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Classification of Handwritten Text Signatures by Person and Gender: A Comparative Study of Transfer Learning Methods

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Abstract

The writing process, in which feelings and thoughts are expressed in writing, differs from person to person. Handwriting samples, which are very easy to obtain, are frequently used to identify individuals because they are biometric data. Today, with human-machine interaction increasing by the day, machine learning algorithms are frequently used in offline handwriting identification. Within the scope of this study, a dataset was created from 3250 handwritten images of 65 people. We tried to classify collected handwriting samples according to person and gender. In the classification made for person and gender recognition, feature extraction was done using 32 different transfer learning algorithms in the Python program. For person and gender estimation, the classification process was carried out using the random forest algorithm. 28 different classification algorithms were used, with DenseNet169 yielding the most successful results, and the data were classified in terms of person and gender. As a result, the highest success rates obtained in person and gender classification were 92.46% and 92.77%, respectively.

Keywords

Offline Handwriting Recognition; DenseNet169; Machine Learning.

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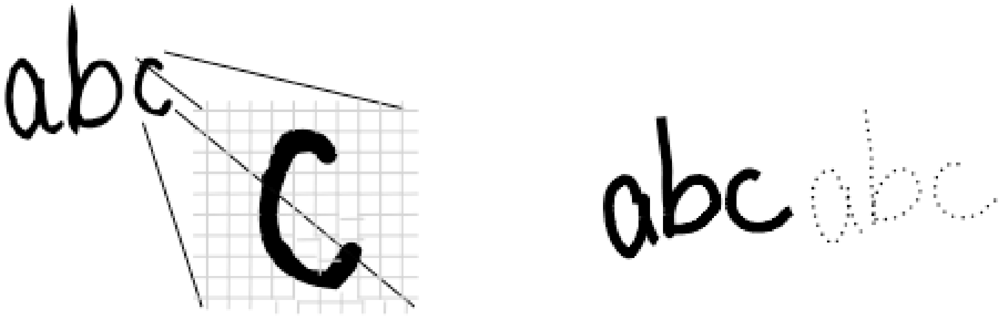
1 Introduction

With the development of information and communication technologies, many transactions are now carried out much faster. Thanks to these systems, it is very easy to reach and transfer the desired information in the digital environment. With the advantages of technology, documents are created and completed in a digital environment. However, today, many documents are still completed with handwriting and then transferred to digital media. These handwritten documents must first be digitized in order to make them workable before being transferred to digital media. The path followed for transferring documents to the computer environment is usually by one or more people making separate transactions for each document. Therefore, this process is quite long and open to incorrect data entry (Şekerci, 2007). The solution to this emerging problem is to digitize the printed documents by means of handwriting recognition systems while they are transferred to the computer environment. Handwriting recognition systems are used to carry out the processes of identifying and interpreting handwritten letters, numbers and symbols on paper, tablets and smartphones (Erdoğan & Tümer, 2021). With the need for handwriting recognition systems, digital writing is integrated into smart systems and offered to individuals with many electronic tablets and smart pens. Today, handwriting recognition systems aiming to facilitate communication between human and machine are used in many areas such as banking services, signature verification systems, education, health and security (Demirkaya & Çavuşoğlu, 2021).

The writing process is a cognitive activity in which words, feelings and thoughts are expressed in writing, and handwriting differs from person to person (Pal & Singh, 2010). Handwriting is not easily recognized by computers. There are many different writing styles/numbers and symbols, letters are written together, the pen or paper structure used and the way/size of the letters differ according to the individual's writing style and speed (Erdoğan & Tümer, 2021). Handwritten character/number recognition is divided into two groups: interactive (online) and non-interactive (offline), depending on the method of obtaining the input data (Plamondon & Srihari, 2000). Non-interactive methods consist of first writing text on paper and then digitizing it and making it workable in the computer environment (Najadat et al., 2019). The non-interactive handwriting/character recognition process consists of preprocessing, segmentation or fragmentation, feature extraction, recognition and postprocessing. In the process of defining non-interactive handwriting, first of all, the document must be converted into a digital form. In document analysis, paragraph, sentence and word division operations should be performed respectively. If the processed document is a form that needs to be filled, the words to be recognized should be divided (Intrator et al., 1999). Interactive methods, on the other hand, are systems developed for recognizing the writing process by monitoring the coordinate movements of the pen while writing text with smart pens on devices such as phones and tablets with touch-enabled features (Ahmad et al., 2004). As can be seen in Figure 1, in the handwriting identification process, offline methods are available as text and images, while in online methods, two-dimensional coordinates of consecutive points of the text are used (Rao & Aditya, 2014).

Handwriting is frequently used by people in daily life (Topaloglu & Ekmekci, 2017). Both online and offline handwriting analysis has become increasingly popular in recent years (Ibrahim et al., 2014). Since handwriting differs from person to person, it is very difficult to identify person and gender from handwriting samples (Navya et al., 2018). The analysis is used in areas that require crime detection and verification of reality, such as identifying person and gender from handwriting, forensic analysis procedures, document authorization activities, verifying the accuracy of historical handwritten samples (Kalsi & Rai, 2017; Bouadjenek et al., 2014; Ibrahim et al., 2014; Bulacu & Schomaker, 2007; Siddiqi & Vincent, 2010; Al-Maadeed & Hassaine, 2014; Djeddi et al., 2013; Yang et al., 2016). As a result of the widespread use of handwriting samples for the solution of real-life problems, the population should be divided into certain subclasses such as gender, age, nationality and hand used for writing (right/left). Thus, handwriting samples can be used for diagnostic purposes in various social, psychological and criminological studies (Bouadjenek et al., 2014; Ibrahim et al., 2014). For example, investigation of crimes generally involves examining documents containing samples of handwriting. Forensic medicine investigators use handwriting samples to identify individuals in these cases (Ibrahim et al., 2014).



Non-interactive (offline) method *Interactive (online) method*

Figure 1. *Examples of non-interactive and interactive handwriting identification. Source: (Rao & Aditya, 2014).*

In forensic and demographic research, it is very important to classify the population according to its biometric characteristics. For example, estimating the age or gender of the author from a handwritten document examined within the scope of the study helps establish the research scope with a more limited population category (Bouadjenek et al., 2015). Gender identification is also very popular in determining the age and psychological state of individuals. It is possible to make predictions about the characteristics of the person writing the text from handwriting samples (Topaloglu & Ekmekci, 2017; Gawda, 2008). Similarly, as a result of developments in technology, identity security is becoming an important issue today. Handwritten signature samples are unique biometric data that are different for everyone, and each individual can identify himself using a handwritten signature. Gender identification is also one of the key features used in human identification situations (Maji et al., 2015).

The following handwritten character/number recognition methods have been used: deep neural network – DNN, convolutional neural network – CNN (Najadat et al., 2019; He et al., 2015; Yuan et al., 2012; Zhao & Liu, 2020), artificial neural network – ANN (Ahmad et al., 2004; Demirkaya & Çavuşoğlu, 2021; Knerr et al., 1992; Seong-Whan, 1996; Lemarié, 1993; Mai & Suen, 1990; Pal & Singh, 2010), support vector machine – SVM (Ahmad et al., 2004; Dağdeviren, 2013; Demirkaya & Çavuşoğlu, 2021; Karakaya, 2020; Sadri et al., 2003), and decision tree – DT (Demirkaya & Çavuşoğlu, 2021; Karakaya, 2020; Topaloglu & Ekmekci, 2017).

1.1 Handwriting identification pre-processing phases

1.1.1 Thresholding

It is the definition of the image taken as input as binary. With thresholding, handwriting input data are converted to black and white data. The purpose of the thresholding preprocessing phase is to bring the image to the foreground from the background. The grayscale histogram of a document has two peaks. These peaks are determined by the proximity of the grayscale to white or black. Thresholding is also used for different purposes such as reducing noise in images or identifying objects (Yılmaz, 2014).

