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ORIGINAL ARTICLE
Electrica 2024; 24(1): 201-209

Arabic Calligraphy Image Analysis With Transfer Learning

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Cite this article as: D. Z. Gürer and İ. Zaim Gökbay, "Arabic calligraphy images analysis with transfer learning," *Electrica*, 24(1), 201-209, 2024.

ABSTRACT

Communication is the exchange of ideas and information between individuals, societies, or locales. Language serves as the primary medium for communication, with writing representing a pivotal tool within linguistic frameworks. The art of Arabic calligraphy, which has its origins in the Arabic script and was historically employed for conveying religious messages associated with Islam, embodies a rich source of knowledge pertaining to Turkish-Islamic art and civilization. These artistic artifacts are integral components of numerous historical sites throughout Turkey. Interpreting the written content within these works holds significant importance for both local inhabitants and tourists, as it enhances the understanding of the historical context and preserves the essence of these locations. It is very difficult to convey the meaning of millions of artifacts to people with a manual process. For this reason, to make this process automatic, the problems of identifying the styles of the writings in the works and recognizing the letters in the writings as a step in the transition from image to text in the literature have been studied. In this study, as a technique that has not been tried in other studies, Arabic calligraphy style determination and letter classification were performed by transfer learning, and an f1 score of over 79% was obtained.

Index Terms—Arabic calligraphy, convolutional neural network, image processing, transfer learning.

I. INTRODUCTION

Arabic calligraphy (AC) is the art of writing Arabic beautifully by considering aesthetic rules and measurements. The architectural structures from the Ottoman period in Istanbul are observed, it is seen that most of the buildings are equipped with verses, hadiths, and Islamic sayings in order to Islamize the works taken from non-Muslims and to bring the society together with divine messages. These works, which we encounter in almost every historical building, carry very deep historical information. The messages in the artifacts need to be understood both historically and spiritually [1].

Arabic calligraphy shows a different representation of Arabic texts using a more cursive style and a mixture of complex constructed word forms. These types of writing styles in Arabic texts give a degree of difficulty in segmenting the letters and reading the text. All Arabic texts are written from right to left, but the difference in calligraphy is that there can be upward, downward, or even circular disordering of words. The words in the text are written in such a way as to represent the final decorative shape, rather than as a readable text, so it is all about connecting the words to form a beautiful piece of art. The fact that there are more than nine different calligraphic styles makes it difficult to perceive what is written in these works [2].

Fig. 1 shows the writing of "بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ" in different styles and with different letter combinations [3].

The challenges of text in these images motivate the search for a way to simplify the reading and digitization processes. There are few studies to investigate the recognition of AC images and the reading of the text drawn in such images [2].

Wen Yuanbo, focusing on style classification in Chinese calligraphy, employed two distinct techniques to categorize five different calligraphy styles. In the first approach, he utilized Fourier transform on the images and evaluated the results using the Euclidean metric, determining classifications based on the similarity between styles. The second technique involved the use of artificial neural networks for classification [4].

