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Abstract. In recent days, recognizing handwritten digits in Arabic and English has been useful for several applications. This paper presents an efficient method to recognize the unlimited variation in human handwriting. We have used freely available datasets, MNIST and MADBase, for English and Arabic handwritten digits, respectively. Each dataset involves enough number of images with ten classes from 0 to 9, so that there are 70,000 images in total, 60,000 images are used for training and 10,000 images are used for testing the models. A Deep Learning-based methodology is suggested for recognizing handwritten digits by using various transfer learning types such as; AlexNet, ResNet-18, GoogleNet, and DensNet-201 aimed at deep feature extractions. Moreover, we utilized three types of classifiers: Decision Tree (DT), k-nearest neighbors (KNN), and Support Vector Machine (SVM) and compared their performances. The results show that the AlexNet features with SVM classifiers provide the best results for both datasets, with error rates of 0.96% and 0.9997% for Arabic and English datasets, respectively.

Keywords: MNSIT Digits handwritten Recognition, SVM, CNN, DT, KNN, and DL.

1 Introduction

Handwritten Digits Recognition (HWR) has been an important area due to its applications in several fields [1]. Recognition is an area that covers various fields such as face recognition, image recognition, fingerprint recognition, character recognition, and numerals recognition [2]. Handwriting recognition means the ability of a computer or device to take as input handwriting from a source such as printed physical documents, pictures, and other devices. It also uses handwriting as a direct input to a touch screen and then interprets it as text, e.g., smartphones, tablets, and PDA to a touch screen through a finger [3]. This is convenient since it enables the user to swiftly enter numbers and text into the devices [3]. Handwritten digit recognition is an important component in many applications: check verification, office automation, business, postal address reading, printed postal codes, and data entry applications [2]. Deep learning (DL) [4] is a hierarchical structure network that simulates the human brain's structure to extract the internal and external input data features. Deep learning is based on algorithms using multilayer networks such as deep neural networks, convolutional deep neural networks, deep belief networks, recurrent neural networks, and stacked auto encoders. These algorithms allow computers and machines to model our world well to exhibit intelligence [5]. In this paper, the Deep Learning based methodology is proposed for recognizing Arabic and English handwritten digits. In order to recognize the variation in the human's handwriting, different types of transfer learning techniques that are AlexNet, ResNet-18, GoogleNet, and DensNet201 are used. On the other hand, the freely available datasets, MNIST and MADBase, are used for Arabic and English, respectively. The main purpose of this study is to make a comparative evaluation of deep learning and machine learning techniques for handwritten digit recognition for Arabic and English. The rest of this paper is organized as follows: In section 2, related work on handwritten digit recognition is summarized. Section 3 describes the datasets used in the study. Section 4 explains the methods applied in this study for handwritten digit recognition. Section 5 briefly explains implementation platforms. Experimental results and their evaluations are presented in Section 6. Finally, Section 7 concludes our study.

2 Related Work

Handwritten digit recognition is a difficult task that has been extensively researched for many years. The study in [6] have proposed a new model which is a hybrid of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) using the MNIST digit datasets. This model uses CNN as an automatic feature extractor and applies SVM as the output predictor. The suggested model's efficiency and practicality were assessed on two levels: recognition accuracy and reliability performance. To improve the handwritten digit recognition, the last two layers of the AlexNet structure are replaced with an SVM classifier. In the new method, the SVM acting as the output predictor and the AlexNet working as a feature extractor automatically, the stochastic diagonal Levenberg-Marqurdt algorithm is introduced to accelerate the network's convergence speed. The results based on the MNIST datasets showed that the proposed method could outperform both SVMs and AlexNet. Moreover, the method gets a faster convergence speed (a round 25-30 epochs) in the training process. The best results in this model have been achieved 94.4% recognition rate without rejection in [7]. In [8] presents a novel perceptual shape decomposition strategy to handwritten digit recognition. Where a new handwritten digit recognition technique that works very correspondingly to human perception, has been proposed. The key feature of the proposed method is the representation of deformed digits using four distinct visual primitives. For geometric modeling and efficient recognition, the proposed approach only requires a few shape parts and their obvious spatial relationships. The proposed system's performance is evaluated on five digit datasets of four popular scripts, Odia, Bangla, Arabic, and English, with the author's MNIST dataset achieving 99.11 percent accuracy for English digit recognition and 97.96 percent accuracy for Arabic digit recognition.

