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Arabic Handwriting Classification using Deep Transfer Learning Techniques

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ABSTRACT

Arabic handwriting is slightly different from the handwriting of other languages; hence it is possible to distinguish the handwriting written by the native or non-native writer based on their handwriting. However, classifying Arabic handwriting is challenging using traditional text recognition algorithms. Thus, this study evaluated and validated the utilisation of deep transfer learning models to overcome such issues. Hence, seven types of deep learning transfer models, namely the AlexNet, GoogleNet, ResNet18, ResNet50, ResNet101, VGG16, and VGG19, were used to determine the most suitable model for classifying the handwritten images written by the native or non-native. Two datasets comprised of Arabic handwriting images were used to evaluate and validate the newly developed deep learning models used to classify each model's output as either native or foreign (non-native) writers. The training and validation sets were conducted using both original and augmented datasets. Results showed that the highest accuracy is using the GoogleNet deep learning model for both normal and augmented datasets, with the highest accuracy attained as 93.2% using normal data and 95.5% using augmented data in classifying the native handwriting.

Keywords: Arabic text recognition, deep learning, handwriting classification, transfer learning

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INTRODUCTION

About 420 million people speak Arabic in more than 20 countries worldwide. We know, the Arabic alphabet consists of 28 characters (Guellil et al., 2021). Features of Arabic writing include cursive style, connected characters, written right-to-left, and points or marks that will change the word's meaning (Burrow, 2004). Conversely, recognition is a field covering various subjects, including recognising the face, fingerprint, image, character, and many more (Najadat et al., 2019), allowing for identifying specific target items (Savchenko, 2020). Recognition of handwriting can be online (real-time recognition from pen tracing) or offline (recognition from images). Due to the endless variation in the writing styles of individual writers, it is indeed a challenging task to recognise the written text. However, this can be achieved through feature extraction of images to eliminate non-essential variation and only retain recognition-related data (Wong & Loh, 2019).

LITERATURE REVIEW

Handwriting identification is the process of identifying a writer or a group of writers, with the assumption that the handwriting of each individual or group is specific (Wang, 2019). On the other hand, deep learning (DL) is generally used for image classification. It learns from the trained data, and the model can then be used on new datasets for recognition or classification (Pouyanfar et al., 2019; Goularas & Kamis, 2019; Wang, 2020; Yildiz et al., 2020). Different approaches can be used to build efficient deep learning models, and one of them is transfer learning, specifically applying a pre-trained model on a different problem. In DL, new data of previously unknown classification is provided to the existing network and is adjusted accordingly. Note that transfer learning is indeed valuable for handling insufficient data for a new domain in the neural network, and there is a big pre-existing data pool that can be transferred to the problem to be solved. The benefit of this approach is that much less data is needed, which significantly reduces the computational time (Razak et al., 2020a; Razak et al., 2020b; Wahdan et al., 2020; Yang et al., 2013).

Furthermore, numerous studies have been published on Arabic text with varying degrees of precision. For instance, a geometric recognition system for handwritten Arabic characters was proposed by Abodi and Li (2014). IFN/ENIT dataset was applied, and the outcome was 93.3% as the average accuracy. This study was based on simplifying characters into images containing features, translating images into orthogonal lines, and using them as single vectors. Alharbi (2018) proposed a genetic learning vector quantisation (LVQ) algorithm comprised of two stages: firstly, a method that selected the features, and secondly, the LVQ neural network learning algorithm for classification. Further, the Optical Character Recognition (OCR) system of the handwritten Arabic characters was proposed by Hussien et al. (2016) with an accuracy of 77.25%. The Hopfield neural network was implemented, and only eight Arabic characters were used. In addition, Younis (2017) used the deep convolutional neural network (CNN) with regularisation parameters, such as batch normalisation, to avoid overfitting. CNN was used to extract features and trained for recognition rather than extracting many gradient or textural features.