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Received: July 13, 2023

Revision Requested: September 20, 2023

Accepted: December 21, 2023

Publication Date: December 28, 2023

DOI: 10.5152/electrica.2023.23102

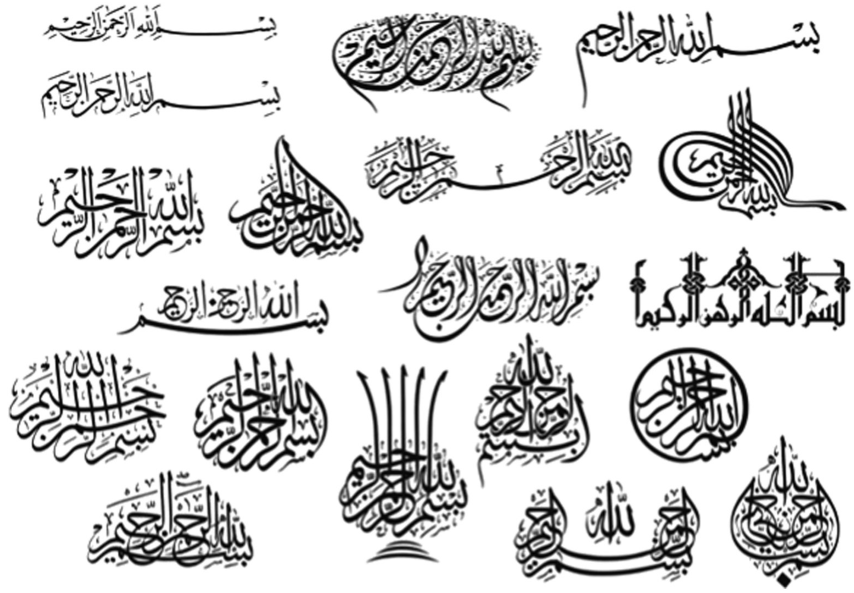

Fig. 1. Same text in different styles and with different letter combinations.

In their study on style determination in calligraphy works, Bataineh et al. employed a back-propagation neural network for style estimation. The dataset, consisting of 14 images, underwent preprocessing to eliminate edges and trapezoids. For classification purposes, a three-layer network was established. The researchers utilized the Edge Direction Matrix to unveil crucial features contributing to the identification of seven different fonts [5].

In his study, Al-Hmouz developed a style recognition system based on autoencoders, employing a deep learning (DL) approach. The study involved working with a dataset of 267 images, addressing a 3-class classification problem focused on sulus, rika, and kufic styles [6].

Ahmed Kawther Hussein employed feature extraction methods such as Local Binary Pattern (LBP), The Local Phase Quantization (LPQ), and Binarized Statistical Image Features (BSIF) for AC style classification. In the classification phase, he compared fast learning neural network and edge learning machine methods [7].

In the domain of character recognition and classification, the dataset used for Latin letters primarily originated from the handwritings published by Marti et al. [8]. Diverse studies have tackled the challenge of letter recognition in various alphabets. For instance, Parsad et al. employed transfer learning, a DL method, to classify letters in the Devanagari alphabet used in India [9]. Kawatani et al. focused on the classification of Chinese letters, specifically Kanji, utilizing linear discriminant analysis [10].

In the realm of Arabic letters, Bar-Yosef et al. conducted the initial study utilizing linear discriminant analysis to distinguish the letters “elif,” “lam,” and “ayn” from a document. They employed K-nearest neighbor and Naive Bayes methods for letter classification [11]. Other studies on Arabic handwriting and letter recognition have employed diverse methodologies, including hidden Markov models [12], support vector machines [13], residual neural networks [14], and transparent neural networks [15].

Despite this, there remains a scarcity of studies specifically addressing the recognition and classification of letters in calligraphy works. AlSalamah curated a dataset of letters used in calligraphy, featuring 32 letter classes, and employed support vector machines for classification [16]. Alyafei et al. contributed to the field by publishing a dataset consisting of 2500 sentences, each with individually labeled letters [17].

The paper is structured into distinct sections. Section II provides information regarding the datasets utilized, along with the definitions of the methods and metrics employed in the study. Section III outlines the techniques employed and presents the experimental results. Finally, the discussion and conclusions derived from the study are detailed in the last section.

II. METHODS

A. Dataset

This study utilized three distinct datasets, one of which is the “Arabic Calligraphy Letters” (ACL) dataset [16], employed for calligraphic letter classification. This dataset, curated by Seetah Al Salamah and Ross King in 2018, was specifically assembled for the study to demonstrate that the quantity of images is not a prerequisite for the effective processing of calligraphic images. The calligraphy lettering dataset comprises a total of 3467 images distributed across 32 categories. These letter images, obtained from various calligraphy styles, were collected from the internet and uniformly resized to 64 × 64 dimensions in black and white format. Permission for the use of this dataset was obtained from the author, and it has been incorporated into the study accordingly. The class examples in the dataset are provided in Fig. 2.