The Arabic digits recognition described by [9], a large amount of handwritten digits dataset had been collected to examine and demonstrate a powerful Deep Convolution Neural Network (DCNN) utilized for classification. . Moreover, A vital CNN parameter is carefully chosen and modified to produce the final concrete model. The obtained dataset is trained using an efficient CNN model, and the model is thoroughly analyzed by carefully picking their parameters and demonstrating their resilience for handling the collected dataset. The detection performance reached 95.7%.

A unique CNN deep learning architecture has been presented in [10] for the recognition of handwritten Multilanguage digits (mixed numbers belonging to various languages). It was created for manually writing Eastern Arabic and Persian numerals, while studies are also done with other languages like Urdu, Devanagari, and Western Arabic. The results of the experiment of this approach provide superior accuracy for datasets of separate languages as well as datasets of combined languages with the same geometrical features or with combined geometrical features, respectively. With use of CNN one layer the accuracies were 99.21% and 99.13% for Eastern Arabic and Western Arabic (English) respectively.

A unique Local Feature Extraction method is also proposed in [11] for designing an unifying multi-language handwritten numeral recognition system using various languages (namely Arabic Western, Arabic Eastern, Persian, Urdu, Devanagari, and Bangla) with different number of digits. Using an RF classifier, the proposed technique is evaluated on six different well-known datasets of various languages, the Eastern Arabic digits recognition accuracy was 98.1%, for Western Arabic (English) accuracy reached to 95.3%, and the average accuracy of all used languages were 96.73%.

In the study given by [12], a Decision Tree (DT) classifier approach is used to recognize handwritten English digits from the standard Kaggle digits dataset. To identify handwritten numerals, they assessed the model's precision against each digit from 0 to 9. With 720 columns and 42000 rows in the Kaggle dataset used for training and testing, the method's accuracy was 83.4 percent.

The use of ResNet on a standard ISI Kolkata Handwritten Oriya numeral datasetse on 4970 handwritten samples was used to evaluate a deep learning strategy for Odia numeral digit recognition that was introduced in [13]. According to the statistics, ResNet achieves a true recognition rate of 99.20 percent, which is the highest accuracy for Odia numeral digit recognition when compared to other approaches.

. To avoid the complicated ensemble (classifier combination) expensive feature extraction, and sophisticated pre-processing, Convolutional neural network approaches to classic recognition systems have been evaluated in [14], and has shown the importance of several hyper-parameters. The error rate of the algorithm reached 0.11% with the Adam optimizer for the MNIST dataset.

In our study, we utilized MNIST and MADBase datasets to experimentally evaluate the performance of hybrid of transfer learning with SVM, KNN and DT classifiers on recognizing English only, Arabic only, and English – Arabic mixed handwritten digits recognition.

3 Data-Set

This paper has utilized freely available datasets: MNIST and MADBase for English and Arabic handwritten digits, respectively [15] and [16]. Each dataset contains 70,000 images in 10 classes, from which 10,000 images are used for testing and the remaining

60,000 images are used for training the models. The images in the dataset have low resolution, with size 28×28×1 pixels in grayscale. An example from each dataset is presented in Fig 1.

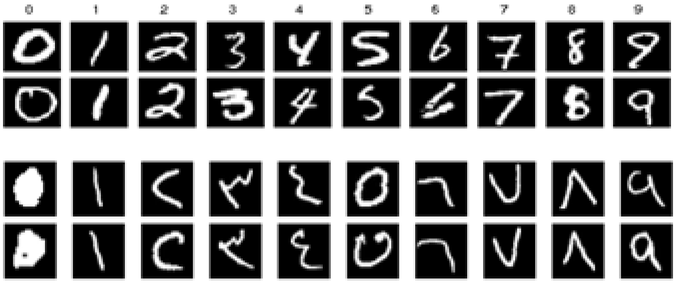

Fig. 1. Examples from MNIST (for English) and MADbase (for Arabic) Datasets.