Conversely, Elleuch et al. (2016) applied Support Vector Machine (SVM) and CNN with IFN/ENIT as the database to classify 56 classes with an error rate of 7.05%. In addition, Eladel et al. (2015) proposed fast wavelet transform (FWT) and neural network (NN) architecture that is based on multi-resolution analysis (MRA) and the Adaboost algorithm. The Arabic handwriting recognition training and testing were set using IESK-arDB datasets, containing 6000 characters. Moreover, Najadat et al. (2019) obtained 16,800 images of isolated characters from the Arabic Handwritten Character Dataset (AHCD). Thus, to train and check the datasets, CNN's deep learning architecture was developed using a suitable optimisation technique, and results attained showed an accuracy of 94.9% using testing data. Belabiod & Belaïd (2018) implemented a line segmentation method using the RU-net and end-to-end word segmentation approach, namely the CNN followed by the bidirectional long term memory (BLTM) and the connectionist temporal classification (CTC) functions that automatically learned the alignment of text line images with the transcription words.

Based on the previous works mentioned above and to the extent of our knowledge, no studies have reported using more than one Arabic handwritten character for classification, and no studies have reported the deep learning transfer models, specifically the AlexNet, the GoogleNet, the residual neural network (ResNet) 18, the ResNet50, the ResNet101, the VGG16 and the VGG19 for classifying Arabic handwriting images as native writers or otherwise. Hence, findings from this study can assist the non-native writers to confirm and ensuring that their Arabic handwriting is correctly written. Therefore, the main aim of this study is to classify Arabic handwriting images either written by native writers or otherwise with deep learning neural networks as classifiers. The motivation of this study is to investigate if there are differences in writing styles of Arabic handwriting written by foreign and native writers that the human vision could not detect due to the irregular and complex nature of Arabic handwriting. New deep learning algorithms will be developed for this purpose based on the seven transfer learning models mentioned earlier in classifying the Arabic handwriting images as native or foreign (non-native) writers. This study can later be used in the text transcription process application, for instance, ancient or historical documents written in Arabic by the native writers.

RESEARCH METHOD

This section will elaborate on the methods developed in this study. Firstly, the database used will be explained, followed by the transfer learning models and the performance measure used to evaluate the effectiveness of the proposed method.

Dataset

As mentioned earlier, large datasets for training were not the main issue in the case of transfer learning, hence in this study, for the handwriting Arabic images dataset, the dataset comprised of handwritten images written by 22 subjects, specifically 11 natives and 11 foreigners. All the participants are male, aged between 22 and 27 years old. Foreign participants are from the following countries: Bosnia and Herzegovina, Turkey, Kenya, Ghana, and Tanzania. On the other hand, the native Arabic participants are from Egypt, Saudi Arabia, Algeria, Lebanon, Palestine, Jordan, Syria, Libya, and Iraq. Each subject was required to write 45 sample images; therefore, 990 handwritten images were generated as the database. All images are captured using a mobile phone. In addition to the original database, the on-the-fly augmentation approach involves the transformation of the database. Two augmentation approaches are utilised by mirroring or creating a mirror image, and the other is augmentation by random crops.

The datasets were categorised into two types, namely the native writers and foreign writers. Figure 1 shows some samples of sentences written by both categories of writers.

