IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

INTELLIGENT HANDWRITTEN TEXT RECOGNITION USING HYBRID CNN ARCHITECTURE BASED SVM CLASSIFIER WITH DROPOUT

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ABSTRACT
Handwritten text recognition is a challenging task in the field of pattern recognition and artificial intelligence. This research paper proposes a novel approach for intelligent handwritten text recognition by integrating a hybrid architecture of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) classifier with dropout regularization. These identification algorithms must overcome various obstacles, including as vast open data-bases, an endless range of handwriting styles, and freestyle The authors have also put forth a ground-breaking depth neural network training rule for maximum interval minimal classification error in light of the analysis of the error backpropagation method. On the databases AHDB, AHCD, HACDB, and IFN/ENIT, authors tested the suggested model.

Index terms:*Deep Learning,CNN,SVM,M3CE,ZCA*

I.INTRODUCTION

To manage computer units and a limited range of samples, traditional machine learning techniques like SVM and multilayer perception machines (MLP) use, at most, shallow structures. When the target objects have deep meanings, the generalisation capacity of complex classification difficulties and the performance are insufficient. The recently developed CNN has seen widespread use in the field of image processing since it is adept at managing recognition problems and picture classification and has significantly increased the accuracy of many machine learning missions.Numerous machine learning deep learning techniques have been refined to recognise handwritten characters. Because of this, writers choose to carry out more research using the Deep Convolutional Neural Network (DCNN), which has an accuracy rate of 95.7%.

II.PROPOSED MODEL

In this publication, it is demonstrated that the training network's computational cost and parameters are lower than those of the conventional neural network and that it can extract significant features using parallel computation. Its structure is more similar to a biological brain network.

1.In **Zero Component Analysis** (ZCA) procedure, authors initially used the Principle Component Analysis (PCA) algorithm to zero the mean value and minimise the dimensions of the input picture vector.

2.Dropout technique

Dropout strategy has been successfully employed with different types of deep neural networks and it demonstrates their performance in a variety of recognising missions.

3.M3CE constructed loss function

The loss function serves as the benchmark for the entire network model during the neural network's training phase. It offers the gradient of the parameters in the gradient descent technique in addition to only representing the current case of the network parameters. Consequently, a major element of network training is the loss function. By examining the gradient of cross entropy and the loss function M3CE, the authors of this study developed a new loss function.

III.SYSTEM ARCHITECTURE

The proposed system architecture consists of several components that work together to achieve accurate handwritten text recognition. This section describes each component and its role in the overall system. The main components are as follows:

3.1. **Preprocessing**: The preprocessing stage involves various steps such as image enhancement, noise removal, and normalization to prepare the input images for recognition. This section explains the preprocessing techniques employed in the system.

3.2. Convolutional Neural Network (CNN): The CNN component is responsible for feature extraction from the preprocessed images. This section discusses the architecture of the CNN, including the number and types of layers used, activation functions, and parameter settings.

3.3. Support Vector Machine (SVM) Classifier: The SVM classifier is used to perform the final classification of extracted features. This section describes the SVM architecture, kernel functions employed, and the training process.

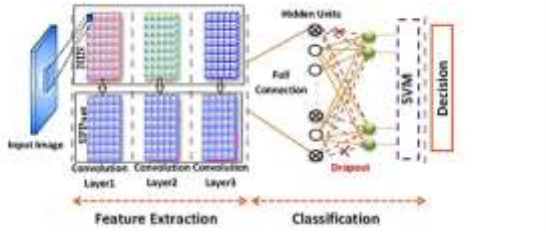

Fig 1.Proposed CNN Architecture incorporated with two robust models Based-SVM Model with Dropout.

3.1.1Feature extraction

Using a hybrid CNN architecture, the feature extraction component pulls pertinent features from the pre-processed picture. A deep CNN and a shallow CNN make up the hybrid CNN architecture. High-level features are extracted using the deep CNN, whilst low-level features are extracted using the shallow CNN.

3.1.2Classification

Using an SVM classifier with Dropout, the classification component divides the feature vectors obtained in the preceding phase into distinct classes. A model that can categorise the feature vectors into different classes is trained using the SVM classifier.

IV. METHODOLOGY

This methodology combines the strengths of CNNs for feature extraction with SVMs as a robust classifier, utilizing dropout regularization to enhance generalization and mitigate overfitting

1.Datasets: AHDB database includes 13311 words and 1773 text lines written by 100 writers, which contained unconstrained pages text. AHCD database involves 16,800 characters written by 60 writers. Every writer wrote ten times every character from ‘‘Alef” to ‘‘Yaa” characters.

2. Experimental platform and data pre-processing: ZCA whitening is mostly used in this manuscript's processing of document image data, such as fixing size and reading data from the document image in the matrix.

