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Classification Libya cities database of optical handwriting recognition using MLP

Iswikan, K.
Sebha University, Libya
kho.iswikan@sebhau.edu.ly

Abstract—**This paper aims to describe the process of classifying the Libyan Cities database for handwriting recognition using the Multi-Layer Perceptron (MLP) network, MLP consists of multiple layers of neural units. The Libyan cities data set for optical recognition of handwriting consists of 5000 digital samples of Libyan city names as binary images. The training data set was used to train the MLP model, and the test data set was used to evaluate the model's performance, reaching an accuracy of 80.6%.**

Index Terms—**classification, Libyan Cities, MLP, optical handwriting recognition.**

I. INTRODUCTION

Neural networks are powerful tools in the field of classifying handwritten Arabic letters and words[1]. Neural networks are used to model human mentality, relying on neural-like technology to process information and extract patterns[2].

In this case, neural networks learn different patterns and relationships in handwritten data, allowing them to classify letters and words with high accuracy. e.g., multi-layer neural networks[2], such as Multi-Layer Perceptron (MLP) are used to achieve the best performance in classifying handwritten characters and words[3] .

Consequentially, in the classification process, a database is collected containing samples of handwritten Arabic letters and words. These samples are converted into a digital representation suitable for input into the neural network. The database is divided into a training set and a test set to train and evaluate the model[4] .

Using deep learning techniques and training neural networks, the model is trained to recognize distinct patterns of handwritten Arabic letters and words. The weights of the neural network are adjusted during the training process to achieve the best classification performance.

After the training process is completed, the trained model can be used to classify unknown handwritten Arabic letters and words. The new sample is fed into the model, and the proposed classification of the sample is output .

Accordingly, the use of neural networks in classifying handwritten Arabic letters and words is an innovative and powerful technology that achieves excellent results in recognizing handwritten Arabic texts automatically and reliably. This technology is an important field in areas such as machine writing recognition, paper-to-digital text conversion, machine translation, and other related applications[5] .

The remaining part of this paper is structured as follows: Section 2 presents the related work, section 3 presents the materials and methods, section 4 presents the experiment's result, and section 5 presents the conclusion.

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II. II. LITERATURE REVIEW

A study [6] presents a model for Arabic handwriting recognition that blends Hidden Markov Models (HMM) with Convolutional Neural Networks (CNN). A Hidden Markov Model (HMM) classifier is used to perform the classification. For Arabic handwriting recognition, the Convolutional Neural Network (CNN) serves as a feature extractor and the HMM as a recognizer. The well-known IFN/ENIT database served as the study's dataset. In the case of Arabic handwriting recognition, the combined CNN-based HMM model performed better than a simple HMM with handmade characteristics.

Similarly, in the study [7] in the context of Arabic handwritten character recognition, researchers utilized convolutional neural networks (CNN) for image classification tasks. The dataset used in this study is the AHCD dataset, which consists of 16800 Arabic handwritten characters and achieved a high accuracy of 94.9% with a misclassification error of 5.1%.

Mahmoud Shams in [8] proposes a classification approach that combines support vector machines (SVM) with deep convolutional neural networks (DCNN). SVM is used to make judgments based on the learned features, while DCNN is used to extract features and identify patterns from the input data. With an error classification rate (ECR) of 4.93%, the study's classification accuracy is given as a 95.07% correct classification rate (CRR).

Additionally,[9] the classification method used in this paper for recognizing isolated handwritten Arabic characters is a two-stage hybrid classifier. This classifier consists of a Support Vector Machine (SVM) in the first stage and a neural network (NN) in the second stage. The SVM classifies characters into two classes based on the presence or absence of dots, while the neural network further refines this classification to identify specific Arabic characters.the dataset used in this study is the Alex U Isolated Alphabet (AIA9K) database, which contains 8,737 images of handwritten Arabic characters. The experimental findings showed that the first-stage classifier achieved a high recognition accuracy rate of 99.14%. The overall average recognition accuracy rate for all Arabic alphabet characters using the proposed two-stage hybrid classifier was reported as 91.84%.