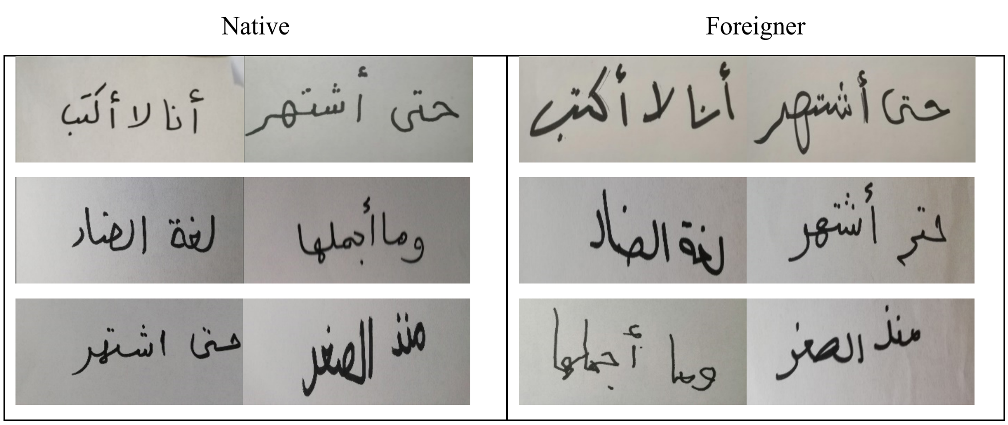

Figure 1. Samples of handwriting images

Transfer Learning Models

In this section, the seven models of transfer learning methodology used in this study will be discussed. The first one was AlexNet, a CNN designed by Krizhevsky et al. (2017) trained with over one million ImageNet database images. It represented an extensive network structure with sixty million parameters and 650 thousand neurons with eight layers, five convolutional layers and, three fully connected layers. The fully connected layer could classify 1000 classes, and the remainder of the network was regarded as the feature extractor. Next is the GoogleNet. GoogleNet was also known as Inception-V1.

GoogleNet is a pre-trained CNN comprised of 22 layers trained on ImageNet. In the centre of the network, the network architecture is comprised of a 1 to 1 Convolution layer. Further, global average pooling was used at the end of the network rather than fully connected layers (Szegedy et al., 2015). Next, are the ResNet-18, the ResNet-50 and the ResNet-101. Finally, ResNet was proposed by He et al. (2016). The ResNet is a neural network constructed from pyramidal cells in the cerebral cortex. ResNet was applied to skip connections or shortcuts to move across some layers. Regular ResNet models were developed with two or three-layer that skips, including the nonlinearities (ReLU) and batch normalisation in between. ResNet transformed the NN architectural competition by introducing the residual learning concept in the NNs and further included an effective technique for training the deep network. For instance, ResNet-18 is a pre-trained deep learning model for image classification, the network was 18 layers deep and was trained on one million images based on 1000 categories. While the ResNet-50 is a pre-trained model for image classification; the network was 50 layers deep and was trained on one million images of 1000 classes. On the other hand, ResNet-101 is a pre-trained deep learning model for image classification, with 101 layers trained on one million images of 1000 categories.

The sixth transfer learning used is VGG 16. VGG16 is a CNN model presented by Simonyan and Zisserman (2015). This model obtains 92.7% top-5 testing accuracy in ImageNet, comprising 1000 classes with over 14 million images. The name VGG-16 is from the fact that it has 16 layers and the layers include convolutional layers, max-pooling layers, activation layers, and fully connected layers. It has 13 convolutional layers, five max-pooling layers, and three dense layers, which sum up to 21 layers, but there are only 16 weight layers. Lastly is the VGG19, a pre-trained deep learning model for image classification. This network comprises 19 layers and is trained on one million images of 1000 categories from the ImageNet database. As mentioned by Simonyan and Zisserman (2015), the VGG19 has 19 layers, specifically 16 convolutional, three fully connected CNN that utilised 3 by 3 filters with stride and padding of 1, along with 2 by 2 max-pooling layers

Conversely, data augmentation was also developed and used as an additional dataset generated from the existing images. As for data augmentation, two methods were used: augmentation by mirroring or creating a mirror image, and the other is augmentation by random crops. The experimental results and analysis are discussed in the next section.

RESULTS AND DISCUSSIONS

This section discusses the results attained based on the proposed method. First, all the seven transfer learning approaches were evaluated. Then, the numerical results, specifically, the training loss rates, training accuracy, validation loss rates, and validation accuracy for each model, are reported and elaborated.

Training Loss Rate Analysis

As shown in Figure 2, the training loss rate of AlextNet with and without data augmentation decreases significantly after 100 iterations, while the loss rate for data augmentation decreases after 300 iterations. It is observed that for the GoogleNet, the training loss rate converges after 2000 iterations for the augmented datasets; however, the loss rate significantly decreased at 1000 iteration for normal datasets, and the loss reduces and prolongs until the end of the analysis. As for the ResNet18, the training loss rate for normal datasets decreases significantly after 200 iterations, while the model with data augmentation only shows a decremental pattern after 400 iterations. Further, for the ResNet50, the training loss significantly decreases after 100 iterations for normal datasets; nevertheless, it decreases longer, specifically after 300 iterations for the case of data augmentation. Moreover, the training loss for the ResNet101 decreases to zero after the completion of 100 iterations based on the normal data, while for the augmented dataset, there are decreases after 300 iterations.