Figure 2. *Changing image background colour with thresholding preprocessing phases. Source: (Yılmaz, 2014).*

1.1.2 Noise removal

Undesirable noise may occur while images are being transferred to digital media. Noise is blurring caused by motion or atmospheric uncertainty, or focusing problems when taking pictures, geometric distortions caused by lenses or errors due to electronic sources. Noises create a mottled appearance in the image, causing loss of details and lower image quality. The image quality is increased as much as possible with the noise removal pre-processing phase. Image processing algorithms are used to remove noise. Noise is removed from the image using filters such as mean, median and gaussian from image processing algorithms. Some types of image noise are as follows (Küpeli & Bulut, 2020):

1. salt and pepper noise,
2. gaussian noise,
3. Rayleigh noise,
4. Erlang (gamma) noise,
5. exponential noise,
6. shaped noise.

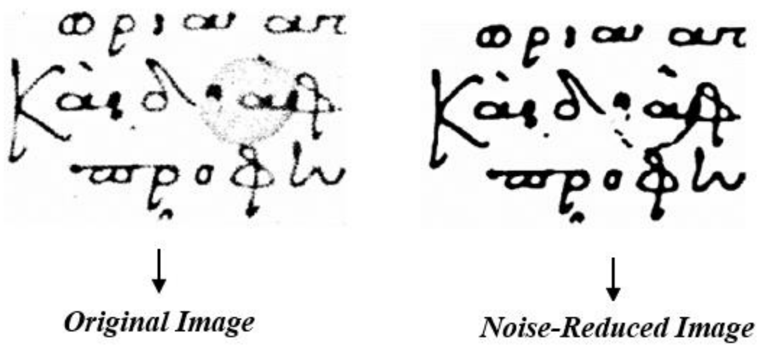


Figure 3. *Reducing image noise with noise removal preprocessing phase. Source (Yılmaz, 2014).*

1.1.3 Normalization

Another of the handwriting identification preprocessing phases is normalization. With normalization, the slant and slope of the text are corrected. The angle between the vertical axis that should be and the vertical axis of the written text is called slant, and the angle between the horizontal axis that should be and the horizontal axis of the written text is called slope (Yılmaz, 2014).

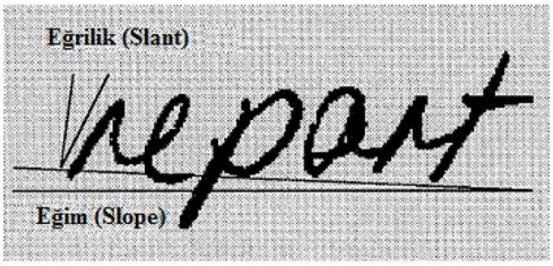


Figure 4. *Correction of text slope and slant with normalization preprocessing phase. Source: (Yılmaz, 2014).*

1.2 Literature review

Many studies have been carried out using different methods of handwriting identification. Karakaya (2020) used the "Modified National Institute of Standards and Technology (MNIST)" dataset, which consists of 60,000 handwritten numbers (0-9) collected from 250 different subjects. The study used support vector machines, decision trees, random forest, artificial neural network, k-nearest neighbour and k-means as handwritten digit recognition algorithms. The compared algorithm efficiency results were as follows: support vector machines were determined as 90%, decision trees 87%, random forest 97%, artificial neural network 97%, k-nearest neighbour 96% and k-means 98%.

Dağdeviren (2013) used the MNIST dataset for handwritten digit recognition (HDR) comparison and performance benchmarking. The study carried out a performance comparison process using artificial neural networks and support vector machines. As a result of the study, it was determined that both test and training processes of ANN were concluded faster than SVM, and SVM had higher accuracy on the same test and training data. The accuracy rates were 91.47% for ANN and 99.99% for SVM. The reason why Dağdeviren (2013) in his study on the classification of handwritten characters achieved greater success than our study is the content of the dataset used in the analysis. While Dağdeviren (2013) performed the classification process from handwritten characters, in our study the classification process was carried out from handwritten text samples. The use of a dataset made of handwritten characters in the classification process increases the success rate. This is because handwriting differs from person to person and is affected by many factors such as the type of pen used, paper structure, writing speed. As can be seen in Figure 6 in our study, it is understood that the writing samples differ from each other even where the same text is repeated by the same person. Therefore, the process of classifying handwriting as text is more complex than the classification of handwritten characters.

Khandokar et al. (2021) used the NIST dataset for handwritten character recognition (HCR). As a result of the study carried out using the convolutional neural network (CNN) method, the accuracy of handwritten character recognition was 92.91%. Yuan et al. (2012) used the UNIPEN dataset for handwritten English character recognition (HECR). An uppercase and lowercase recognition process was performed using the CNN method. As a result of the study, the accuracy rate was found to be 90.02% for lowercase letters and 93.07% for uppercase letters.

Al Jarrah et al. (2021) used a dataset named AHCD (Arabic handwritten character database) for Arabic handwritten character recognition. The accuracy rate of the recognition process performed using the CNN method on a dataset consisting of 16,800 different Arabic handwritten characters was determined as 97.2%. Table 1 contains information about the studies conducted on different datasets related to handwritten character recognition.

Table 1. *Studies on handwriting recognition.*

Study	Dataset	Aim	Method and rate of accuracy
Karakaya (2020)	MNIST	Handwriting recognition	Support vector machines, 90% Decision trees, 87% Random forest, 97% Artificial neural network, 97% K nearest neighbour, 96% K-means, 98%
Dağdeviren (2013)	MNIST	Handwriting recognition	Artificial neural network, 91.47% Support vector machines, 99.99%
Younis (2018)	AHCD	Arabic handwriting character recognition	Convolutional neural network, 97.6%
Sadri et al. (2003)	CENPARMI	Arabic/Persian handwriting character recognition	Support vector machines, 94.14% Artificial neural network, 91.25%
Erdoğan and Tümer (2021)	EMNIST	Handwriting recognition	Convolutional neural network, 87.81%
Khandokar et al. (2021)	NIST	Handwriting recognition	Convolutional neural network, 92.91%
Nasien et al. (2010)	NIST	Upper/lowercase handwritten character recognition	Uppercase: support vector machines, 88% Lowercase: support vector machines, 86%
Alyahya et al. (2020)	AHCD	Arabic handwriting character recognition	Deep neural network, 98.30%
Almansari and Hashim (2019)	AHCD	Arabic handwriting character recognition	Convolutional neural network, 95.27%
Katiyar et al. (2017)	CEDAR	Digit/upper/lowercase handwritten character recognition	Digit: support vector machines, 97.16% Uppercase: support vector machines, 95.74% Lowercase: support vector machines, 92.19%

2 Study Objective

Biometric systems are frequently used in daily life to identify people. One of the reasons for the widespread use of these systems is that security has a very important place in the digital age we live in (Tolosana et al., 2015). Individuals can provide the authentication process in three different ways. Firstly, there are passwords known only to the individual himself. In this method, there is a risk that the password may be captured by others without permission or that the person forgets the password. Another method of authentication is the use of smart cards or tokens. In this method, there are risks such as theft, copying and loss of smart cards or tokens. Biometric data, which are created by the person and represent his/her own characteristics, are another method used for authentication. Biometric data, whether biological or behavioural, can directly identify an individual with uniqueness. Fingerprint, gait, palm, voice, face, DNA and signature are biometric data that people can use to identify themselves without an identity card (Erdinç, 2020).