The “Arabic Calligraphy” dataset [18], employed for style classification in calligraphy, was compiled by Zineb Kaoudja et al. in 2019 to address the scarcity of style datasets in the literature. The “AC” style dataset encompasses nine distinct styles, featuring nine categories and a total of 1685 images. The artifacts were collected from books,

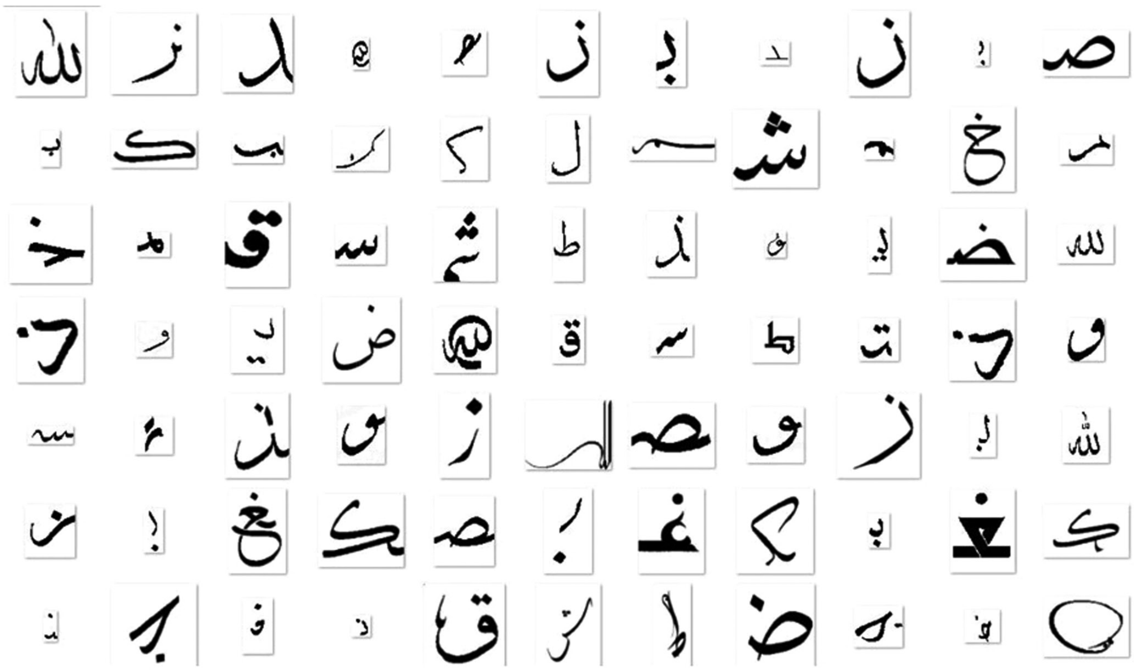

Fig. 2. Different samples from the generated "Arabic calligraphy letters" dataset.

manuscripts, and the internet, resulting in images with varying sizes, ranging from the smallest at 84 × 55 to the largest at 23 338 × 1654. These images are available in both color and black and white formats. The dataset was obtained via email from the author and has been utilized in this study with the stipulation that it is not combined with any other dataset. The class examples in the dataset are provided in Fig. 3.

The "Arabic Handwritten Character Dataset" (AHCD), developed by Mohamed Loey et al., serves as a solution to the problem of Arabic handwritten character recognition through the application of DL techniques. Comprising 16 800 characters authored by 60 participants, the dataset encompasses 28 classes, representing Arabic letters. Notably, this dataset has been publicly released by the author on the Kaggle website [19]. The class examples in the dataset are provided in Fig. 4.

A summary of all dataset information is presented in Table 1.

