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1- Architecture used in the paper

• This research has highlighted the general architectural methodology that can use for Arabic handwritten Recognition based on deep learning thoroughly and criticized.

Depending on the classifiers combination and the feature extraction.

Deep learning for Arabic Handwriting Recognition

Computer vision (CV) refers to the study of the computer simulation of human visual science. Major task of CV is to collect images (or video) so that they could be used for analysis, gathering information, and making decisions or judgements.

(DL) dramatically improved the state-of-the-art in visual object recognition, object detection, handwritten recognition and many other domains.

Handwritten recognition technique is one of this tasks that targeted to extract the text from documents or another images type.

This paper highlighted the pre-processing and binarization methods that have been used in the literature along with proposed numerous directions for developing.

Literature	Brief Description	Dataset	dataset Type	Results
Porwal, Zhou [1]	Deep Belief Networks which incrementally learns complex structure of the data	AMA Arabic PAW dataset	Arabic Handwriting Character	75,05%
Tamen, Drias [2]	Combine several classifiers integrated at the decision level in classification phase	IFN/ENIT	Arabic Handwritten Words	87,00
Ashiquzzaman and Tushar [3]	CNN model uses several convolutional layers + Dropout used to reduce overfitting	CMATERDB 3.3.1	Arabic Handwritten Digit	97.4
Rabi, Amrouch [4]	Hidden Markov Models (HMMs)	IFN/ENIT	Arabic Handwritten Words	87.93%.
Elleuch, Mokni [6]	Deep learning model based on Support Vector Machine(DSVM)	HACDB	Arabic Handwriting Character	Error rate: 8.86%
Elleuch, Maalej [8]	CNN based-SVM model without and with dropout for training and recognizing Arabic characters	HACDB and IFN/ENIT	Arabic Handwriting Character	Error rate: HACDB: 5.83 IFN/ENIT: 7.05
Elleuch, Tagougui [9]	Deep Belief Network (DBN) + with dropout/dropconnect	Arabic handwritten script recognition	HACD B	Error classification rate of 2.73% using dropout.
				2.27% using dropconnect

2- Dataset Details

Train Data:

Test Data:

3- Implementation Details

- Reshape for data to (-1,32,32, 1)
- Make Conv2D(80,(5,5) activation='relu', input shape=(32,32,1)
- Make MaxPooling2D(2,2)
- Make Conv2D(64, (5,5), activation='relu')
- Make MaxPooling2D (2,2)
- Make Flatten() to returns a copy of the array in one dimensional
- Make CNN Dense (1024, activation='relu') with name 'featurs'
- Make CNN Dense(28 ,activation='softmax')
- Make compile for the model with optimizer= 'adam'

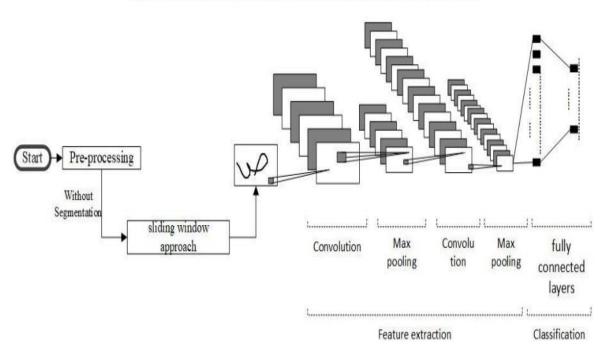


Figure 2 flowchart of Arabic Handwritten recognition based on CNN model

4- Results and Visualization

Layer (type) Output Shape Param #
conv2d (Conv2D) (None, 28, 28, 80) 2080 max_pooling2d (MaxPooling2D (None, 14, 14, 80) 0) conv2d_1 (Conv2D) (None, 10, 10, 64) 128064 max_pooling2d_1 (MaxPooling (None, 5, 5, 64) 0
conv2d_1 (Conv2D) (None, 10, 10, 64) 128064 max_pooling2d_1 (MaxPooling (None, 5, 5, 64) 0
max_pooling2d_1 (MaxPooling (None, 5, 5, 64) 0
flatten (Flatten) (None, 1600) 0
featurs (Dense) (None, 1024) 1639424
dense (Dense) (None, 28) 28700

```
Epoch 1/50
209/210 [==========] - ETA: 0s - loss: 1.9950 - accuracy: 0.4418WARNING:tensorflow:Learning rate reduction is conditioned on metric
210/210 [===========] - 16s 23ms/step - loss: 1.9908 - accuracy: 0.4430 - val loss: 0.8253 - val accuracy: 0.7729 - lr: 0.0010
Epoch 2/50
209/210 [==========] - ETA: 0s - loss: 0.9953 - accuracy: 0.7190WARNING:tensorflow:Learning rate reduction is conditioned on metric
210/210 [===========] - 5s 22ms/step - loss: 0.9944 - accuracy: 0.7193 - val loss: 0.5861 - val accuracy: 0.8408 - lr: 0.0010
Epoch 3/50
210/210 [==========] - 5s 22ms/step - loss: 0.7795 - accuracy: 0.7827 - val loss: 0.5135 - val accuracy: 0.8491 - lr: 0.0010
Epoch 4/50
208/210 [==========] - ETA: 0s - loss: 0.6736 - accuracy: 0.8077WARNING:tensorflow:Learning rate reduction is conditioned on metric
210/210 [=========] - 5s 22ms/step - loss: 0.6734 - accuracy: 0.8078 - val loss: 0.4087 - val accuracy: 0.8982 - lr: 0.0010
Epoch 5/50
210/210 [============] - ETA: 0s - loss: 0.6067 - accuracy: 0.8284WARNING:tensorflow:Learning rate reduction is conditioned on metric
210/210 [===========] - 5s 22ms/step - loss: 0.6067 - accuracy: 0.8284 - val loss: 0.3934 - val accuracy: 0.9104 - lr: 0.0010
Epoch 6/50
208/210 [=========].] - ETA: 0s - loss: 0.5601 - accuracy: 0.8455WARNING:tensorflow:Learning rate reduction is conditioned on metric
210/210 [============] - 5s 22ms/step - loss: 0.5596 - accuracy: 0.8456 - val loss: 0.3195 - val accuracy: 0.9256 - lr: 0.0010
Epoch 7/50
210/210 [==========] - 5s 22ms/step - loss: 0.5124 - accuracy: 0.8574 - val loss: 0.3168 - val accuracy: 0.9238 - lr: 0.0010
Epoch 8/50
210/210 [===========] - 5s 22ms/step - loss: 0.4724 - accuracy: 0.8712 - val loss: 0.3125 - val accuracy: 0.9199 - lr: 0.0010
Epoch 9/50
show more (open the raw output data in a text editor) ...
metric `val acc` which is not available. Available metrics are: loss,accuracy,val loss,val accuracy,lr
210/210 [===========] - 5s 22ms/step - loss: 0.2368 - accuracy: 0.9423 - val loss: 0.1746 - val accuracy: 0.9652 - lr: 0.0010
Epoch 32/50
208/210 [============] - ETA: 0s - loss: 0.2412 - accuracy: 0.9404WARNING:tensorflow:Learning rate reduction is conditioned on
metric `val_acc` which is not available. Available metrics are: loss,accuracy,val_loss,val_accuracy,lr
210/210 [============] - 5s 22ms/step - loss: 0.2413 - accuracy: 0.9403 - val loss: 0.1829 - val accuracy: 0.9655 - lr: 0.0010
```