4 Method

Fig. 2 displays the workflow of the proposed method. At first, CNN and Transfer Learning is used to extract features from the images, then Decision Tree (DT), k-nearest neighbors (KNN), and Support Vector Machine (SVM) classifiers are utilized to classify handwritten digit images into 10 classes.

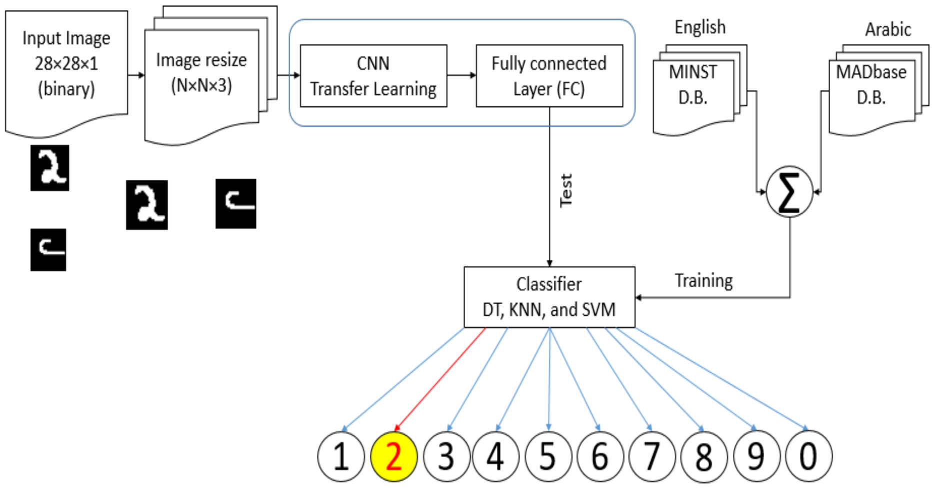

Fig. 2. The workflow of the proposed method.

4.1 Dataset usage:

In this paper, we did four ways of handwritten digit identification as described in the followings:

- **English (10 classes):** The classification is done for only English digits, and each digit has one class label. We have 10 classes from 0 to 9.

- **Arabic (10 classes):** The classification is done only for Arabic digits, and each digit has one class label. We have 10 classes from 0 to 9.
- **English and Arabic (10 classes):** We classify the combination of English and Arabic digits. Each digit represents one class in English and Arabic digits. We mixed each English digit with an equal Arabic digit to be all zeros in one file (class), and other digits have the same procedure. Finally, the number of classes will be 10 from 0 to 9.
- **English and Arabic (20 classes):** The classification of English and Arabic digits are done together, but each digit is classified as English or Arabic separately. That means the zero digits in Arabic have a different class label than zero in English; as we described, we have 10 Arabic digits classes, and 10 English digits classes, totally we have 20 classes.

4.2 The stages of the workflow

4.2.1 Pre-processing

In order to improve the accuracy of digits recognition, the solution to the digits identification problem requires beating some main problems, like differing image size and quality of image, different levels of illumination, and employing a high number of images. Therefore, it is important to use pre-processing stages of the images before processing them. This paper's pre-processing stage involve Histogram Equalization (HE), image resize techniques.

- **Histogram Equalization (HE):** For the illumination normalization, we used the Histogram Equalization (HE) technique, which reduces the light effect and luminosity of unity of all images in the dataset. This stage will positively affect the performance of the proposed model. Histogram Equalization (HE) [17] is a fast, easy, and effective image enhancement that can effectively confirm the image density information in all regions.
- **Image Resizing:** The size of the cropped images is a very important step in making the test image sizes the same as the size of train images, and the more important thing is to be the same size as the input layer of the used CNN. We have used image sizes in this experiment as 28×28×1 pixels, however we resized the images according to input size of the CNN architectures for example the input layer of AlexNet was 227×227×3 and in DensNet-201, ResNet-18, and GoogleNet the input sizes were 224×224×3.