B. Otsu Method

The process of converting an image to binary form and applying a threshold is fundamental in eliminating background and digital noise, ensuring a clearer representation of the image. This crucial step is essential to prevent misdetection or confusion arising from non-text elements when analyzing the image. The application of thresholding, specifically using the Otsu threshold selection method introduced by Nobuyuki Otsu in 1979 in his paper "A threshold selection method from gray-level histograms" is a common technique to achieve this objective [20]. With the Otsu thresholding method, images are binarized into black and white, effectively reducing noise and facilitating object detection. The process begins by calculating the histogram, which represents the distribution of pixel intensities in the grayscale image. Subsequently, each histogram range is normalized by dividing it by the total number of pixels, and these normalized values are then used to compute cumulative totals. The average intensity value is determined for each intensity level.

Fig. 3. Nine different styles in the "Arabic calligraphy" dataset.

The primary goal of the Otsu method is to identify the threshold value that maximizes the variance between two classes: foreground and background. To achieve this, the inter-class variance is

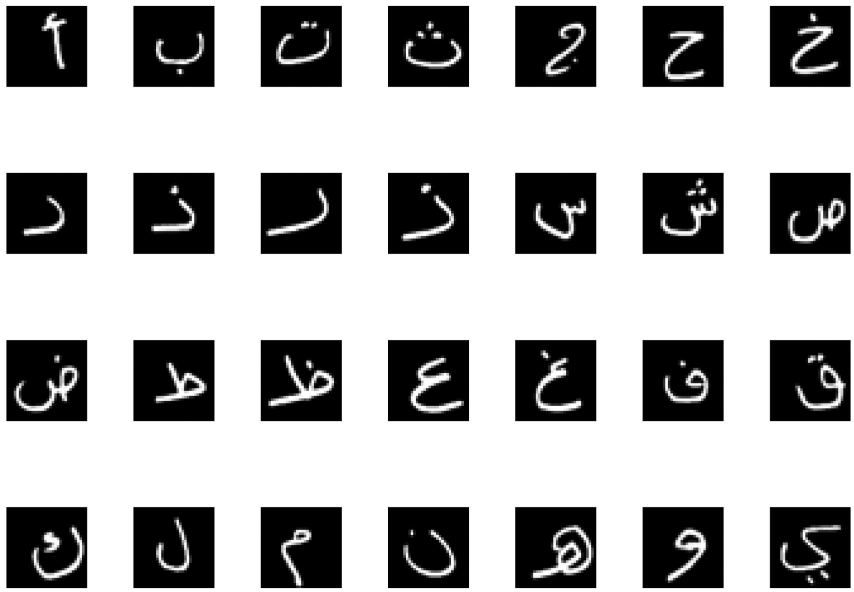

Fig. 4. Samples from "Arabic handwritten character dataset."

computed for every potential threshold value, and the value that maximizes this variance is selected as the optimal threshold. In the final step, pixel intensities below the threshold value are assigned to the background, while intensities above the threshold value are assigned to the foreground. This process effectively distinguishes objects from the background in a black-and-white representation of the image [21]. After determining the threshold value T, the process for the image x(i,j) unfolds as follows [1]:

$$x(i,j) = \begin{cases} 1, if\,(i,j) > T \\ 0, if\,(i,j) \leq T \end{cases}$$

C. Convolutional Neural Network

Deep learning, in contrast to traditional approaches, operates by automatically learning patterns and features without the need for explicit programmed instructions [22]. It constitutes a subset of machine learning (ML) and is designed to enable computers to perform tasks analogous to human activities in daily life, such as sentence translation, image classification, and road sign detection. Deep learning involves the utilization of multiple layers in its architecture [23]. Among the prominent architectures prominent in DL is the convolutional neural network (CNN), which has demonstrated notable accuracy rates, particularly in the domain of image processing [24].

TABLE I. INFORMATION ABOUT DATASETS

Dataset Name	Number of Images	Size of Images	Number of Classes
ACL	3467	64 × 64	32
AC	1685	83 × 55–2338 × 1654	9
AHCD	16 800	32 × 32	28

AC, Arabic calligraphy; ACL, Arabic calligraphy letters; AHCD, Arabic handwritten character dataset.