Elleuch in the study [10], presents a method for classification using Convolutional Neural Networks (CNNs). These CNNs are utilized in conjunction with deep learning techniques like ResNet, VGG16, and Inception-v3. Additionally, transfer learning is employed to enhance the classification performance of these models.
The dataset used consists of images extracted from the IFN/ENIT database. transfer learning is utilized to refine pre-trained models for deep characteristics' extraction, which has shown good performance for frequent recognition problems in this context.

A new study [11] aims to develop a system for recognizing handwritten Arabic text using deep learning, The method used for classification in this study is a convolutional long short-term memory (ConvLSTM) network. The dataset used in this study is the IFN/ENIT database. The classification accuracy achieved in this study was 99.01%, indicating a high level of accuracy in recognizing handwritten Arabic text using the ConvLSTM-CTC approach.

The focus of this paper is classifying the data set of Libyan cities for optical handwriting recognition using MLP.

III. MATERIAL AND METHOD

In this section, showS how to classify a database used for optical text recognition using neural networks. The database represents the handwritten names of Libyan cities.

A. Data Acquisition

Data Collection: The database was created using A4-sized blank paper and 50 digital images of 100 cities in Libya. Writers from various backgrounds and ages contributed to the collection. The forms were scanned and cropped using a Fast Stone image viewer to extract all names. Figure 1 shows the original and scanned versions of the form.

Figure 1. The original and the scanned versions of the form.

The cropping technique was employed to remove unnecessary white space and superfluous text from scanned forms, as the scanning process faced issues with empty spaces, potentially causing a large storage area and affecting system speed. Figure 2 shows the process of cropping the name of a city.

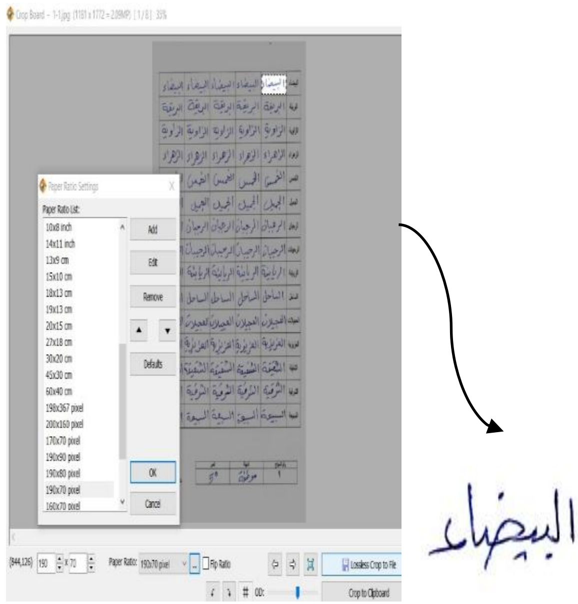


Figure2. The process of cropping the name of a city

Data Processing: any recognition system requires a process known as preprocessing to build a database. The goal of image preprocessing is to extract features to help the system later recognize These photos are kept into separate files. There are 50 images for each city name. After being cropped, they were put in separate folders, and we used a 3×3 median filter to eliminate all noise and irregularities. Figure 3 shows how to organize cropped photographs into separate folders.

Figure 3. placing images in isolated folders.

- Data Normalization: Each folder is read independently, and each image in the folder is resized to a width of 180 and a length of 100. Figure 4 shows choosing the appropriate size for images. After converting all the images to binary form and assigning labels to each image, Images are saved in the Bitmap format.

Figure 4. Choosing the appropriate size for images

With this, we have obtained a database consisting of 5,000 digital images of the names of Libyan cities in binary mode, which we will use for optical handwriting recognition in offline mode. The next step is to classify them using neural networks.

B. Database classification .

Orange Data Mining is an open-source software used for data analysis and mining. It was developed by the University of Ljubljana in Slovenia and provides an easy-to-use visual interface for building and running data analysis models.

The tool offers a wide range of techniques and algorithms available to users. They can be used to create classification and clustering models,predictions, exploratory analyses, and analyses of correlations between variables.

Overall, Orange Data Mining is a powerful and flexible data analysis and mining tool used in a variety of fields, such as scientific research, business analysis, education, and industrial applications.