Signature, which is one of the biometric data types, is the symbol that each individual has, created with his own consent, and that the person has verified himself in official documents. In some cases, the signature can also be performed in a form containing name and surname information. Despite the developments in information and communication technologies today, signature is widely used in many public and private institutions to ensure document validity (Tuncer et al., 2022). The document, which is a comprehensive information transfer tool, is created from handwritten notes, figures, symbols, texts, printed/scanned data or a combination of these. Used as personal notes, banknotes, credit cards, transportation tickets, ID cards, wills, receipts, contracts, etc., documents have a very important place in our lives. For this reason, the rate of crimes related to such documents is quite high today (Sharma et al., 2021). Technological developments also make identity security an important issue today. Handwritten signature samples are unique biometric data that are different for everyone, and each individual can identify himself using a handwritten signature. Gender identification is also one of the key features used in human identification situations (Maji et al., 2015). Forensic document examiners often encounter situations where it is necessary to identify the author as part of the investigation. Document reviews try to find answers to questions about whether a particular letter or signature samples were written by person A or person B (Sharma et al., 2021). Similarly, when it is possible to automatically identify from the handwriting sample found at the crime scene that the person who wrote the letter is a "left-handed woman", it allows the suspect group to be narrowed down within the scope of the investigation (Morera et al., 2018).

Suicide letters, threatening messages, letters containing abusive or offensive expressions, or handwriting on property or lease documents are a very important requirement for person and gender identification in order to avoid criminal suspicion and create evidence. For example, murder as a result of domestic violence can be reflected as suicide. A note with a statement such as: "No one is responsible for my death." is sometimes found at the crime scene. This note may have been placed at the crime scene by the person or persons who committed the murder to mislead the investigation. Similarly, a family member may accuse another family member of forged signature on a check or promissory note for financial reasons. In all these cases, it is very important to identify the person or gender from the handwriting samples in order to reach the truth (Sharma et al., 2021).

Topaloglu and Ekmekci (2017), aimed to determine the gender of the author by analysing handwriting samples. The study revealed that handwriting changes according to person and gender, and it is possible to determine gender from handwriting samples. Cha and Srihari (2001) proposed a system that divides the US population into various categories such as "white/male/15-24 age group" and "white/female/45-64 age group". As a result of the study, performances of 70.2% and 59.5% were obtained for the estimation of gender and hand preference, respectively. Liwicki et al. (2011) performed classification using support vector machines and gaussian mixture models to predict gender and hand preference from online handwriting samples. In the dataset consisting of 200 authors, classification processes were performed for the estimation of gender and hand preference with a success rate of 67% and 85%, respectively. Tomai et al. (2003), applied the k-nearest neighbour classification method to the extracted microfeatures of offline characters from the CEDAR letter database. As a result of the study, the correct classification rate for gender was obtained as approximately 70%. The objective of this study is to reveal whether handwriting samples such as signature, which is one of the authentication methods, are biometric data that can be used to identify the individual and determine their gender.

3 Research Methods

3.1 Dataset and image preprocessing phases

The data within the scope of the study were collected from a total of 68 participants, 36 male and 32 female, on a completely voluntary basis in March 2022. Participants were asked to write "Sakarya University" on a blank paper divided into sections of 50 lines, by distributing pens that had the same characteristics and had not been used before. The writing was regardless of uppercase or lowercase letters. After the data were collected, 3 forms that were found to be completed incorrectly by 2 male and 1 female participants were not included in the study. Since the data in this study were obtained by non-interactive handwriting, they were first scanned in a browser to make them processable in computer environment. The following steps were followed in naming each scanned document and cutting lines:

- Documents were first scanned according to gender, and two separate outputs with the ".pdf" extension were obtained as "Male" and "Female".
- Documents in pdf form were later converted to ".jpg" format, with each image as a separate file.

- Documents converted to jpg format were named "M_1", "M_2",….., "M_34" for the 34 male participants, and "F_1", "F_2",…., "F_31" for the 31 female participants.
- After this stage of the naming process, the *x* and *y* points of the upper left corner points of the first row and the *x* and *y* points of the lower right corner points were determined to automatically cut the full version of the document belonging to each participant, line by line, and use Python to operate on the picture. Using the cv2 library, these points were kept in a matrix and automatically saved as a separate image. After the collected images were converted into a single dimension, grayscale conversion from RGB colour space was performed and the image preprocessing stages were completed.
- After the gender and ID identification process, a total of 3250 data were obtained when cutting line by line for each of the 65 participants.

Table 2 below contains information on the number of participants and the number of data obtained.

Table 2. *Number of participants and disaggregated data.*

Gender	Number of participants	Disaggregated data
Male	34	1700*
Female	31	1550**
Total	65	3250

** The number of data obtained by parsing the distributed forms with 50 lines for each male participant.*
***The number of data obtained by parsing the distributed forms with 50 lines for each female participant.*

The blank version of the form used as a data collection tool in the study is shown in Figure 5.

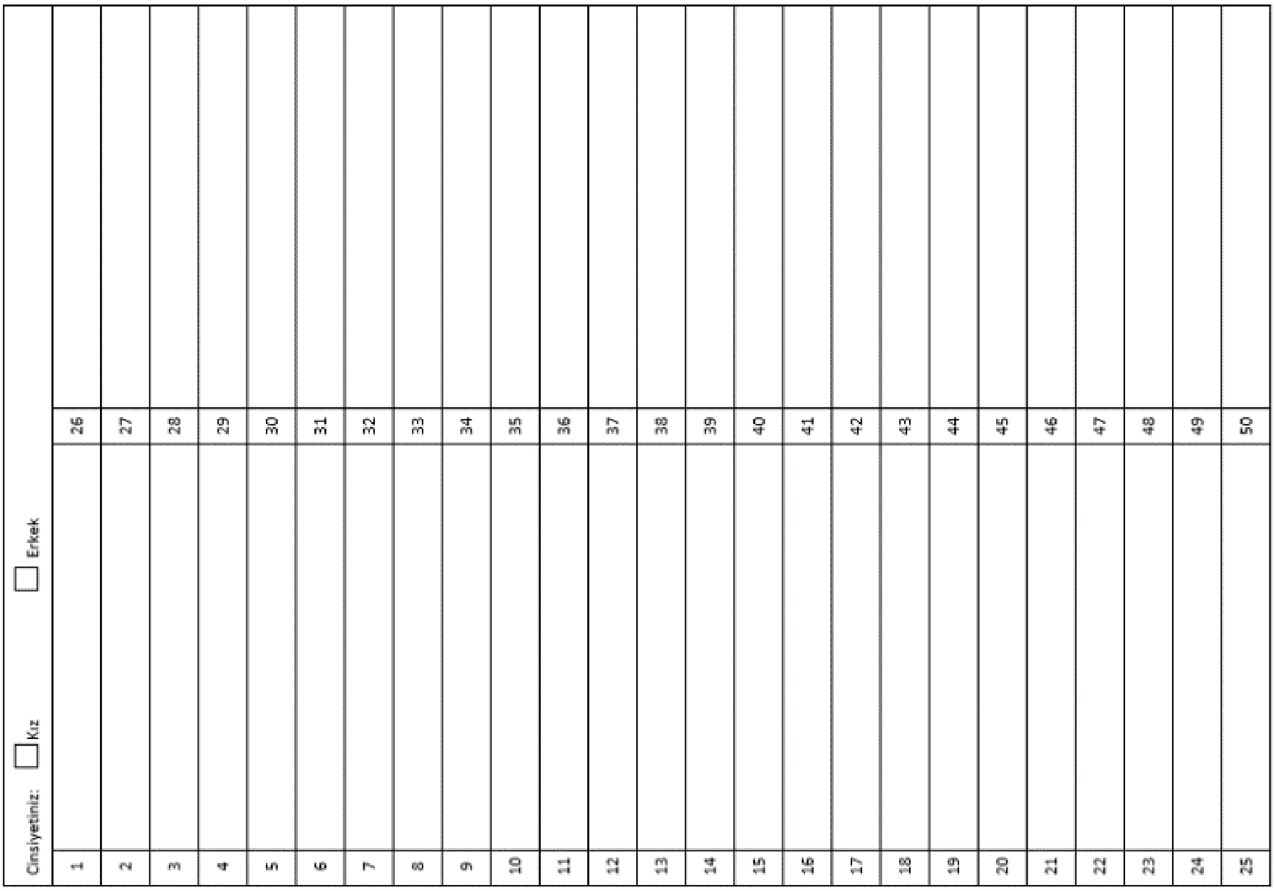


Figure 5. *Handwriting collection form. Source: (Tuncer et al., 2022)*

Handwriting samples from male and female participants in the study are shown in Figure 6. As can be seen in the figure below, the handwriting differs from person to person: there are many different writing styles/numbers and symbols, letter joining, pen, paper structure, and the shape/size of the letters vary according to the person's writing style and speed (Erdoğan & Tümer, 2021).