4.2.2 Convolution Neural Network (CNN)

When dealing with huge datasets, it is very difficult for a human, to determine which label or class a data point belongs to. Instead, a classifier, which is a supervised machine learning method, is used. A classifier is trained from a dataset with known class labels, then it is used on data of the same type and feature length to assign class label to new test data. To train a classifier, features from the data needs to be extracted and CNN is used for feature extraction purpose in this study.

Multiple abstract data representations can be learned by multi-layered computational models using Deep Learning (DL). From training to testing, the success of deep artificial neural networks varies. Conventional learning assumes that the model family's properties or the regularization techniques used in training have minor generalization errors.

Convolutional neural networks (CNN) are a type of DL [18] and [19]. Despite the fact that neural networks were not popular at the time, they have achieved a great deal in practice, and the computer vision community has recently embraced them. CNN are powerful visual models that generate hierarchies of features. Full color RGB image composed of three two-dimensional arrays including pixel intensities in the three color channels, for example, is intended for the processing of data in the form of multiple arrays.

In this study, handwritten digit images are given as input to a CNN model, then it produces the feature vector for each image where the length of the feature vector depends on the CNNs model and feature layer. These traits are entered into a classifier to identify handwritten digits.

4.2.3 Classifiers

In the current study, we utilized three classifiers: Decision Tree, KNN, and Support Vector Machine (SVM) to check the performance, and the best classifier will be used to identify the handwritten digits.

- **Support Vector Machine (SVM):** is a supervised machine learning algorithm that finds some soft hyperplanes that separate each class or group by employing a training algorithm [20].
- **Decision Tree (DT):** is a classification algorithm commonly utilized in data mining. The objective is to create a model that detects the label based on the input variables. In each node or stage of a DT classifier, we try to form a pattern condition that separates all classes involved in the dataset to the most accurately [21].
- **k-Nearest-Neighbors (K-NN):** Is a simple supervised machine learning algorithm can be used for classification and regression, It is easy to understand and implement, but the main hurdle is that it slows down significantly with the size of the huge data. In k-NN classification, an object is classified by majority votes of its k nearest neighbors (k is an odd positive integer, usually small). If k is equal to one, the object is simply assigned to the class of that single nearest neighbor [22].

We design the architecture of the hybrid of various types of transfer learning models with various types of classifiers such as SVM, DT, and KNN, by replacing the fully connected layer (FC) of the CNNs model with a classifier. Several different classifiers and transfer learning models have been applied because of the No Free Lunch (NFL) theorem which means that there is no unique machine learning algorithm that performs best for all problems [23]. If an algorithm does particularly well on one class of problems, then it is highly probable that it does more poorly over the remaining problems. That’s why we need to test several different classification and transfer learning models to see their performances.

For example in the AlexNet model, we have three fully connected layers as layers 6^{th}, 7^{th}, and 8^{th} in each layer we have different features and lengths as displayed in Table 1. In our study, we combine the deep features with a classifier and will test each transfer learning model with different fully connected layer and classifier in order to select the best performance.

The output units of the fully connected layer in a CNN’s network are the estimated probabilities of the input samples. An activation function computes each output probability. The activation function's input is that the output of the previously hidden layer has trainable weights plus a bias term. It is pointless to look at the output values of the hidden layers just for the CNN network itself; however, these values can be considered as features of any other classifier. In this paper we presented four type of transfer learning namely AlexNet, DensNet 201, ResNet18, and GoogleNet combined with various type of classifiers such as SVM, DT, and KNN.

5 Implementations

All the requirements in this study were implemented using Transfer Learning, image processing, and classification applications in MATLAB 2018-b and a computer equipped with an Intel (R) Core™ -i7-7500U (2.9 GHz) processor. 12 GB of RAM, which helped us get good performance and good processing times.