To classify an OCR database of Libyan city names using the Orange Data Mining tool, I followed the following steps:

Use the import images component to load the database. The Libyan cities database of 5,000 digital images has been included. Figure 5 shows the images being uploaded and viewed using the image viewer.

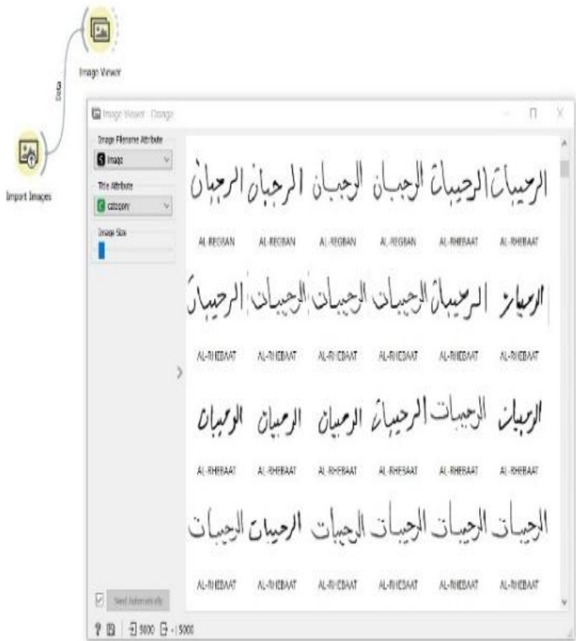
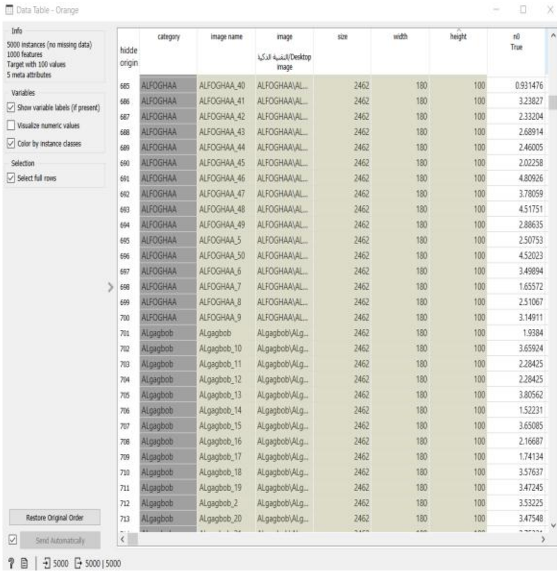


Figure 5 .the images being uploaded and viewed using the image viewer.

The Data table component was also added to display the data set with its properties, and select features for each image within the database. Figure 6. shows the display of the data set with its properties.



Data Table - Orange

Info
5000 instances (no missing data)
1000 features
Target with 100 values
5 meta attributes

Variables
Show variable labels (if present)
Visualize numeric values
Color by instance classes