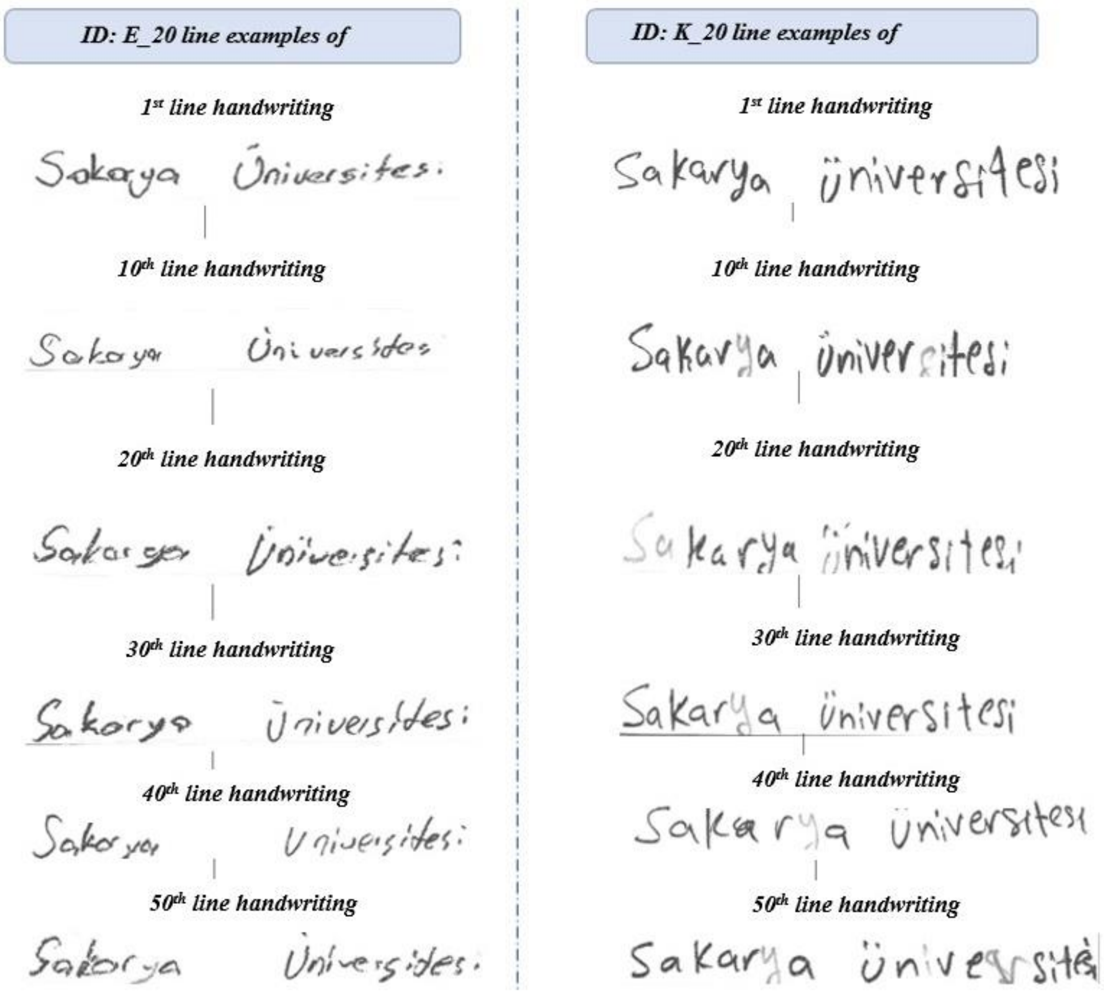


Figure 6. *Handwriting samples from male and female participants. Source: (Ağduk & Aydemir, 2022).*

3.2 Analysis of data and workflow

The data analysis was made using a computer with a Windows operating system, 8GB RAM and an Intel(R) Core(TM) i5-10210U CPU, 1.60GHz 2.11 GHz processor. Thirty-two different transfer learning methods were used to extract features from handwritten image files. Two different attribute files were obtained from the images to define person and gender. Data were divided into training and testing using the 10-fold cross-validation method. In this method, the data are first divided into 10 separate groups, and one group is used for testing purposes, while the remaining nine groups are used for training purposes. This process is repeated 10 times and the groups are changed in order to use all the data in the dataset, consisting of handwritten images, for both testing and training. Attribute files created for person and gender were tested using 28 different classification algorithms in the Python program, and the best classification success was aimed at. The Findings section includes the transfer learning methods used in the study, classification algorithms and success rates achieved. The study workflow is shown in Figure 7 below.

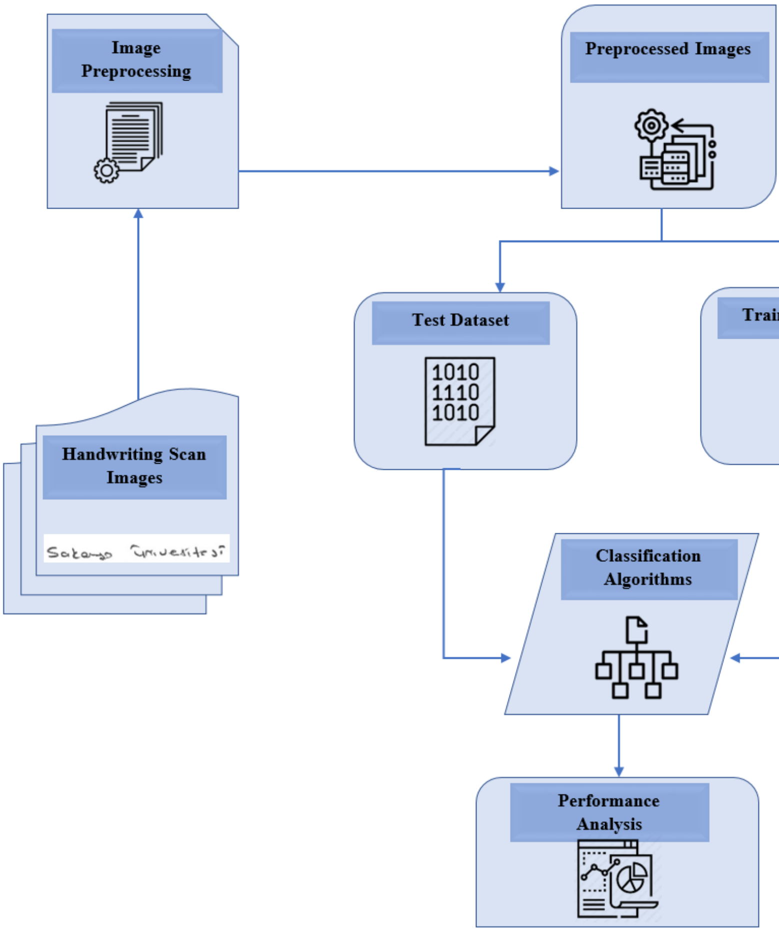


Figure 7. *Steps followed in classifying handwriting samples according to person and gender using transfer learning methods. Source: (Tuncer et al., 2022).*

3.3 Random forest classification method

Random forest, one of the machine learning models, is a supervised classification method that uses decision trees in its basic working principle. With a random forest, a forest is created randomly, there is a direct relationship between the number of trees in the algorithm and the result to be obtained. An increase in the number of trees provides more precise results. The fact that the root node is included in the random forest method and the division processes of the nodes work randomly prevents the biggest problems of decision tree models, which are data memorization/over-learning. To avoid memorizing/over-learning the random forest data, it selects and trains hundreds of different subtrees, thus creating hundreds of decision tree models. The resulting decision tree models give their own prediction results. After the trees in the forest have completed the estimation process, the problem is a regression, the average of the estimations of the decision trees, and the classification selects the most votes among the estimations (Akyiğit & Taşçı, 2022). An example random forest algorithm is shown in Figure 8 below.