In this architecture, two main components are involved: feature selection and classification. The feature extraction layer comprises three stages: convolution, activation function, and pooling. The objective of the feature extraction layer is to prepare the image for the classification task by extracting low-dimensional features from the inherently high-dimensional image data.

During the initial convolution stage, the image undergoes filtering through element-wise matrix multiplication with various masks like 2 × 2, 3 × 3, or 5 × 5. This results in the derivation of image derivatives, such as horizontal edges, vertical edges, angular edges, softened image, and sharpened image, all maintaining the same size as the original image. Following the convolution process, it involves no learning of parameters or weights during the activation phase. In this phase, input values are mapped to a specific range to generate the output. In the final stage of the convolution layer, pooling is executed. This step involves reducing the matrix size obtained from the previous layer's output using methods like maximum pooling and average pooling. The resulting low-dimensional images are then forwarded to the classification layer. In the classification layer, the low-dimensional features are matched with categories, typically utilizing a fully connected neural network architecture. The error value calculated at the neural network output is employed to update the convolution filter coefficients and the weights of the fully connected structure layers through the backpropagation method [25].

In CNNs, similar to the traditional machine learning model training process, there are parameters that can be learned directly from the data and others that need to be predefined. Some of the most influential parameters include the number of classes and samples, the number of filters, filter size, activation function, optimization algorithm, learning rate, and batch size [26], [27]. Proper selection of these hyperparameters is crucial to achieving cost-effective and high-performance artificial neural network training [28], [29].

Here are detailed explanations of some key parameters:

The size of the dataset plays a crucial role in positively influencing model learning, with larger datasets generally producing better results, provided there are sufficient training frequency and storage capacity.

In DL, data in the dataset are processed in batches, not simultaneously, to reduce time and memory costs. Learning occurs on these small groups during the training process.

During backpropagation, the learning rate is a critical factor. The difference is found by taking the backward derivative when determining new weights, and this difference is multiplied by the learning rate, which can be set as a constant or changed after a certain step.

Optimization algorithms, including stochastic gradient descent, adagrad, adadelta, adam, and adamax, are fundamental components of the DL process.

The number of epochs, representing training rounds, is a key consideration. Updating weights by backpropagation in specific training rounds constitutes an epoch. Initial training rounds may exhibit lower performance as the model begins learning, with constant learning decreasing after a certain number of rounds.

The initial weight values are determined at the start of model training. This can involve initializing all weights to 0, distributing them with a standard deviation of 0.5, or using the weights of a pre-trained model.

Activation functions, such as sigmoid, tanh, ReLu, and PreLu, are employed for non-linear transformations in multilayer artificial neural networks.

Dropout, the process of discarding nodes below a certain value, enhances learning speed and results. Nodes are either determined or randomly selected for dropout from the network.

The number of layers in a neural network positively affects learning. However, in very deep networks, backpropagation may exhibit diminishing effects towards the first layers, negatively impacting the learning process.

Kernel size, referring to the kernels operating on the matrix in the layer, is utilized for post-layer size reduction. Using large kernels results in smaller sizes but may lead to information loss.

The pooling process, applied to kernel outputs, involves filtering using types such as maximum, minimum, and mean [30], [31].

D. Transfer Learning

"Transfer Learning," is an approach that leverages the experiences gained from solving previous tasks and applies that knowledge to learn a new task [25]. This technique involves transferring information obtained from previous tasks to the goal of learning a new task, particularly in situations with limited data [32].

Two notable variants of this technique are the model building approach and the trained model approach. In the model building approach, two different datasets are utilized. In the source dataset, which has large-scale data similar to the original problem, the feature extraction part of a pre-trained CNN is transferred. Subsequently, the convolution and classifier layers in the new network are updated using the new training set. The sequence of this process is as follows:

1. Select a source task relevant to the target task with a large dataset.
2. Build a model for this source task.
3. Use all or part of the model trained on the source data for the target task.