Selection
Select full rows

hidde origin	category	image name	image التقنية الذكية/Desktop image	size	width	height	n0 True
685	ALFOGHAA	ALFOGHAA_40	ALFOGHAA\AL...	2462	180	100	0.931476
686	ALFOGHAA	ALFOGHAA_41	ALFOGHAA\AL...	2462	180	100	3.23827
687	ALFOGHAA	ALFOGHAA_42	ALFOGHAA\AL...	2462	180	100	2.33204
688	ALFOGHAA	ALFOGHAA_43	ALFOGHAA\AL...	2462	180	100	2.68914
689	ALFOGHAA	ALFOGHAA_44	ALFOGHAA\AL...	2462	180	100	2.46005
690	ALFOGHAA	ALFOGHAA_45	ALFOGHAA\AL...	2462	180	100	2.02258
691	ALFOGHAA	ALFOGHAA_46	ALFOGHAA\AL...	2462	180	100	4.80926
692	ALFOGHAA	ALFOGHAA_47	ALFOGHAA\AL...	2462	180	100	3.78059
693	ALFOGHAA	ALFOGHAA_48	ALFOGHAA\AL...	2462	180	100	4.51751
694	ALFOGHAA	ALFOGHAA_49	ALFOGHAA\AL...	2462	180	100	2.88635
695	ALFOGHAA	ALFOGHAA_5	ALFOGHAA\AL...	2462	180	100	2.50753
696	ALFOGHAA	ALFOGHAA_50	ALFOGHAA\AL...	2462	180	100	4.52023
697	ALFOGHAA	ALFOGHAA_6	ALFOGHAA\AL...	2462	180	100	3.49894
698	ALFOGHAA	ALFOGHAA_7	ALFOGHAA\AL...	2462	180	100	1.65572
699	ALFOGHAA	ALFOGHAA_8	ALFOGHAA\AL...	2462	180	100	2.51067
700	ALFOGHAA	ALFOGHAA_9	ALFOGHAA\AL...	2462	180	100	3.14911
701	ALgagbob	ALgagbob	ALgagbob\ALg...	2462	180	100	1.9384
702	ALgagbob	ALgagbob_10	ALgagbob\ALg...	2462	180	100	3.65924
703	ALgagbob	ALgagbob_11	ALgagbob\ALg...	2462	180	100	2.28425
704	ALgagbob	ALgagbob_12	ALgagbob\ALg...	2462	180	100	2.28425
705	ALgagbob	ALgagbob_13	ALgagbob\ALg...	2462	180	100	3.80562
706	ALgagbob	ALgagbob_14	ALgagbob\ALg...	2462	180	100	1.52231
707	ALgagbob	ALgagbob_15	ALgagbob\ALg...	2462	180	100	3.65085
708	ALgagbob	ALgagbob_16	ALgagbob\ALg...	2462	180	100	2.16687
709	ALgagbob	ALgagbob_17	ALgagbob\ALg...	2462	180	100	1.74134
710	ALgagbob	ALgagbob_18	ALgagbob\ALg...	2462	180	100	3.57637
711	ALgagbob	ALgagbob_19	ALgagbob\ALg...	2462	180	100	3.47245
712	ALgagbob	ALgagbob_2	ALgagbob\ALg...	2462	180	100	3.53225
713	ALgagbob	ALgagbob_20	ALgagbob\ALg...	2462	180	100	3.47548

Restore Original Order
Send Automatically
5000 5000 | 5000

Figure 6. the data set with its properties

Use the Image Embedding component, which is a function used in the field of machine learning and image processing. The function works to generate a compressed and abstract representation of an image, extract basic information from it, and convert it into a mathematical vector that can be used in classification and analysis. Figure 7. shows the use of the Image Embedding component.

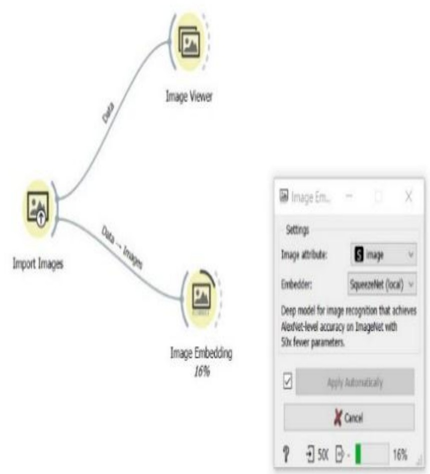


Figure 7. Using the Image Embedding component

The Data Sampler component was also used to identify and select the training sample on the data set, where 80% of the original data set was set for training, and the rest of the data for testing. Figure 8 shows the addition of the Data Sampler component to select the training sample.