6 Results and Discussion

The experiment tested the handwritten digits recognition in many ways, such as the outcome obtained by the MNIST dataset for English digits only. In this case, we have 10 classes, one class for each digit. MADbase dataset contains Arabic digits only. In this case, we classify data into 10 Arabic digits classes. After that both datasets are mixed and all the images with related classes for Arabic and English are merged. As an example, all Arabic zero (0) images and English zero images are combined to form zero class images. Therefore we have 10 classes from 0 to 9. Finally, we classify the digits separately with respect to either being Arabic or English. Again, we combine the two datasets without combining the classes. Each class has digits either in Arabic or English (here, we have two classes of each digit, one for Arabic and the other for English). We have a total of 20 classes, 10 for Arabic and 10 for English digits.

We have utilized Transfer Learning for feature extraction and various classifiers such as DT, KNN, and SVM and compared their performances. The experimental results are displayed in Table 1, Table 2, Table 3 and Table 4. As well as the examples of confusion matrix obtained by a combination of Alex-Net and SVM are displayed in Fig. 3 to 7. The results show that the combination of AlexNet-6th fully connected layer ('Fc6') with the SVM classifier provides best results with less than 1% error in both datasets.

The hybrid of CNN with a Decision Tree (DT) as well as CNN with KNN classifiers also has been done in our study, however the accuracy was lower than SVM classifier; DT was better than KNN. About running time-consumption, the KNN was faster than SVM and DT classifiers; for example in order to test 10000 samples SVM takes 2349 second, DT takes 14.4 seconds, and KNN takes 1.38 second. According to the results, the hybrid of CNN with KNN was faster than other classifier but lower accuracy.
The Transfer Learning (AlexNet-fc6) with SVM classifier shows the best results in all cases (Table 1 – 4). The accuracy reached more than 99% in Arabic, and English datasets shows the proposed method is successful and can be used in many applications to recognize the digits.

Table 1. The classification results of the handwritten English digits by using various types of CNN and classifiers.

DL Name	Feature Layer	Size of input Layer	Total Layer	Feature Length	Accuracy of classifiers (%)		
					SVM	DT	KNN
AlexNet	fc6	227×227×3	25	4096	**99.0003**	98.393	98.002
AlexNet	fc7	227×227×3	25	4096	98.7785	97.98	95.68
AlexNet	fc8	227×227×3	25	1000	97.7279	96.9476	93.84
DensNet201	fc1000	224×224×3	709	1000	96.375	95.8159	93.85
ResNet18	fc1000	224×224×3	72	1000	95.9125	94.8789	86.13
GoogleNet	loss3-classifier	224×224×3	144	1000	95.095	92.93	84.423

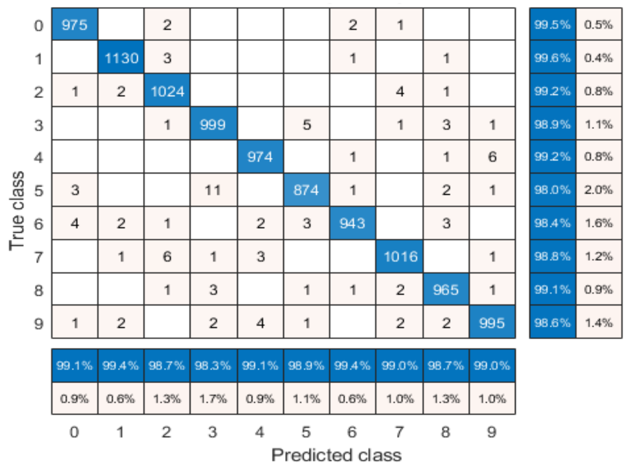

Fig. 3. Confusion matrix of handwritten English digits only (10 classes) by using AlexNet-fc6 with SVM.

Table 2. The classification results of the handwritten Arabic digits by using various types of CNN and classifiers.