Likewise, the training loss rate for VGG16 shows a slight decrease at 200 iterations for the augmented dataset. However, for the normal dataset without augmentation, there is a decrease after 100 iterations. Additionally, the loss rate is unstable after 600 iterations and remains the same until the analysis ends. Finally, for VGG 19, the training loss rate reduces after 100 iterations for the dataset without augmentation. Nonetheless, there is a reduction after 200 iterations, and instability occurs up to 400 iterations for the augmented dataset. Overall, as observed from Figure 2, the training loss for these models mostly converges around 500 epochs. Thus, the loss rate for models without data augmentation can converge to zero earlier as compared to data augmentation. That is due to the less variation amongst the datasets.

Training Accuracy Analysis

In this section, the training accuracy, as depicted in Figure 3 for all seven utilised deep learning models, is described. Firstly, the training accuracy by AlexNet reaches 100% after 100 iterations for normal datasets; however, for data augmentation, AlexNet requires 500 iterations to reach 100%. Again, it is due to the variation in images and the larger number of datasets. Next, is the GoogleNet using both normal and augmented data showing similar trends with both plots reaching 100% accuracy at 2000 iterations. Finally, as for ResNet18, normal datasets reach 100% instantly, compared to data augmentation.

Further, for ResNet50, both models achieve 100% accuracy at less than 200 iterations, with the model for the normal dataset being faster since the datasets are fewer. Moreover, for ResNet101, the training accuracy reaches 100% for normal and augmented datasets before 200 iterations. Additionally, for VGG16, for datasets without data augmentation, the accuracy increases up to 600 iterations but decreases and becomes unstable until the end.