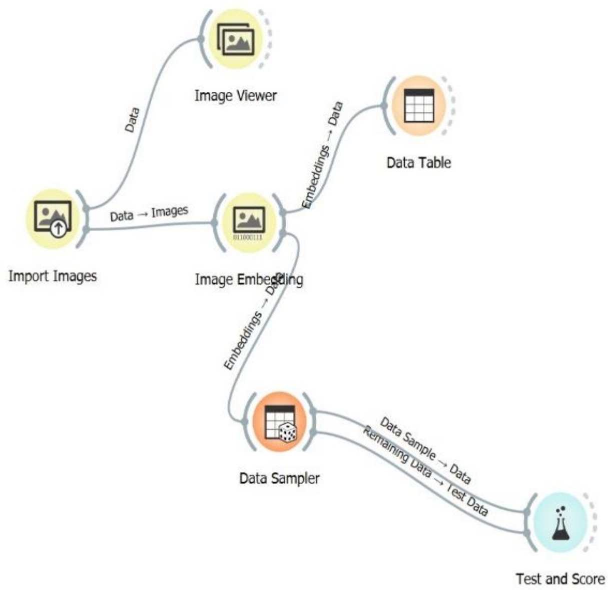


Figure 8. Adding the Data Sampler component to select the training sample

We also use the test and score component in data mining orange to show the results of the model used for classification. Figure 9 shows the use of the test and score component.

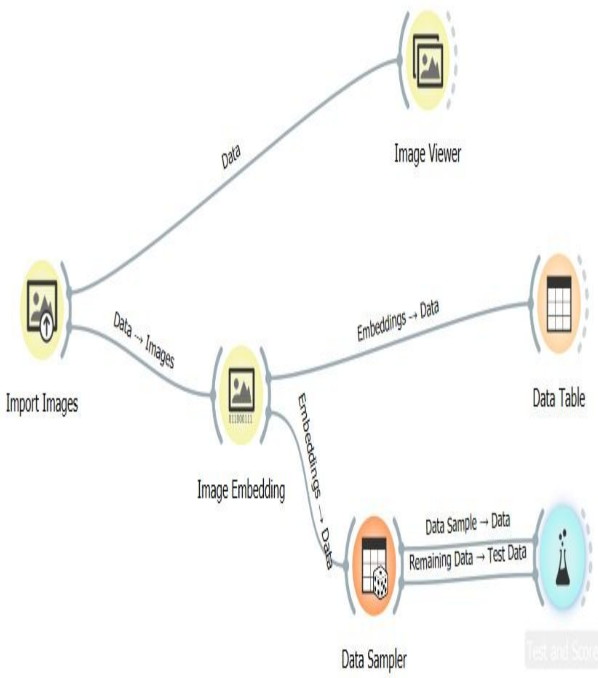


Figure 9. Using the Test and score component

A multi-layer perceptron (MLP) neural network classifier was used, and the parameters were set, specifying the number of hidden layers, the number of neurons in each layer, the activation function used in each layer, and the number of periods to be trained on. It was also connected to the Test and Score component to show the results. Figure 10 shows the use of a neural network classifier.

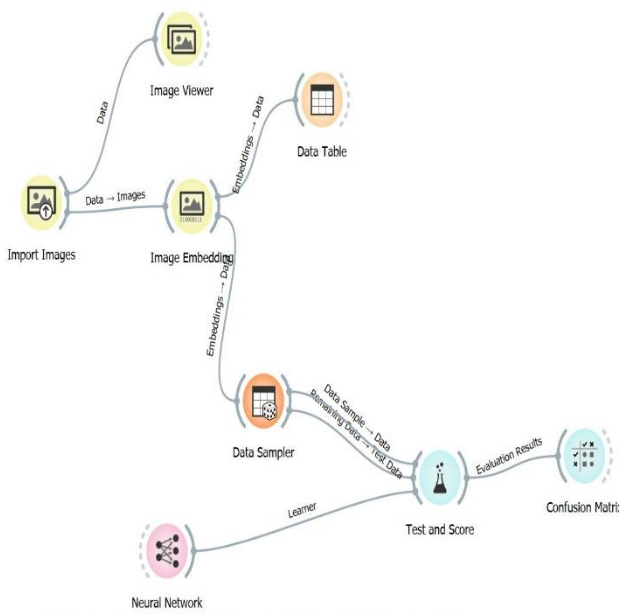


Figure 10. Using a neural network classifier

To adjust MLP (Multi-Layer Perceptron) parameters:

1. Number of layers and number of units in each layer: can specify the number of layers and the number of units in each layer for the MLP network. They can be an input layer that contains the appropriate number of attributes for the data set, hidden layers that can specify the number of and the number of units in each layer, and an output layer that contains the number of possible classes or outcomes.

