trained model was employed to extract features from our input dataset automatically. Only the Convolutional and Pooling layers were imported, but the "upper portion" of the model was left out (the fully-Connected layer), which can be seen in FIGURE 5. Deeper layers of each CNN were used to extract features, which were then sent to an SVM classifier. We used the output of "Pool5" layer and the "inception_4e-1x1" layer from both ResNet and GoogleNet architectures, respectively.

5. EXPERIMENTS AND RESULTS

This section presents the experiments and the results obtained by the proposed systems. the experimental setup is described in section 5.1. The results are analyzed and discussed in section 6.

5.1 Experimental Setup

Gender Detection System Experimental Setup: The FSHS dataset (Section 3) consists of 2424 samples handwritten by 57% female writers and 43% male writers. 2000 samples, divided equally between female and male handwritten documents, were chosen to run the experiments and evaluate the proposed method where 70% of the documents were used for training, 15% for testing and 15% for validation.

To compare the performance of our proposed method with other researcher works, we applied our system to the public Kaggle (ICDAR2013) dataset, consisting of 1900 images written by 475 writers in Arabic and English. We used both languages individually to train and test our system. Again, 70% of each category was used for training, 15% for testing and 15% for validation.

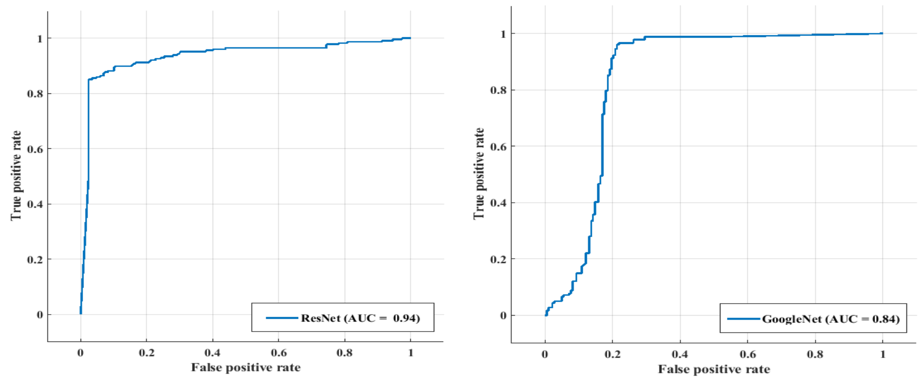
Age Detection System Experimental Setup: We used a subset of the FSHS dataset consisting of 2000 samples in our experiments. The images were divided into two main classes: youth adult class with ages ranging between 16 and 24 years old, and Mature adult class with ages ranging from 25 to 55, where each class has 1000 samples. To run the experiments and evaluate the proposed method, 70% of the documents were used for training, 15% for testing and 15% for validation.

6. EVALUATION

Our study is a two-class classification problem, with the outcomes being either a young adult writer or a mature adult writer. The transfer learning technique was used to automatically extract the features from the handwritten documents using multiple CNN architectures. The accuracy, precision, and recall metrics were used to evaluate the proposed method.

Table 2: Results of applying transfer learning method to the FSHS dataset.

CNN	Accuracy (100%)	Precision (100%)		Recall (100%)	
		Female	Male	Female	Male
ResNet	84.9	77.7	92.1	90.8	80.5
GoogleNet	82.2	65.6	98.9	98.4	74.1



(a) (b)

Figure 6: ROC curves and AUC values of (a) ResNet and (b) GoogleNet applied to the FSHS dataset.