In the trained model approach, the weights of a network previously trained with a training set and proven to be successful are employed. Training on over a million images with multiple layers requires substantial graphics processing units (GPU) resources and time. Consequently, networks trained in this manner are often made publicly available for other researchers to contribute to their work. The steps to implement transfer learning with this approach are as follows:

1. Select a successful deep network trained with a large dataset.
2. Utilize this network as a starting point or in its entirety for the target task [33]. In this study, both approaches were explored using different datasets based on the specific requirements of the problems.

F. Metrics

In the confusion matrix, columns represent the predictions of the model and rows represent the actual values of the samples in the test set [34]. Table 2 provides information about the confusion matrix.

Accuracy: The ratio of the number of correct predictions to the total number of input samples.

$$\frac{a+d}{a+b+c+d} \tag{2}$$

Recall (Sensitivity): It is also called true positive rate, the fraction of positive samples which are correctly classified.

$$\frac{d}{c+d} \tag{3}$$

Precision: The fraction of positive classifications that are correct.

$$\frac{d}{b+d} \tag{4}$$

F1 Score: F1 score shows the harmonic mean of precision and recall values. The main reason for using the F1 score value instead of

TABLE II. CONFUSION MATRIX DEFINITION

Confusion Matrix		Prediction of the model: Negative	Prediction of the model: Positive
Actual values	Negative	a	b
	Positive	c	d

a: Number of correct predictions of the model when the true value is negative.
b: Number of incorrect predictions of the model when the true value is positive.
c: Number of incorrect predictions of the model when the true value is negative.
d: Number of correct predictions when the true value is positive.

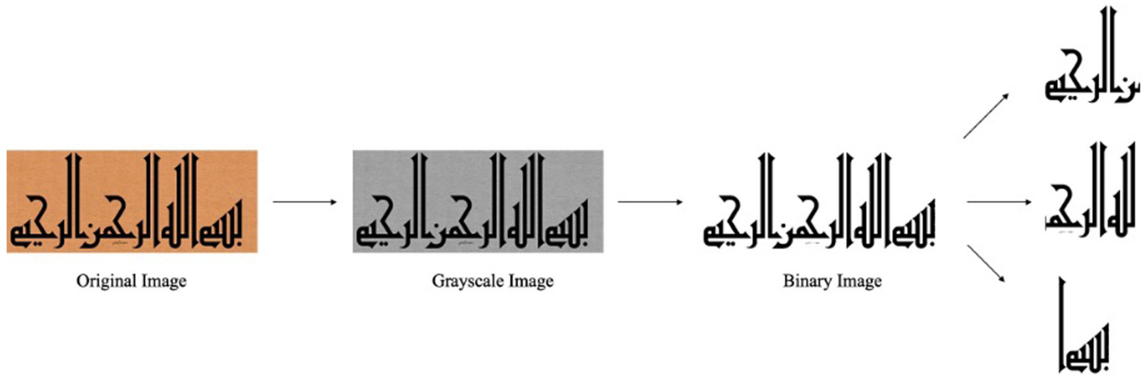

Fig. 5. The sequence of processes applied to the images in the style dataset.

accuracy is to avoid making an invalid model selection in unevenly distributed datasets [35], [36].

$$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

III. EXPERIMENTAL RESULTS

In this study, two DL models are proposed to analyze AC images.

The first classification task involves determining the style of AC in images. To accomplish this, the "AC" dataset was employed, containing both red, green, and blue (RGB) and black and white images. In the preprocessing phase, RGB images were initially converted to grayscale and then further transformed into black and white using the Otsu method. The original dataset consisted of images with varying sizes. To prevent any loss of valuable information that might result from direct size reduction or enlargement, the images were fragmented into appropriately sized portions, effectively increasing the dataset's volume. Through this approach, the initial dataset of 1685 images was augmented, resulting in a dataset that now comprises 3434 images. The sequence of processes applied to the images is shown in Fig. 5.

The resulting images are used to perform style classification using a CNN. To enhance the performance, a transfer learning approach was adopted, with the VGG16 architecture chosen as the base network.