2. Activation function: An activity function must be defined for each unit in the MLP. Popular activity functions include Sigmoid, ReLU, and Tanh. The appropriate activity function can be selected.

3. Learning rate: The learning rate controls how quickly the network weight is updated during training. An appropriate value for the learning rate must be chosen to achieve a balance between learning speed and stability. A high value of the learning rate may lead to instability in training, while a value that is too low may lead to slow learning.

4. Number of training epochs: The number of training epochs must be determined, during which the MLP is trained. The performance of the model on the training set should be monitored and verified over multiple runs, and the stability of performance should be verified.

5. Weight initialization: Various MLP weight initialization methods can be used, such as a specific random distribution or specific initialization methods, such as Xavier or He initialization. You can try different configuration methods to achieve the best performance.After setting the basic parameters in MLP, And experiment with a variety of values and monitor the performance of the model to choose the optimal values. The coefficients shown in the figure were chosen. Figure 11 shows The neural network parameters

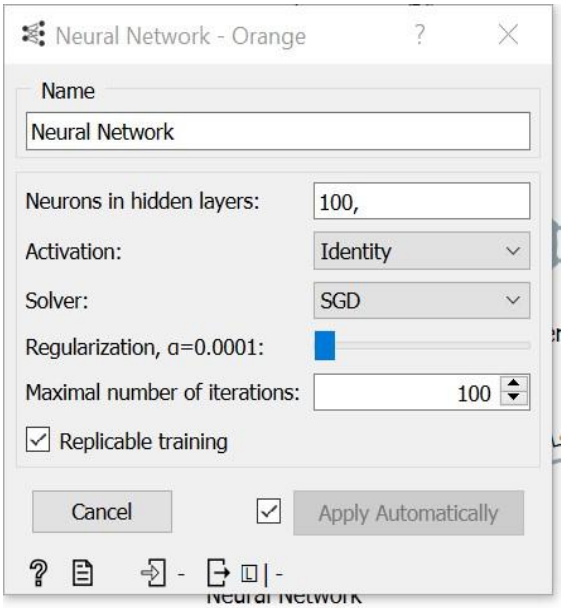


Figure 11. The neural network parameters

Using the neural network classifier, the results of the confusion matrix show that some city names had high percentages of classification and other city names had weak percentages. Figure (8.4) shows the highest-ranking cities with the neural network classifier.

Among the names of the cities that received the highest rating is Al-Azizia, Al-Hawamid, Al-Jabal Al-Akhdar.the Figure 12 shows the highest-ranking cities with the neural network classifier.

ALEZIZYA	ALFOGHAA	ALGIGAB	ALgagbob	ALgatroon	ALharabaa	ALhawamed	ALjabal alakhdar
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	1	0	0	0
0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
0	8	0	0	0	0	0	0
0	0	7	1	0	0	0	0
0	0	1	8	0	0	0	0
0	0	0	0	6	0	0	0
0	0	0	0	0	7	0	0
0	0	0	0	0	0	10	0
0	0	0	0	0	0	0	9
0	0	1	0	0	0	0	0
0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Figure 12. the highest-ranking cities with the neural network classifier.

Among the names of the cities that have a low rating rate is the city of Al-Jawf, Nalut Al-Zahra, and the lowest ranked city is Al-Araban. Figure 13 shows the cities with the lowest rating in the neural network classifier.

ALmayaa	ALmshashya	ALorbaan	ALshagiga
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
9	0	0	0
0	8	0	0
0	0	7	0
0	0	0	7
0	0	0	0
0	0	0	0

Figure 13. lowest-ranking cities with the neural network classifier.

C.Evaluation Metrics

The classification algorithms were evaluated based on some performance metrics, namely: precision, recall, and accuracy:

a) Precision is defined as the fraction of expected positives that are positive, as shown in equation (1):

$$TP/\,TP+FP \qquad (1)$$

b) Recall is the percentage of actual positives that were expected to be positive, as shown in equation (2):

$$TP/\,TP+FN \qquad (2)$$

d) Accuracy is determined by the percentage of correctly categorized test cases on a given test set. As shown in equation (4):

$$TP+TN/\,TP+TN+FN+FP$$

(4) whereby TP/TN stands for the number of True Positives/Negatives occurrences and FP/FN for the number of False Positives/Negatives instances.