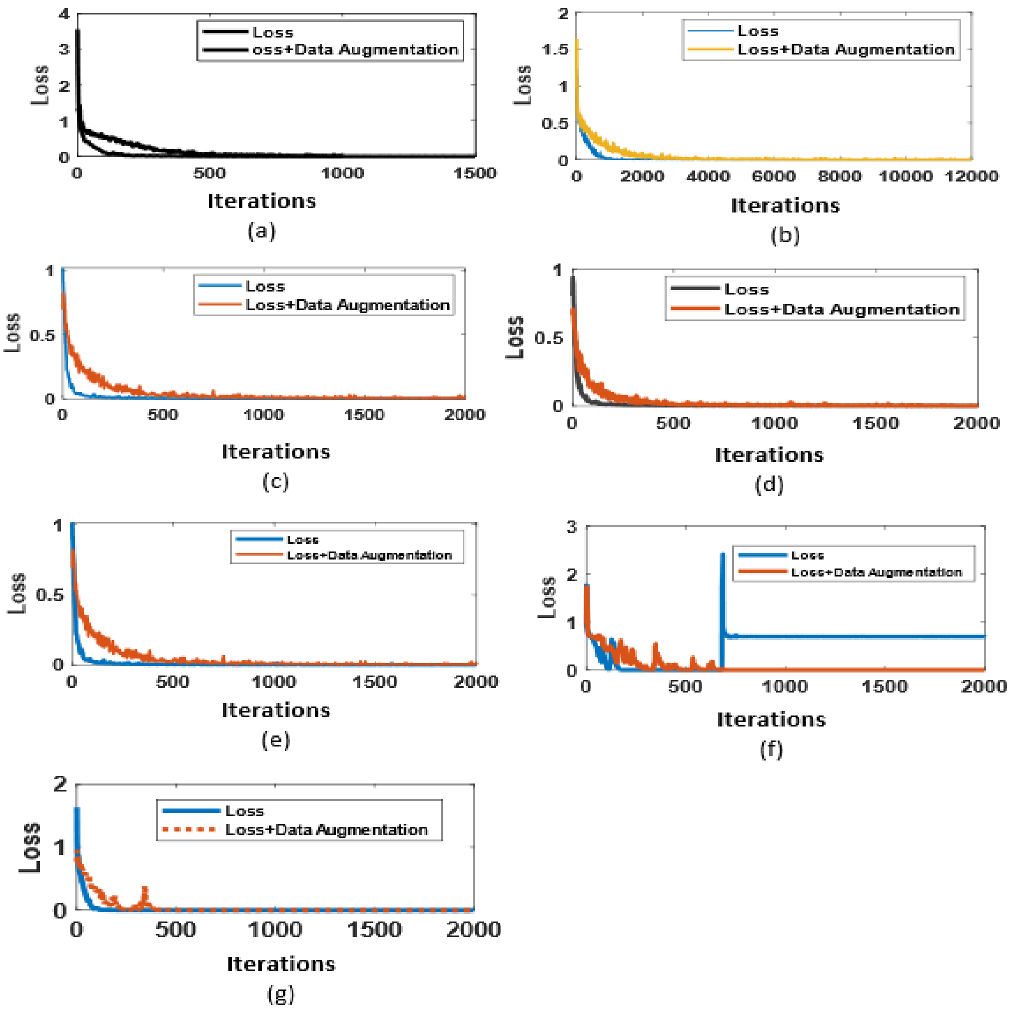

Figure 2. (a) AlexNet, (b) GoogLeNet, (c) ResNet18, (d) ResNet50, (e) ResNet101, (f) VGG16, and (g) VGG19 training loss rates for both original and augmented datasets

As for data augmentation, the accuracy increases to 600 iterations and remains the same until the end. Eventually, for VGG19, the training accuracy increases at 200 iterations for both categories datasets. Nonetheless, the data augmentation becomes unsteady before it stabilises after 400 iterations. Generally, the results show that for all seven deep learning models, the training accuracies for data without augmentation reached 100% accuracy earlier; hence it demonstrates the significant role of data augmentation in classification problems that enrich and enhance the performance of deep learning models that are used in this study.