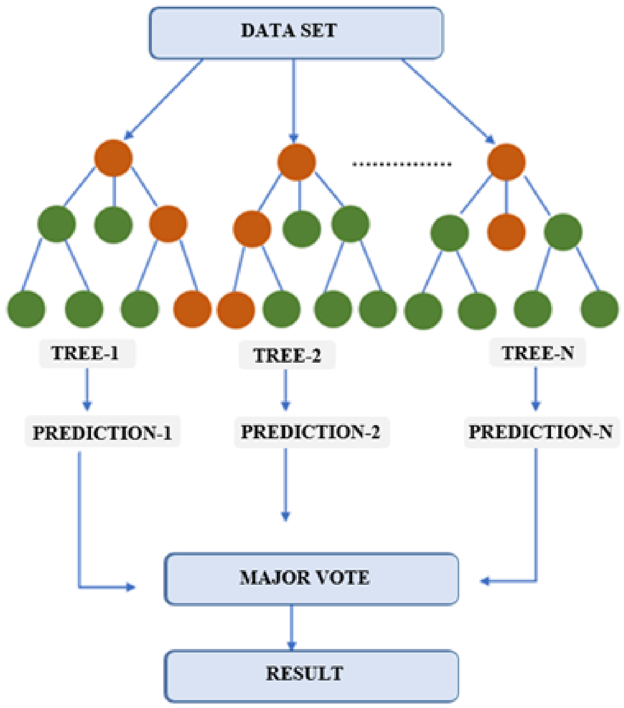


Figure 8. *Random forest algorithm. Source: (Akyiğit & Taşçı, 2022).*

3.4 Transfer learning algorithms used

3.4.1 AlexNet

In the ImageNet (large-scale image recognition) competition, Khrizevsky et al. (2017) divided 1.2 million high-resolution images into 1000 different classes and showed the best performance in the competition with an error rate of 15.4%. AlexNet has 3 fully connected layers with 5 convolution layers, 2 ReLU activation layers, and 3 maximum pooling layers.

3.4.2 VGGNet

VGGNet, recommended by VGG (Visual Geometry Group) members Simonyan and Zisserman (2015), achieved significant success in the ILSVRC 2014 competition, which had more than 14 million data and 1000 classes. VGGNet, which is very similar to AlexNet structure, reduces AlexNet's 11x11 and 5x5 filter structure to 3x3 dimensions. Thus, instead of increasing the width of the mesh, it was revealed that increasing the depth with smaller filters gives better results. The VGGNet architecture has two different models with 16 and 19 layers. There are 13 convolutional and 3 fully connected layers in this model.

3.4.3 ResNet

With ResNet, which was developed by a group of researchers working at Microsoft in 2015, the weight values of the previous layer can be directly transferred to the next layer. The error rate of ResNet is very low and there are versions with different depths such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, with a maximum of 152 layers (He et al., 2016).

3.4.4 DenseNet

In DenseNet, which is based on the small flow of information passing through the layers of ResNet architectures, each layer receives additional inputs from the previous layers and transfers its own attribute maps as input to the next layer. DenseNet, which consists of 121 layers in total with a large number of blocks and three transition layers, has versions with different numbers of layers such as DenseNet-121, DenseNet-169 and DenseNet-201 (Huang et al., 2017).

3.5 Separation of training and test data

The obtained dataset should be divided into training and test sets before the classification process is performed. The main purpose of machine learning algorithms is to produce models that will make accurate predictions on the decomposed training dataset and to check the model accuracy on new data. The data used to test the model accuracy form the model test dataset. The simplest approach used to decompose the dataset for training and testing is to perform a random percentage for 80% training and 20% testing, for example. Partitioning the data as a percentage reveals some errors in determining the model training and test data depending on the data distribution. In order to eliminate this situation, the cross validation method was used to separate all the data into training and test sets. With this method, the data are first divided into 10 separate groups, and one group is used for testing purposes, while the remaining nine groups are used for training purposes; this is repeated 10 times. The final success rate is then calculated by averaging the classification successes in each process (Aydemir & Al-Azzawi, 2021). This situation is explained visually in Figure 9 below.

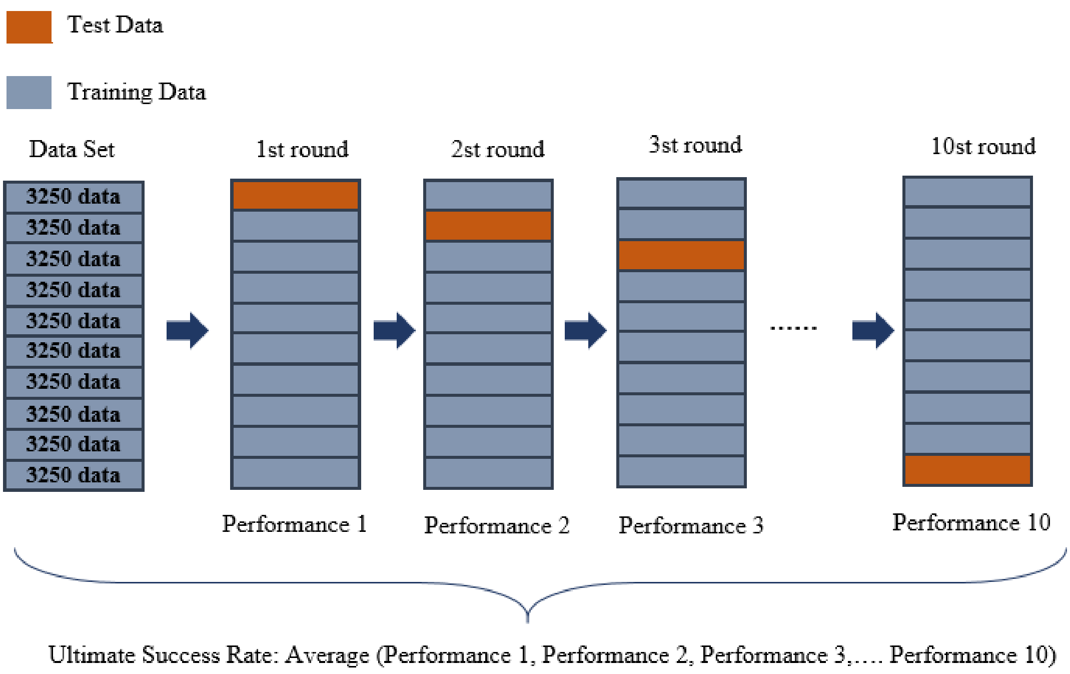


Figure 9. *Tenfold cross validation method. Source: Aydemir & Al-Azzawi (2021).*

3.6 Metrics used in performance analysis

The confusion matrix is used to determine the performance analysis of handwriting identification systems. In the confusion matrix, which consists of a 2x2 matrix, the rows represent the estimated sample data belonging to classes, while the columns contain the actual samples that should belong to each class. The confusion matrix can also be created in a way that the row and column information reversed (Powers, 2011). Using the confusion matrix in Table 3 below, accuracy, recall, precision and F1-score rates are obtained. The values used in this study are explained in Table 3 below.