IV. EXPERIMENT RESULT

After collecting data, which is the first and essential step in creating a Libyan cities database, this matter required prior planning and preparation to obtain data of high quality and sufficient quantity to teach optical recognition models.

Data for the names of one hundred cities were also obtained from the form that was prepared, and special forms were used to collect handwriting samples in a uniform and organized manner. This is to facilitate the process of collecting data from people who differ in their personal characteristics, such as gender and age. This helped expand the scope of the data and increase its diversity. It also leads to improving the accuracy of the optical recognition model and its effectiveness in recognizing handwriting, as no specific category was specified, and no restrictions were placed. To write or determine the type of pen used for writing, and after obtaining data from more than 70 forms, use a high-resolution scanner to obtain an electronic image of the paper forms that have been filled out,

After obtaining the digital samples, it is necessary to choose a program that allows the possibility of modifying and editing images easily. Previous studies used different programs such as Paint and Photoshop to crop letters or words in forming the database. In this research, the names of cities were cropped using modern software known as Faststone, due to the presence of cropping tools that It allows you to select a specific area of the image and cut out the unimportant part.

I used the cropping technique with caution, depending on the intended purpose and taking into account the quality of the resulting image. Because applying cropping technology to the image leads to changing the size of the original image, and this can affect the quality and accuracy of the image.

The results show various samples of handwriting after the samples that were invalid in some of the scanned models were discarded. It cannot be used to obtain accurate and reliable results.

A medium filter was added to text images to improve the quality of the images and make the text clearer. The window size [3,3] was determined according to specific needs and requirements, and the potential effects on the image were evaluated before using the filter, and the desired results were achieved. Figure 14 shows Applying the median filter to a set of images

```
function data_augm(folder_name,num_images)
images_file = getAllFiles(folder_name);
for imag_num= 1:num_images
    img = imread(images_file{ imag_num});
     J = medfilt2(img ,[3,3]);
    imwrite(J,sprintf('%d.png',imag_num))
 end
end
```

Figure14. Applying the median filter to a set of images

To improve the accuracy of the results and reduce errors, the set of images was converted into binary images consisting of zero and one (black and white pixels). Figure15 shows Convert images to Binary Image

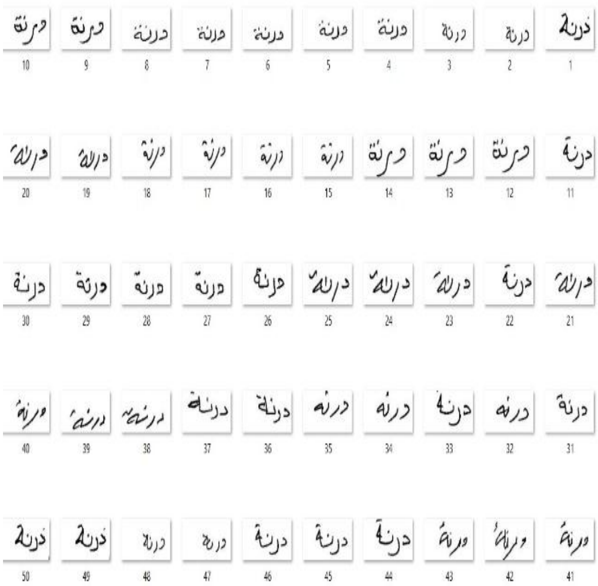


Figure15. Convert images to Binary Image

Then, using a model of a multi-layer perceptron (MLP) algorithm with backpropagation on a database of Libyan cities that was created, classification results were obtained. Table 1 shows the classification report for the neural network model.

Table 1. Classification report for neural networks

Accuracy (%)	Precision(%)	Recall(%)
80.6	80.7	80

V. CONCLUSION

The experiment achieved 80.6% classification results for Libyan city names, indicating a good model's ability to recognize classifications. Future work will focus on improving model performance by adjusting data parameters, experimenting with more complex models like Deep Neural Networks or Convolutional Neural Networks, and adjusting MLP parameters.

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