DL Name	Feature Layer	Size of input Layer	Total Layer	Feature Length	Accuracy of classifiers (%)		
					SVM	DT	KNN
AlexNet	fc6	227×227×3	25	4096	**99.04**	98.93	98.66
AlexNet	fc7	227×227×3	25	4096	99.02	98.66	97.72
AlexNet	fc8	227×227×3	25	1000	98.72	98.48	96.84
DensNet201	fc1000	224×224×3	709	1000	98.25	98.16	95.7
ResNet18	fc1000	224×224×3	72	1000	97.84	97.43	95.02
GoogleNet	loss3-classifier	224×224×3	144	1000	97.59	97.32	94.82

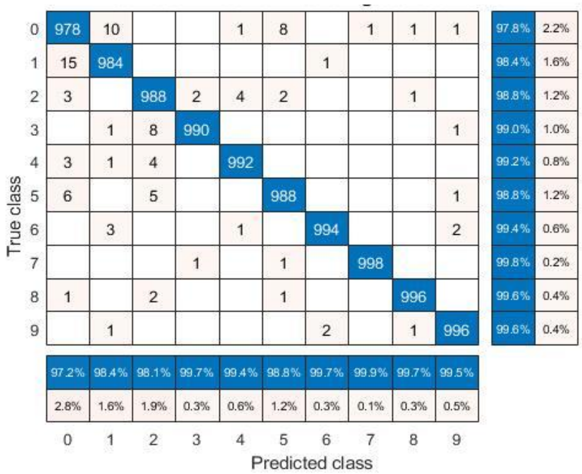

Fig. 4. Confusion matrix of handwritten Arabic digits only (10 classes) by using AlexNet-fc6 with SVM.

Table 3. The classification results of the combined handwritten English and Arabic digits (10 classes) by using AlexNet and GoogleNet as automatic feature extraction and SVM, DT, and KNN as classifiers.

DL Name	Feature Layer	Size of input Layer	Total Layer	Feature Length	Accuracy of classifiers (%)		
					SVM	DT	KNN
AlexNet	fc6	227×227×3	25	4096	**98.23**	97.43	96.87
GoogleNet	loss3-classifier	224×224×3	144	1000	94.39	89.516	86.57

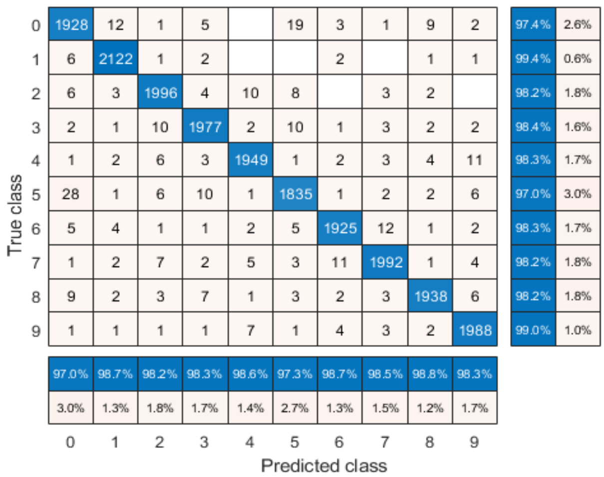

Fig. 5. Confusion matrix of the combination of English and Arabic digits handwritten (10 classes) by using AlexNet-fc6 with SVM.

Fig. 5 shows that some numbers in the two languages have high similarity, such as the numbers one and nine in English are similar to the numbers one and nine in Arabic, which can improve detection performance, especially when using handwriting digits. And some different numbers have similar properties, for example, the number five in Arabic has a high similarity to the number zero in English language, and they have the same properties as displayed in Fig. 1, which can reduce the classification performance. As shown in Fig. 5. The maximum error was in numbers 0 and 5. The overall performance (accuracy) of AlexNet-fc6 with SVM was 98.23%.

Table 4. The classification results of the handwritten English and Arabic digits (20 classes) only by AlexNet and GoogleNet as automatic feature extraction and SVM, DT, and KNN as classifiers.