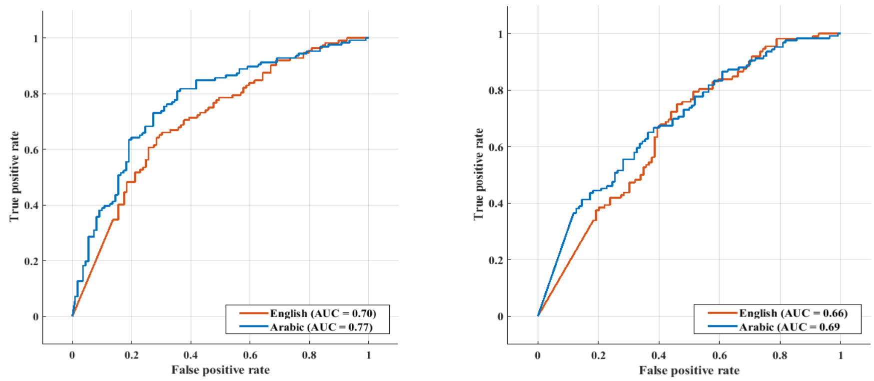
Table 3: Results of applying transfer learning method to the ICDAR2013 dataset.

CNN	Language	Accuracy (100%)	Precision (100%)		Recall (100%)	
			Female	Male	Female	Male
ResNet	English	66.06	67.9	64.2	66.1	66
	Arabic	72	75.4	68.2	73.1	70.8
GoogleNet	English	63.3	67.9	58.7	62.8	64
	Arabic	64	66.7	60.9	66.1	61.5

6.1 Gender Detection System Evaluation

TABLE 2 shows the accuracy, precision, and recall values achieved from applying transfer learning to the FSHS dataset using ResNet and GoogleNet architectures. ResNet attained an accuracy of 84.9%, which is higher than the accuracy reached by GoogleNet, which is 82.2%. FIGURE 6 also shows the ROC and AUC values for the two architectures. For example, the ResNet in (a) has a greater AUC value of 93.5%, whereas the googleNet in (b) has an AUC value of 84.35%.

Moreover, the experimental results of implementing the proposed automatic feature extraction methods on the ICDAR2013 (Kaggle) dataset are also shown in TABLE 3. When applied to English and Arabic subsets, the ResNet network had a better accuracy rate of 66.06% and 72%, respectively. The results of ResNet in terms of accuracy outperform the results obtained by Xue et al. [13] and Rabaev et al. [27], both of which used deep learning in their methodologies. The two CNN architectures were also evaluated using ROC and AUC on the ICDAR2013 dataset. The ROC curves of (a) ResNet and (b) GoogleNet are shown in FIGURE 7. When applied to the Arabic and English

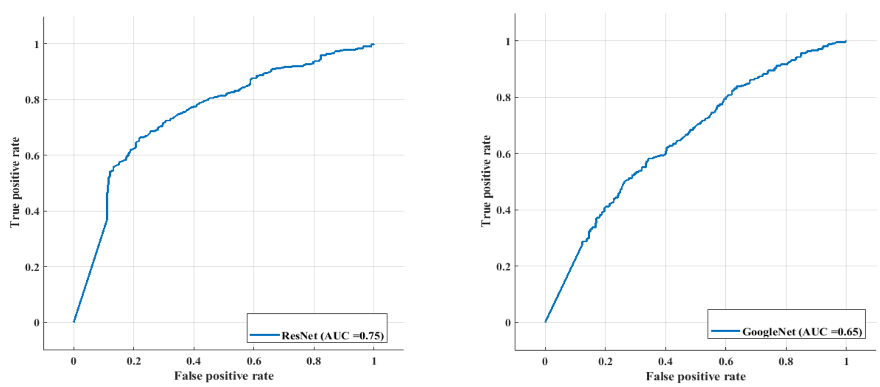


(a) (b)

Figure 7: ROC curves and AUC values of (a) ResNet and (b) GoogleNet applied to the ICDAR2013 dataset.

Table 4: Results of applying the proposed automatic feature extraction method to the FSHS dataset.