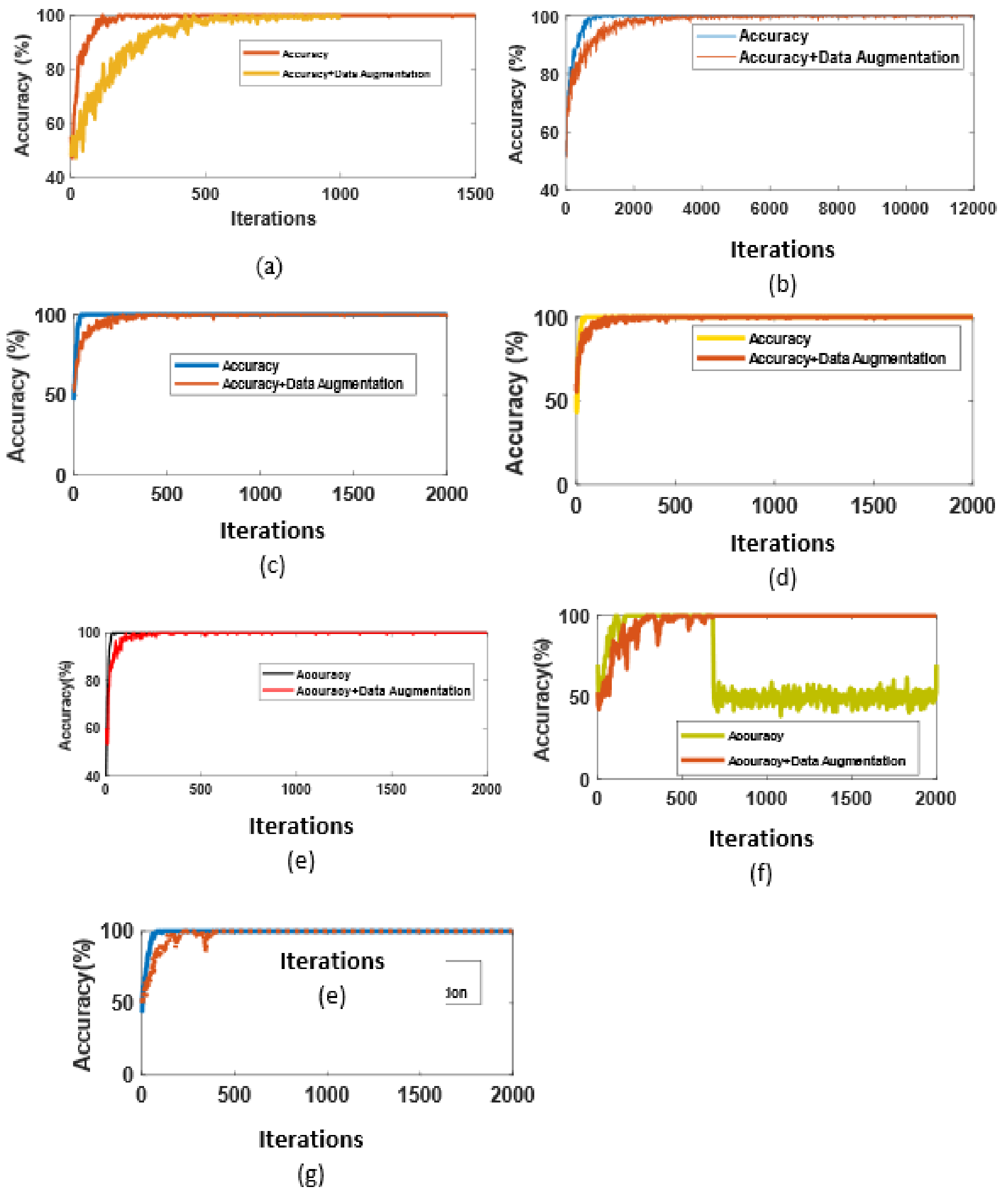

Figure 3(a) AlexNet, (b) GoogLeNet, (c) ResNet18, (d) ResNet50, (e) ResNet101, (f) VGG16, and (g) VGG19 training accuracy for both original and augmented datasets

Validation Loss Rate Analysis

Another essential point to address is the validation loss rates for each model, shown in Figure 4. Firstly, it is observed that the AlexNet validation loss based on the normal dataset is almost similar to the epoch value at 2; however, for data augmentation, the loss increases for the value of epoch above 2. GoogleNet shows no significant improvement except for augmented data with a slight decrease for validation loss. Further, it is observed that the loss rate in both models decreases only at iteration value before 50; however, it increases after that until the end of the analysis. Furthermore, for ResNet18 using both datasets, convergence occurs at epoch 5 and remains the same pattern until the numerical analysis is completed.

Additionally, for ResNet50, validation loss converges at the fifth epoch for both datasets but slightly decreases for the normal dataset. Conversely, for ResNet101, validation loss is low and was not improved until the analysis ended. Moreover, as in the case of VGG16, no significant improvement observes for the validation loss. Finally, for the VGG19, the validation loss shows a slight decrease for unaugmented data before epoch 5, but the loss rate increases after that, while for data augmentation, the loss rate is unstable.