Table 3. *Number of participants and disaggregated data.*

		Actual class	
		True	**False**
Predicted class	**Positive**	True positives – TP	False positives – FP
	Negative	False negatives – FN	True negatives – TN

Accuracy (ACC): This is the rate of how many samples the system correctly predicted from the entire handwritten dataset. The accuracy rate is obtained by the following equation:

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Recall: This is the rate of correctly predicted real handwriting samples to the total number of real handwriting data. It is also called the True Positive Rate (TPR). The sensitivity rate is obtained by the following equation:

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

Precision: This is the rate of the true handwriting samples correctly predicted to the number of handwriting samples expressed as true by the verification system. The precision rate is obtained by the following equation:

$$TPV = \frac{TP}{TP + FP} \tag{3}$$

F1-Score: This is the harmonic mean of the Precision and Recall values. The F1 score is obtained by the following equation:

$$F1\ Score = \frac{2 * TPV * TPR}{TPV + TPR} \tag{4}$$

4 Results

4.1 Person information results

Handwritten image data from 65 people were used in this study. In Table 4 below, the features of the images in the dataset are extracted using a total of 32 different transfer learning methods. Each feature file was tested using the random forest algorithm and the attribute file with the highest success was determined.

Table 4. *Classification results of individuals with different transfer learning algorithms.*

No.	Transfer learning method	Accuracy rate	No.	Transfer learning method	Accuracy rate
1	DenseNet169	0.887719298	**17**	EfficientNetB2	0.785964912
2	EfficientNetB7	0.871929825	**18**	MobileNet	0.784210526
3	DenseNet201	0.861403509	**19**	ResNet152	0.784210526
4	EfficientNetB6	0.854385965	**20**	EfficientNetV2L	0.775438596
5	EfficientNetV2B3	0.849122807	**21**	EfficientNetV2S	0.773684211
6	ResNet50	0.840350877	**22**	VGG19	0.773684211
7	EfficientNetB5	0.831578947	**23**	EfficientNetB3	0.771929825
8	ResNet101	0.831578947	**24**	MobileNetV2	0.752631579
9	EfficientNetB0	0.826315789	**25**	NASNetLarge	0.735087719
10	EfficientNetV2B2	0.819298246	**26**	DenseNet121	0.726315789
11	EfficientNetB1	0.814035088	**27**	EfficientNetV2M	0.726315789
12	EfficientNetB4	0.810526316	**28**	InceptionV3	0.71754386

No.	Transfer learning method	Accuracy rate	No.	Transfer learning method	Accuracy rate
13	EfficientNetV2B1	0.8	**29**	Xception	0.673684211
14	EfficientNetV2B0	0.798245614	**30**	AlexNet	0.670175439
15	VGG16	0.789473684	**31**	NASNetMobile	0.540350877
16	ResNet50V2	0.787719298	**32**	InceptionResNetV2	0.524561404

When Table 4 is examined, it is seen that the DenseNet169 transfer learning algorithm achieved the highest success rate of 88.77%. The DenseNet169 transfer learning method features extracted person data tested using 28 different classification algorithms after being divided into 20% test and 80% training. The results of the DenseNet169 attributes of people obtained by different classification algorithms are shown in Table 5 below.

Table 5. *Results of DenseNet169 attributes of individuals obtained using different classification algorithms.*

Classification method	Accuracy	Recall	Precision	F1
discriminant_analysis.LinearDiscriminantAnalysis	0.9246	0.9233	0.9256	0.9315
linear_model.RidgeClassifier	0.9000	0.9007	0.9109	0.9038
linear_model.RidgeClassifierCV	0.9000	0.9007	0.9109	0.9038
linear_model.LogisticRegressionCV	0.8954	0.8955	0.9023	0.9032
svm.LinearSVC	0.8877	0.8885	0.8947	0.8912
neural_network.MLPClassifier	0.8677	0.8703	0.8832	0.8734
linear_model.LogisticRegression	0.8431	0.8399	0.8499	0.8515
ensemble.HistGradientBoostingClassifier	0.8154	0.8164	0.8286	0.8234
ensemble.RandomForestClassifier	0.8154	0.8109	0.8282	0.8229
ensemble.ExtraTreesClassifier	0.7769	0.7732	0.7925	0.7847
svm.NuSVC	0.7738	0.7711	0.7862	0.7863
linear_model.PassiveAggressiveClassifier	0.7569	0.7553	0.7751	0.8185
ensemble.BaggingClassifier	0.7108	0.7073	0.7266	0.7195
ensemble.VotingClassifier	0.7108	0.7006	0.7238	0.7243
naive_bayes.BernoulliNB	0.6815	0.6825	0.7025	0.7095
linear_model.SGDClassifier	0.6738	0.6843	0.6978	0.8030
naive_bayes.GaussianNB	0.6723	0.6733	0.6785	0.6942
neighbors.KNeighborsClassifier	0.6723	0.6650	0.6864	0.7035
naive_bayes.MultinomialNB	0.6492	0.6469	0.6606	0.6861
linear_model.Perceptron	0.6369	0.6411	0.6513	0.7808
neighbors.NearestCentroid	0.6185	0.6080	0.6276	0.6331
ensemble.GradientBoostingClassifier	0.5954	0.6192	0.6214	0.6672
svm.SVC	0.5723	0.5454	0.5982	0.5809
tree.ExtraTreeClassifier	0.3215	0.3302	0.3332	0.3461
naive_bayes.ComplementNB	0.2908	0.2619	0.3114	0.4197

Classification method	Accuracy	Recall	Precision	F1
tree.DecisionTreeClassifier	0.1077	0.1020	0.1502	0.0952
discriminant_analysis.QuadraticDiscriminantAnalysis	0.0446	0.0464	0.0493	0.0587
ensemble.AdaBoostClassifier	0.0308	0.0166	0.0423	0.0152

The obtained correct classification rates and algorithm information are shown in Table 5. The most accurate classification was obtained using the LinearDiscriminantAnalysis algorithm, with 92.46%. The results related to person verification are shown in Table 6 below. According to the results of the success rate, sensitivity, precision and F-score in the table, very good results were obtained in person validation. These results show that it is possible to identify and verify the person variable from handwritten images with great success.

Table 6. *Person verification table.*

Person ID	Accuracy	Recall	Precision	F-score
11	0.966667	0.971429	0.969048	0.966550
110	0.931061	0.939286	0.935714	0.930886
111	0.973485	0.976190	0.975000	0.973427
112	0.947727	0.950714	0.954464	0.946904
113	0.957576	0.958571	0.963988	0.956651
114	0.946970	0.947857	0.953274	0.946045
115	0.955303	0.957857	0.956667	0.955245
116	0.932576	0.935952	0.934762	0.931565
117	0.893182	0.898571	0.904107	0.891461
118	0.965152	0.967381	0.967857	0.964724
119	0.956818	0.957381	0.961607	0.955835
12	0.990909	0.991667	0.991667	0.990909
120	0.869697	0.879524	0.895456	0.867587
121	0.921212	0.926905	0.930774	0.919687
122	0.939394	0.944762	0.942381	0.939126
123	0.894697	0.893571	0.905595	0.892603
124	0.981818	0.981667	0.984524	0.981507
125	1.000000	1.000000	1.000000	1.000000
126	0.878030	0.883810	0.896548	0.875781
127	0.973485	0.974524	0.976190	0.973116
128	0.982576	0.984524	0.983333	0.982517
129	0.912879	0.911905	0.927103	0.909276
13	0.991667	0.992857	0.991667	0.991608
130	0.956818	0.960238	0.961905	0.956449
131	0.955303	0.956190	0.957857	0.954782
132	0.981818	0.981667	0.984524	0.981507