VGG16 architecture is a well-established CNN that was initially trained on a subset of the ImageNet dataset, which comprises a vast collection of more than 14 million images belonging to 22 000 categories. The model was introduced by K. Simonyan and A. Zisserman in their 2015 paper [37] titled "Very Deep Convolutional Networks for Large-Scale Image Recognition." The VGG16 notably achieved an impressive 92.7% classification accuracy during the 2014 ImageNet Classification Challenge. This achievement is significant because the model was pretrained on a substantial number of diverse images.

In the adopted transfer learning approach, the pretrained layers of VGG16, referred to as "frozen" layers, were utilized to extract visual features in a conventional manner. Simultaneously, the non-frozen, or "trainable," pretrained layers were further trained on our custom dataset, with updates being influenced by the predictions generated by the fully connected layer.

Specifically addressing the problem of classifying calligraphy styles, the classification layer was customized to categorize images into nine distinct classes, tailored to the specific task. With this classification

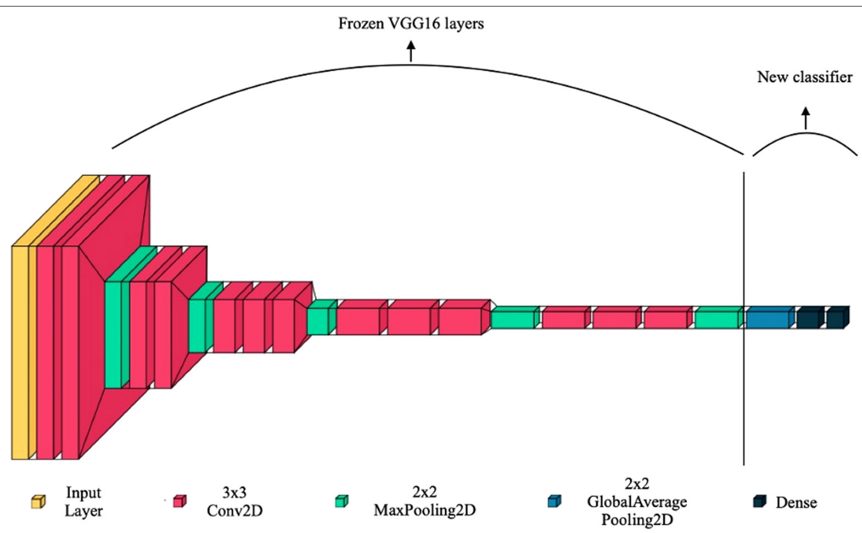

Fig. 6. The network for Arabic calligraphy style classification.