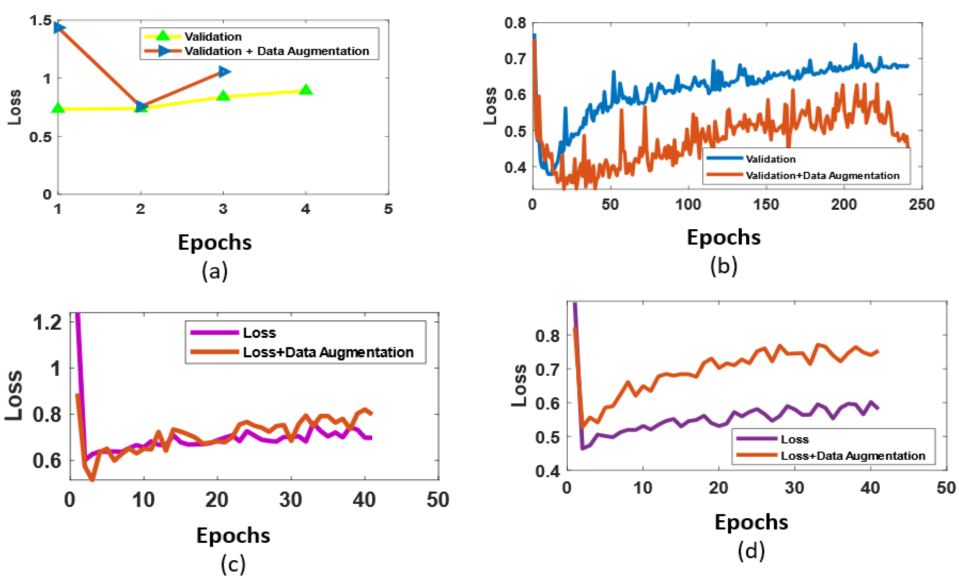

Figure 4. (a) AlexNet, (b) GoogLeNet, (c) ResNet18, (d) ResNet50

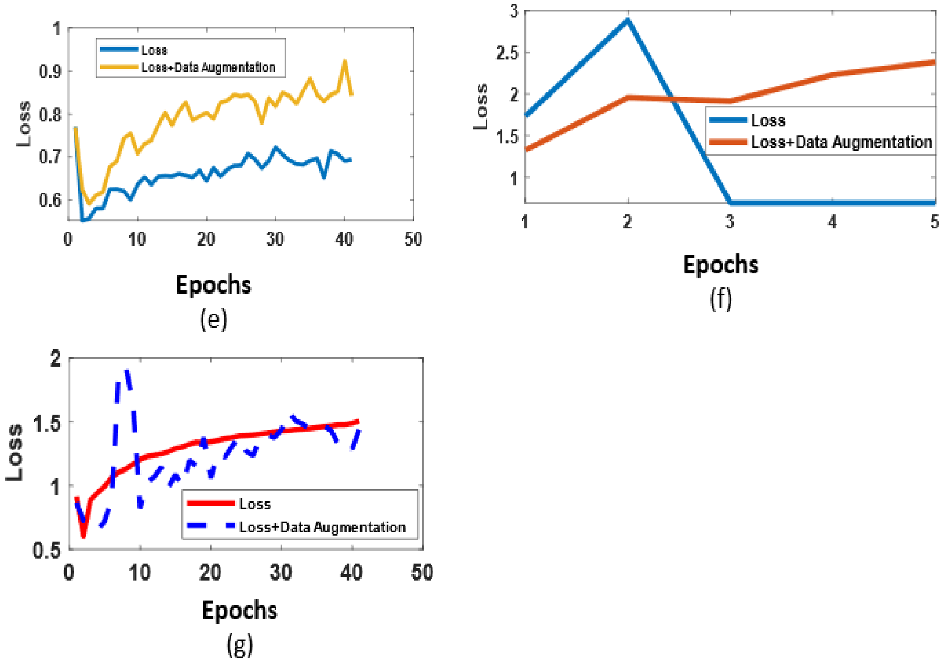

Figure 4. (e) ResNet101, (f) VGG16, and (g) VGG19 validation loss rates for both original and augmented datasets

Validation Accuracy

Figure 5 depicts the validation accuracy for each deep learning model. As observed, validation accuracy for both datasets using AlexNet shows similar trends, with the accuracy improving and sustaining at epoch values of 2 and above. In the case of GoogleNet, both datasets show similar trends, specifically from 0 to 50 iterations with 80% accuracy. The accuracy increases slightly after that and maintains similar accuracy until the numerical analysis ends. Further, for ResNet18, it is observed that the validation accuracy increases at epoch 5 for both models and demonstrates similar trends until the numerical analysis session ends. Furthermore, the validation accuracy for ResNet50 increases for both datasets up to the fifth epoch and sustain similar values.

On the other hand, for ResNet101, the validation accuracy shows incremental accuracy for both datasets at epoch 5 and maintains the same pattern. As for VGG16, the validation accuracy increases for both normal and augmented datasets at the second epoch. After that, for the augmented dataset, the accuracy increases, while for the normal dataset, the accuracy drops at epoch 3 and maintains a similar accuracy value onwards. Finally, for the VGG19 model, the validation accuracy increases for both datasets at epoch 5, and after the 10th epoch, both accuracies achieve stability.