CNN	Accuracy (100%)	Precision (100%)		Recall (100%)	
		Youth (Adult)	Mature (Adult)	Youth (Adult)	Mature (Adult)
ResNet	69.7	64.8	74.8	72.9	67
GoogleNet	61.1	63.2	58.9	61.6	60.5



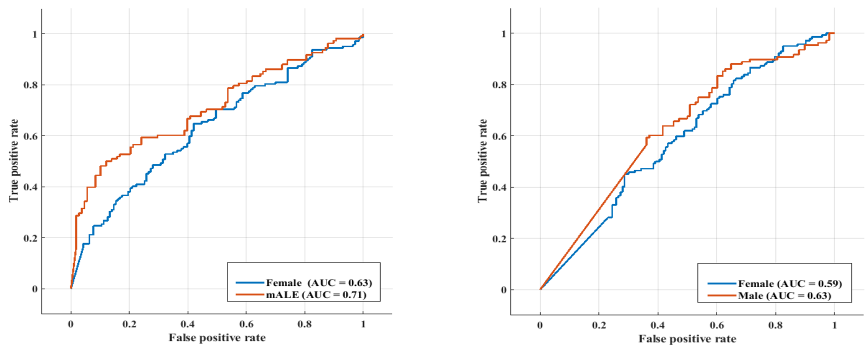
(a) (b)

Figure 8: ROC curves and AUC values of applying transfer learning to FSHS dataset using (a) ResNet and (b) GoogleNet.

subsets, the ResNet has an AUC of 0.77 and 0.70, respectively. While the GoogleNet has an AUC values of 0.69 and 0.66 when applied on Arabic and English subsets, respectively.

Table 5: Results of applying the transfer learning technique to the female and male subsets of FSHS dataset.

CNN	Subsets	Accuracy (100%)	Precision (100%)		Recall (100%)	
			Youth (Adult)	Mature (Adult)	Youth (Adult)	Mature (Adult)
ResNet	Female	60.4	58	62.7	61	59.7
	Male	61.6	55.6	67.6	63.2	60.3
GoogleNet	Female	56.5	51	62	57.5	55.7
	Male	59.7	39.8	79.6	66.2	57



(a) (b)

Figure 9: ROC curves and AUC values of applying Transfer learning using (a) ResNet and (b) GoogleNet to female and male subsets of the FSHS dtataset.

6.2 Age Detection System Evaluation

TABLE 4 displays the outcomes of applying transfer learning to the FSHS dataset using ResNet and GoogleNet architectures, in terms of accuracy, precision, and recall. ResNet achieved an accuracy of 69.7%, which is higher than GoogleNet's accuracy of 61.1%. Moreover, FIGURE 8 also shows the ROC and AUC values for the two architectures. For example, the ResNet in (a) has a greater AUC value of 0.75, whereas the GoogleNet in (b) has an AUC value of 0.65.

The transfer learning technique was also applied to two separate subsets of the FSHS dataset: female and male subsets. The results of utilising ResNet and GoogleNet for female and male subsets are shown in TABLE 5. When applied to the male subset, the ResNet had a better accuracy rate of 61.6%, compared to 60.4% when applied to the female subset. GoogleNet, on the other hand, appears to be better when applied to the male subset, with an accuracy rate of 59.7%, but only 56.5% when applied to the female subset.

FIGURE 9 shows the ROC curves and AUC values of applying the transfer learning technique to the female and male subsets. The AUC values of 0.63 and 0.71 obtained by applying the ResNet to female and male subsets are shown in FIGURE 9 (a). FIGURE 9 (b) depicts the ROC and AUC values obtained from applying GoogleNet on the female subset, with an AUC of 0.59 and an AUC of 0.63 when applied to the male subset.

7. CONCLUSION AND FUTURE WORKS

This study demonstrates that employing a computer to detect gender and age from handwritten documents without human involvement is a viable option. Gender detection from handwritten images is a widely discussed topic in a variety of fields, including psychology, document analysis, and forensics. At the same time, age detection systems are crucial in the forensic and health care fields.

The features extracted from handwritten documents determine the success of handwritten classification systems, which is a difficult task due to the high degree of similarity between people's handwriting. In this research, transfer learning technique was utilised to automatically extract features. These features were then fed to SVM classification method to detect gender and age of the writer. Moreover, we propose a new Arabic dataset written by 2200. This dataset can be used for several research purposes such as gende and age detection and handwriting analysis and recognition. The dataset is available upon request. For the future work, new languages will be analyzed to detect the age and the gender of the writer. In addition to exploring new writer characteristics to be detected from handwritten documents.

8. ACKNOWLEDGEMENTS

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