Person ID	Accuracy	Recall	Precision	F-score
133	0.903788	0.910952	0.912619	0.902999
134	0.860606	0.862143	0.862738	0.858594
14	0.981818	0.983333	0.985714	0.981667
15	0.906818	0.911667	0.909048	0.906259
16	0.947727	0.953571	0.952381	0.947401
17	0.949242	0.953095	0.954464	0.948570
18	0.940909	0.944286	0.949702	0.939984
19	0.938636	0.940238	0.944762	0.937805
21	0.940152	0.947619	0.944048	0.939977
210	0.956818	0.961905	0.958333	0.956643
211	0.912879	0.916429	0.915714	0.911765
212	0.956061	0.959048	0.961905	0.955482
213	0.920455	0.925238	0.926905	0.919934
214	0.974242	0.977381	0.977381	0.974242
215	0.938636	0.939048	0.941964	0.937032
216	0.912879	0.918095	0.921845	0.912323
217	0.930303	0.935238	0.933333	0.930070
218	0.938636	0.942381	0.946131	0.937813
219	0.963636	0.965000	0.965000	0.963636
22	0.965152	0.964524	0.969940	0.964227
220	0.982576	0.984524	0.983333	0.982517
221	0.919697	0.921190	0.928988	0.918621
222	0.893939	0.896905	0.904405	0.891583
223	0.875000	0.875000	0.898810	0.871636
224	0.927273	0.931667	0.948016	0.923888
225	0.936364	0.940000	0.951111	0.933442
226	0.909848	0.914524	0.936409	0.905314
227	0.919697	0.925714	0.933036	0.918462
228	0.954545	0.958333	0.966964	0.953462
229	0.927273	0.931667	0.951885	0.923107
23	0.868182	0.868095	0.879008	0.864436
230	0.946212	0.948333	0.960714	0.944573
231	0.928030	0.934524	0.945833	0.926107
24	0.884848	0.885714	0.902024	0.881214
25	0.918182	0.920000	0.923929	0.916946
26	0.975000	0.978571	0.977381	0.974942
27	0.901515	0.906190	0.913512	0.900598
28	0.928788	0.935714	0.942857	0.928333

Person ID	Accuracy	Recall	Precision	F-score
29	0.921970	0.925238	0.928988	0.920670

4.2 Gender variable findings

The gender data, whose features were obtained using the Densenet169 transfer learning method, were tested using 28 different classification algorithms after being divided into 20% test and 80% training. The results of the DenseNet169 gender features obtained by different classification algorithms are shown in Table 7 below.

Table 7. *Results of DenseNet169 gender features obtained using different classification algorithms.*

Classification method	Accuracy	F1	Recall	Precision
ensemble.HistGradientBoostingClassifier	0.9277	0.9275	0.9270	0.9290
neural_network.MLPClassifier	0.9154	0.9153	0.9154	0.9153
ensemble.GradientBoostingClassifier	0.9000	0.8997	0.8991	0.9018
ensemble.AdaBoostClassifier	0.8862	0.8858	0.8852	0.8880
svm.LinearSVC	0.8815	0.8813	0.8809	0.8824
linear_model.RidgeClassifierCV	0.8800	0.8798	0.8795	0.8805
linear_model.SGDClassifier	0.8769	0.8760	0.8752	0.8829
linear_model.LogisticRegressionCV	0.8754	0.8750	0.8745	0.8770
ensemble.ExtraTreesClassifier	0.8754	0.8747	0.8740	0.8794
linear_model.RidgeClassifier	0.8738	0.8735	0.8731	0.8750
linear_model.LogisticRegression	0.8677	0.8673	0.8669	0.8688
neighbors.KNeighborsClassifier	0.8662	0.8658	0.8655	0.8669
svm.NuSVC	0.8662	0.8655	0.8648	0.8696
ensemble.RandomForestClassifier	0.8646	0.8638	0.8631	0.8687
discriminant_analysis.LinearDiscriminantAnalysis	0.8631	0.8628	0.8624	0.8638
linear_model.Perceptron	0.8569	0.8543	0.8539	0.8752
ensemble.VotingClassifier	0.8385	0.8367	0.8362	0.8470
svm.SVC	0.8292	0.8281	0.8276	0.8335
ensemble.BaggingClassifier	0.8292	0.8267	0.8265	0.8421
linear_model.PassiveAggressiveClassifier	0.7846	0.7810	0.7888	0.8143
tree.DecisionTreeClassifier	0.7600	0.7563	0.7572	0.7699
tree.ExtraTreeClassifier	0.7185	0.7174	0.7174	0.7190
naive_bayes.BernoulliNB	0.7185	0.7131	0.7152	0.7289
naive_bayes.GaussianNB	0.6908	0.6861	0.6879	0.6969
naive_bayes.ComplementNB	0.6723	0.6694	0.6702	0.6746
naive_bayes.MultinomialNB	0.6723	0.6694	0.6702	0.6746
discriminant_analysis.QuadraticDiscriminantAnalysis	0.5923	0.5849	0.5891	0.5944
neighbors.NearestCentroid	0.5600	0.5562	0.5579	0.5593

The most correct classification was obtained using the HistGradientBoostingClassifier algorithm with 92.77%. The confusion matrix of the HistGradientBoostingClassifier algorithm for gender classification is shown in Figure 10 below.

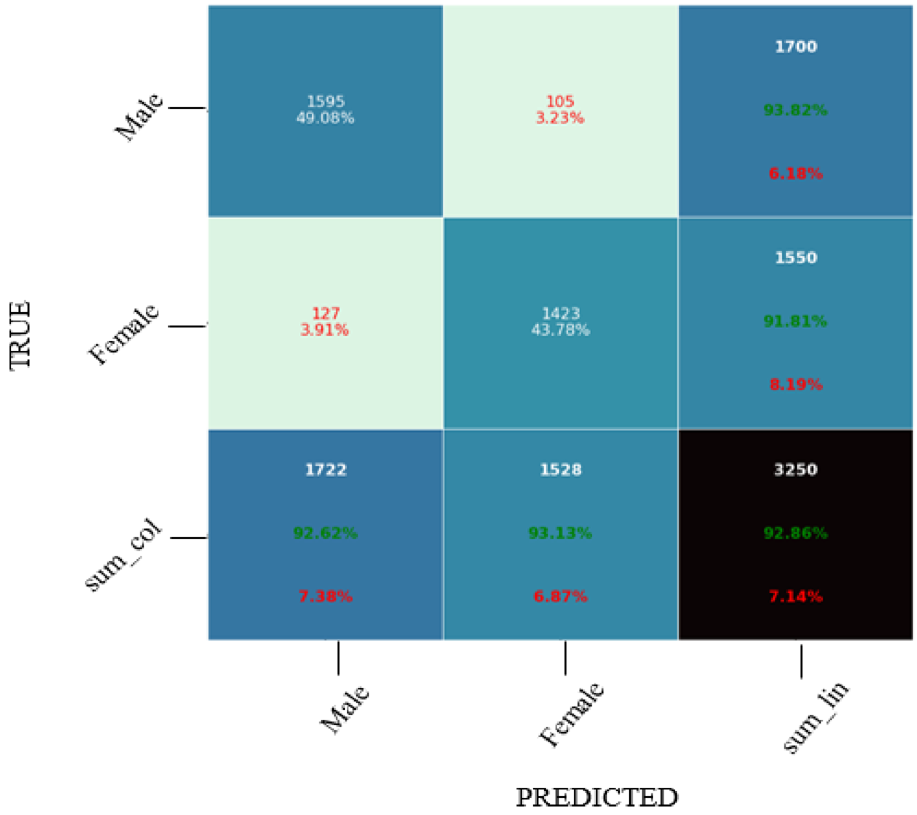


Figure 10. *Densenet-169 confusion matrix.*

When the confusion matrix in Figure 10 is examined, 1595 of the 1700 samples that are actually "Male" for gender were correctly predicted as "Male", while 105 were incorrectly predicted as "Female". Of the 1550 samples that were actually "Female", 127 were incorrectly predicted as "Male", while 1423 were correctly predicted as "Female".