Performance Measure

The performance measure was used to select the optimum deep transfer learning amongst all seven under evaluation for the Arabic handwriting classification based on the highest accuracy among these models. The performance measures for the two classes are the 'native writer' and 'foreigner writer.' Accuracy (Acc), sensitivity (Sens) and, specificity (Spec) were used in this study as the performance measures. Here, the acc represents the correctness of the deep learning classifier, whilst the sens represents the correctly classified of 'foreigner' handwriting, and the spec represents the correctly classified of the 'native' handwriting. The datasets were partitioned with 60% of the images for training and 40% for testing. All trained models were evaluated and tested using 396 as unseen images for both classes as either 'foreigner' or 'native.' Table 1 tabulates the results of each DL model for both unaugmented and augmented datasets.

Table 1

Performance measure of each DL model using both original and augmented data

DL Model	Original Data			Augmented Data		
	Acc	Spec	Sens	Acc	Spec	Sens
AlexNet	78.3	74.2	82.3	75.0	79.3	70.7
GoogleNet	93.2	92.4	93.9	95.5	93.9	97.0
ResNet18	78.8	75.8	81.8	80.6	78.8	82.3
ResNet50	78.5	75.3	81.8	82.8	87.9	77.8
ResNet101	78.5	83.8	73.2	81.6	79.3	83.8
VGG16	50.3	0.6	0.7	78.5	78.3	78.8
VGG19	79.0	74.2	83.8	78.0	91.4	64.6

From Table 1, GoogleNet shows the highest accuracy for both original and augmented data. The same goes for specificity and sensitivity. GoogleNet uses inception modules to decrease the required computation time and replace fully connected layers with global average pooling. AlexNet achieves higher accuracy without data augmentation with an accuracy of 78.3% and 82.3% sensitivity. Consequently, AlexNet could recognise the 'native' handwriting better as compared to 'foreigner' handwriting. Among foreigner and native classes, GoogleNet outperforms for both original and augmented datasets with the highest accuracy using augmented data at 95.5% accuracy, and the class native scores 97.0% as specificity. As for the ResNet18 model, the outcome shows higher accuracy for augmented data with 80.6% accuracy and 82.3% specificity for the native class. Once again, for ResNet50, the performance of augmented data attains higher accuracy, specifically 82.8% but lower specificity of 77.8% for the class native.

Moreover, for ResNet50, 81.6% accuracy achieves for augmented data compared to 78.5% for the original data. Compared to AlexNet, training the ResNet requires high computation; therefore, AlexNet is the second option for original data. As for VGG16, this deep learning model obtains a higher accuracy rate for augmented data, specifically 78.5%. However, for VGG19, accuracy for unaugmented data is higher that is 79%, as compared to data augmentation accuracy, specifically 78%. Generally, only two deep learning models obtained higher results based on original data, namely AlexNet and VGG19. Although the VGG19 performed slightly better, it requires more memory. The rest of the deep learning models attain higher accuracy using augmented datasets. The overall results prove that GoogleNet is the optimum deep learning model and outperforms other models based on both original and augmented datasets.

CONCLUSION

In conclusion, handwritten Arabic images classification was analysed in this study using seven deep learning transfer learning to evaluate and validate the ability of each model to distinguish the Arabic handwriting images written by either 'native' or 'foreigner'. Datasets of written Arabic handwriting images were created to train and test these models. The participants in these datasets are Arabic writers and non-Arabic writers. On the whole, training and testing using the seven transfer learning models, namely AlexNet, GoogleNet, Resnet18, ResNet50, ResNet101, VGG16, and VGG19 with both original and augmented datasets, have proven the ability of these models to differentiate the Arabic handwriting according to two categories specifically native writer or foreign writer. In addition, these transfer learnings are also suitable for small-size datasets. Results show that the GoogleNet is the most suitable deep learning model, with 93.2% using the original dataset and 95.5% using augmentation data compared to other transfer learning models. For future work, findings from this study will use a more extensive and diverse database specifically for identifying ancient Arabic handwritten recognition written by the native writer based on deep learning.

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