DL Name	Feature Layer	Size of input Layer	Total Layer	Feature Length	Accuracy of classifiers (%)		
					SVM	DT	KNN
AlexNet	fc6	227×227×3	25	4096	**98.56**	97.25	96.14
GoogleNet	loss3-classifier	224×224×3	144	1000	94.86	90.63	84.74

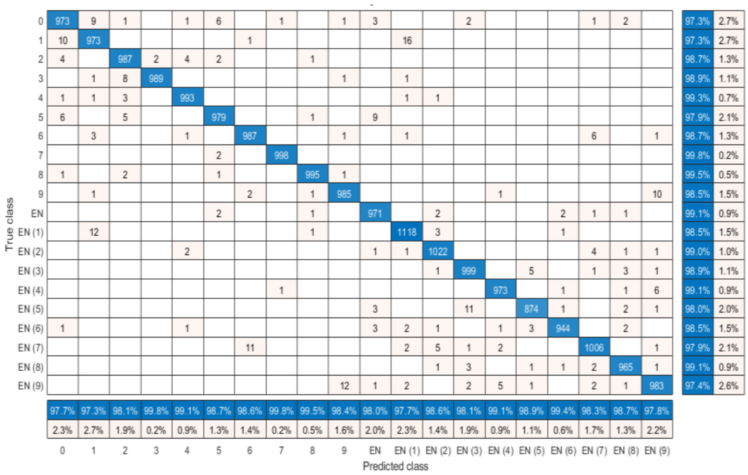

Fig. 6. Confusion matrix of English and Arabic digits handwritten separately in each (20 classes) by using AlexNet-fc6 with SVM.

In this method, the handwritten numbers were classified on the basis of the different numbers for each language, where the English numbers were separated from the Arabic numbers, and each dataset contains 10 classes, and the classification will be done for 20 classes in total. As shown in Fig. 6, it was noted that the error rate occurred in the numbers with similar features in both languages, such as the numbers 1, 9, 0, and 5 as shown in Fig. 1, where the error rate was the largest, as it was noted that the error rate in the mentioned numbers is about 2%. The overall performance reached to 98.56% by AlexNet-fc6 with SVM, it is better than the mixing of both dataset. In the MNIST dataset the number of images was unbalanced but in average was 10000 test images in each class.

According to experimental evaluation, we have observed that, for all 4 types of dataset usage, the best handwritten digit recognition is performed by the combination of the AlexNet-fc6 with SVM classifier.

Results show that the proposed method gives low error rate and high accuracy of the handwritten digits recognition as compared to previous studies. When we compare our results with the previous studies we observed that, we improved the results of the study presented in [12] by 15.6%,our results are 0.94% better than that of results in [11], for Arabic digits we improved results of [9] by about 3.34%, and again for Arabic digits we improved results of [8] by 1.08%. Our results are better than many previously reported accuracies.

7 Conclusion

The supervised machine learning algorithm in the application field is so vast that it depends on the theorem (no free lunch) [23], so we cannot choose a unique machine learning approach that can give us a good performance in all fields. Moreover, the accuracy of a machine learning algorithm is based on the input features and the required class name in the output. Hence, various machine learning algorithms should be checked to know which method will provide us with better accuracy. Therefore, we have implemented, tested, and trained three different classifiers accuracies in this project: DT, KNN, and SVM. To calculate the accuracy of each model and select the best one, as well as four CNN architectures (AlexNet, GoogleNet, DensNet201, and ResNet18) were used to features extraction. The difference in the performance of CNNs model came from the design of CNNs layers and size of convolution window etc. The SVM classifiers introduced the best results in all used CNNs, the DT classifier was the second best, and KNN performed worst. However, DT run faster than SVM, while KNN required the longest classification time as it is lazy method.

The results show that the deep feature obtained by (AlexNet) from 6^{th} fully connected layer with features length 4096 values, combined with the SVM classifier shows the best results in all cases. The error reached is less than 1% in Arabic and English Datasets which shows the proposed method is successful and can be used in many applications to recognize the digits. Our future work will be highlighted improving the accuracy of handwriting Arabic and English digit recognition by utilizing other classifiers, and changing the parameters as well as an improved CNNs model.

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