5 Discussion

Handwriting, which is a type of personal biometric data, has distinctive features or habits that cannot be imitated by another person (Kırlı & Gülmezoğlu, 2012). This study aimed to make person recognition/verification and gender classification from handwritten images independently of the text content. Regardless of the handwritten text content, 68 participants were asked to write "Sakarya University" on a blank paper divided into 50 line sections, using pens that had the same characteristics and had not been used before, regardless of capital/lowercase letters, for the process of person identification/verification and gender classification. After parsing of any missing or incorrectly completed documents and various pre-processing stages, a dataset consisting of 3250 handwritten images was created. By using 32 different transfer learning methods in Table 4, the features of the images in the dataset were extracted and each feature file was tested using the random forest algorithm, and the feature file with the highest success rate was determined.

When Table 4 is examined, it is seen that DenseNet169 has the highest success rate of 0.88, and the InceptionResNetV2 transfer learning algorithm has the lowest success rate of 0.52 in the feature extraction study. The highest success rate, sensitivity, precision and F-measure values according to gender and person identification results are shown in Table 8 below. When the table is examined, it is seen that the highest accuracy rate for gender identification is 92.77%, while it is 92.46% for the individual.

Table 8. *Most successful methods and success criteria for person and gender classification.*

Category	Method	Accuracy	Recall	Precision	F-score
Gender	HistGradientBoostingClassifier	0.9277	0.9270	0.9290	0.9275
Person	LinearDiscriminantAnalysis	0.9246	0.9233	0.9256	0.9315

When the relevant literature is examined, it is seen that the studies carried out on letter/number/word handwritten datasets have reached similar results. As is shown in Table 9, Xue et al. (2021), in their study on the dataset named “ICDAR 2013” for gender identification from handwriting samples, achieved the highest success using ATP-DenseNet169; the highest success rate on the dataset named “IAM” was achieved by ATP-DenseNet201, and the highest success rate on the dataset named “KHATT” was achieved by the ATP-DenseNet169 transfer learning algorithm. Similarly, Bonyani et al. (2021) analysed datasets named “HODA”, “Sadri” and “Iranshahr” consisting of Persian handwritten numbers, letters and words using deep neural networks, namely different DenseNet and Xception architectures for handwriting identification. When the results in Table 9 are examined, it is seen that DenseNet121+TTA was the most successful for the dataset consisting of numbers named "HODA", DenseNet121+TTA for the same dataset consisting of letters, DenseNet121 was the most successful for the dataset consisting of numbers named “Sadri”, DenseNet121+TTA for the same dataset consisting of letters, DenseNet121 and DenseNet161 for the same dataset consisting of words. The authors concluded that the best success for the dataset consisting of words named "Iranshahr" belongs to the DenseNet121 transfer learning algorithm. Dağdeviren (2013) used the MNIST database of handwritten numbers. Support vector machines and artificial neural networks were preferred as classification methods. The training data were created in clusters of five, ten, twenty, thirty and sixty thousand randomly selected from the MNIST database. Accuracies for the support vector machines are 97.06%, 99.97%, 99.98%, 99.97% and 99.99%, respectively. Accuracy rates for artificial neural networks are 88.30%, 89.39%, 91.78%, 91.62% and 91.47%, respectively. In the study, it was concluded that support vector machines achieved higher accuracy rates for the same test data.

Table 9. *Different handwriting datasets and accuracy rates.*

Author and year	Dataset	Method	Accuracy (%)
Xue et al., 2021	ICDAR 2013	ResNet-50	68.7
		DenseNet-169	70.2
		ATP-DenseNet-121	69.8
		ATP-DenseNet-169	71.8
		ATP-DenseNet-201	70.5
	IAM	ResNet-50	73.8
		DenseNet-169	73.4
		ATP-DenseNet-121	75.5
		ATP-DenseNet-169	76.1
		ATP-DenseNet-201	77.6
	KHATT	ResNet-50	70.0
		DenseNet-169	72.5

Author and year	Dataset	Method	Accuracy (%)
		ATP-DenseNet-121	72.5
		ATP-DenseNet-169	74.1
		ATP-DenseNet-201	73.5
Bonyani et al., 2021	HODA-digit	DenseNet121	99.71
		ResNet50	98.58
		VGG16	99.05
		DenseNet121+TTA	99.72
	HODA-letter	DenseNet121	98.24
		ResNet50	93.47
		VGG16	96.50
		DenseNet121+TTA	98.32
	Sadri-digit	DenseNet121	99.44
		ResNet50	97.71
		VGG16	98.32
		DenseNet121+TTA	99.38
	Sadri-letter	DenseNet121	89.67
		ResNet50	85.43
		VGG16	82.29
		DenseNet121+TTA	89.97
	Sadri-word	DenseNet121	98.89
		DenseNet161	98.89
	Iranshahr-word	DenseNet121	98.89
Islam et al., 2022	ISI-digit	LeNet-5	98.50
		ResNet-50	99.13
		DenseNet-121	99.55
	BanglaLekha-Isolated-digit	LeNet-5	98.38
		ResNet-50	98.71
		DenseNet-121	98.72
	CMATERdb-digit	LeNet-5	98.72
		ResNet-50	99.27
		DenseNet-121	98.90
Dağdeviren, 2013	MNIST-digit	Artificial neural networks Support vector machines	91.47 99.99

In this study on gender and person classification from handwriting samples, 93.82% and 91.81% were classified correctly for men and women, respectively. A success rate of 92.46% was achieved in identifying persons. When the relevant literature is examined, it is seen that there are similar results. Navya et al. (2018) used QUWI, IAM-1 + IAM-2, KHATT and their own datasets in their study on handwriting-based gender determination. As a result of the study, a successful classification of 90% for females and 84% for males was obtained for their dataset. For the QUWI dataset, successful classification rates of 69.9% for women and 70.1% for men were obtained; it was 73.2% for women and 80.1% for men for the IAM-1 + IAM-2 dataset. In the KHATT dataset, 74.1% of women and 77.1% of men were successfully classified. Ibrahim et al. (2014), using a classification method based on support vector machines to determine the author's gender from offline handwriting samples in Arabic and English, 81% accuracy was obtained in classifiers using global features and 94.7% accuracy in classifiers using local features for both languages.

Liwicki et al. (2011) analysed a number of online and offline features using support vector machine and gaussian mixture models to predict gender and hand preference from offline handwriting samples. In the dataset consisting of handwriting of 200 different people, 67% correct classification was performed for gender and 85% for hand preference. Sharma et al. (2021) tried to predict the authors' gender from handwriting samples. As a result of the analysis of the dataset consisting of handwriting samples of 150 people, 80% correct classification was performed for women and 76.4% for men. Tomai et al. (2003) analysed offline handwritten characters from the CEDAR database for gender classification using the k-nearest neighbour method. As a result of the study, a classification result of 70% was obtained. Al Maadeed and Hassaine (2014) used the random forest classification method in their study on gender prediction from handwriting. As a result of the study, 69.8% correct classification was performed using random forest.

6 Conclusion

This study aimed to determine the person who wrote the text and their gender from handwritten sample images, which differ from person to person. For this purpose, a dataset was created from a total of 3250 handwritten sample images belonging to 65 different people. The features of the handwritten images were extracted using 32 transfer learning methods and the classification process was carried out using 28 different algorithms in the Python program. As a result of the study, the classification success rate achieved was 92.46% for the person and 92.77% for the gender. The classification success rates achieved in the study show that person and gender recognition from handwritten sample images is possible with a high degree of success. Considering the high success rates achieved, the study can be further expanded by using different demographics, different handwritten samples, different classification algorithms or transfer learning methods.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: S.A.: Data curation, Writing – Original draft preparation, Supervision, Writing – Reviewing and Editing. E.A.: Conceptualization, Methodology, Software, Visualization, Investigation, Validation.

Data Availability: The dataset used in this study is freely available online: https://doi.org/10.34740/KAGGLE/DSV/3328630.

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