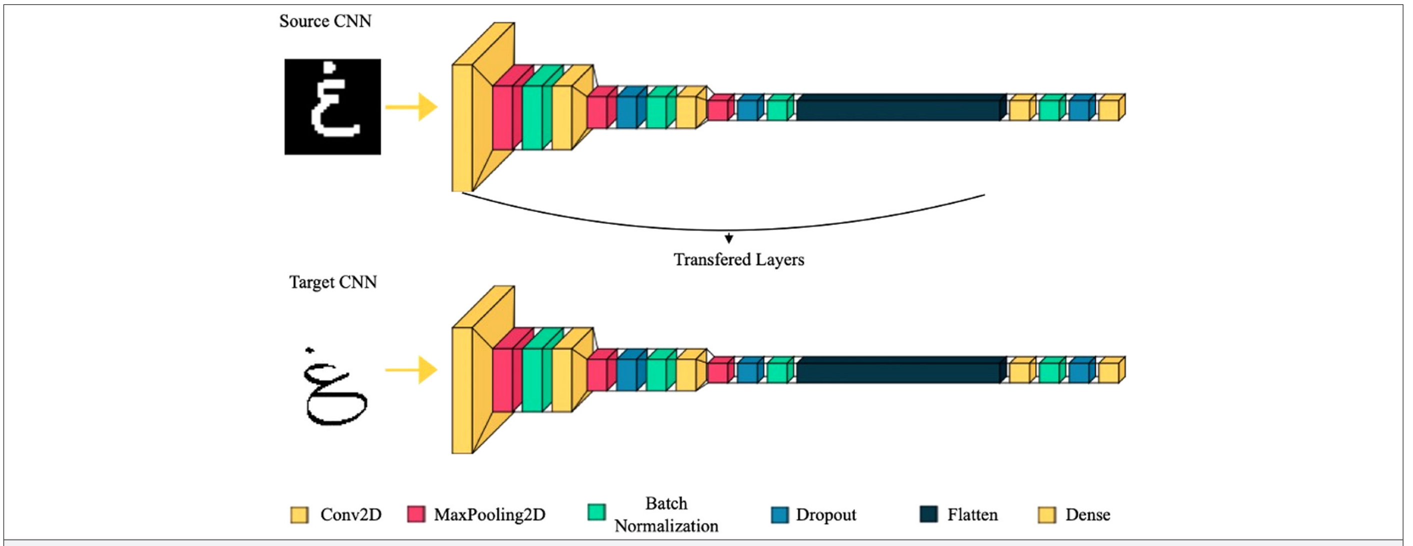

Fig. 7. The convolutional neural network for the classification of letters in Arabic calligraphy images.

layer, the network was trained with a batch size of 32 and 50 epochs. The performance results are as follows: accuracy: 0.91, recall: 0.89, precision: 0.92, and an F1-score of 0.90. The network for this problem is shown in Fig. 6.

In the second task, the primary objective is the classification of artistic letters within AC images. To accomplish this, two datasets were employed, with the first being the "AHCD." A CNN with 18 layers was established to handle the large volume of data in the "AHCD" dataset. Various optimizers ("RMSprop," "Adam," "Adagrad," "Nadam") and activation functions ("relu," "linear," "tanh") were experimented with, ultimately selecting "Adam" for optimization and "relu" for activation as the optimal parameters. The final network underwent training for 30 epochs with a batch size of 64, achieving an impressive accuracy of 95.89%.

The high-performing network and its transferred weights were then utilized to classify artistic letters in the "ACL" dataset, a collection of artistic letters in AC images. The last 4 layers of the transferred network were left trainable for the target classification task. Addressing the 32-class classification problem, the network underwent further training for 50 epochs with a batch size of 32. The model was designed with the understanding that individuals familiar with Arabic letters would find it easier to predict the artistic forms of these letters. The results of this artificial neural network are as follows: accuracy - 0.78, recall - 0.79, precision - 0.80, and F1-score - 0.78.

The CNN for this problem is shown in Fig. 7.

IV. DISCUSSION AND CONCLUSION

Utilizing various transfer learning methodologies, two distinct calligraphy datasets were subjected to analysis for the examination of calligraphic works. The first dataset has 9 distinct calligraphy styles, while the second dataset consists of 32 class representing letters in diverse calligraphic styles, and both used for the classification problems.

The dataset was partitioned into 80% for training and 20% for testing, yielding results with an F1 score of 90% for style classification and 79% for letter classification.

Future research endeavors will focus on the geometric distinctions inherent in calligraphy styles. Specifically, geometric features unique to each style will be extracted, thereby enhancing letter classification accuracy. This approach aims to recognize individual letters within works and subsequently derive the written content based on the frequency distribution of identified letters.

Moreover, forthcoming studies intend to integrate artificial intelligence models into mobile applications. These applications will serve the dual purpose of translating the text within calligraphic works from Arabic into a target language, contributing to a broader accessibility and understanding of the artistic content.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – I.Z.G., D.Z.G.; Design – I.Z.G., D.Z.G.; Supervision – I.Z.G.; Resources – I.Z.G., D.Z.G.; Materials – I.Z.G., D.Z.G.; Data Collection and/or Processing – D.Z.G.; Analysis and/or Interpretation – D.Z.G.; Literature Search – D.Z.G.; Writing – D.Z.G.; Critical Review – I.Z.G.

Declaration of Interests: The authors have no conflict of interest to declare.

Funding: The authors declared that this study has received no financial support.

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