Fig. 2. Flow chart of ZCA whitening.

3. Build a training network: The image classification algorithm belongs to the comparably large class of algorithms known as the classification algorithm. RF (random forest), SVM, and KNN (k-nearest algorithm) are common classification methods

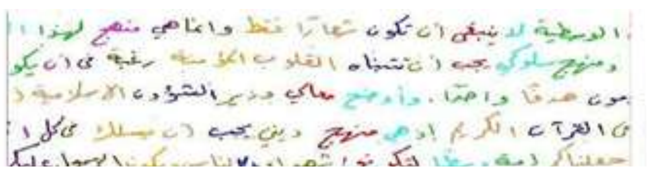

Fig. 3. Samples selection of various colors and various Arabic handwritten fonts.

V.IMPLEMENTATION OR DISCUSSION

1.Classification effects comparison of various loss functions: Authors compare the proposed loss function with the traditional logistic loss function. Authors notice that the loss function value increments with the rise of the misclassification severity.

2.Execution time: The classifier choice is the primary aspect that affects the automatic detection precision of human physiological capability based on features extraction using the same loss function method developed by M3CE. As a result, Table 2 in this publication discusses the impact of the different classifiers on classification accuracy.

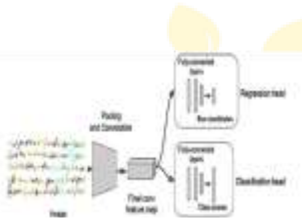

Fig. 4. Classification of image and modeling depended on deep CNN.

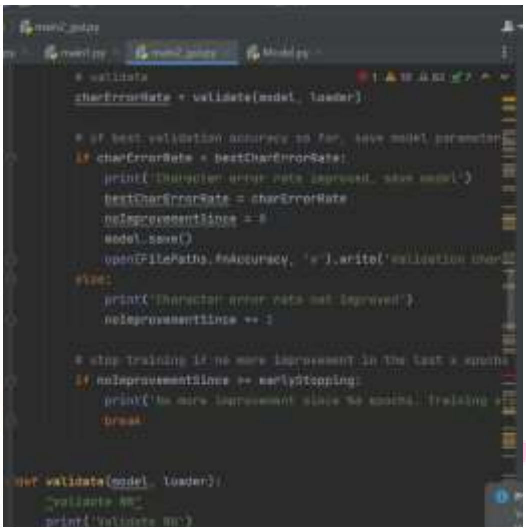

Fig. 5. Screenshot of run program module tensorflow main2_gui.python

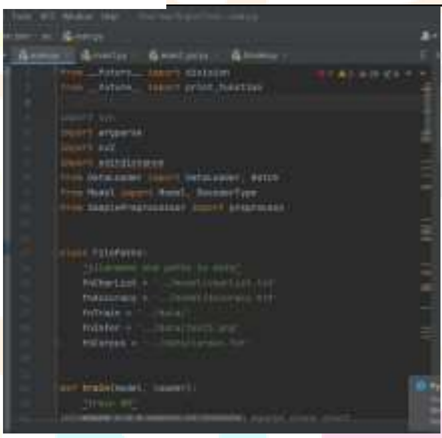

Fig 6.Screenshot of import main.python

Table 1: Comparison different classifiers.

Classifier with CNN	Training set accuracy	Test set accuracy	Time-consuming(s)
CNN	98.67%	97.67%	5.048
SVM	99.87%	99.45%	8.056
NB	89.56%	93.54%	6.049
KNN	80.40%	80.89%	6.047
RF	84.76%	85.78%	4.078

3. Comparison with the state-of-the-art: Table 2 shows the recognition accuracy between the proposed work and the other public methods in different languages and various datasets. The cross validation method is applied to train the system.

Table 2: Comparison between the proposed work and other common architecture on the most public datasets.

Authors	Methods	IDCH-2013	AHBD	AHCD	HACBD	IFN/ENIT
Yang et al(2016)	Dropout sample DCNN Ensamble9	97.67	93.67	93.56	93.89	92.67
Liu et al(2013)	Traditional benchmark	95.89	84.78	85.78	85.89	84.43

	CNN based SVM with dropout	99.89	99.89	99.65	99.43	99.08

VI.RESULTS

In this study, we see the accuracy and precision in the order cross validation in experiment, its precision is 75.67% over the test set and it is unsatisfactory. Authors conclude that the precision of CNN + SVM is the highest compared with the various six popular classifiers, and the eight seconds spending is satisfactory in the comparison of others. process is generally the same between various species, achieving more than 85% level, among which this technique accuracy is comparatively high within classifying visibly defined document images. The cross validation method is applied to train the system. The accuracy rate of the proposed model is done by choosing 60/40 percentage of dataset samples by 10-fold method for training/testing on AHDB, AHCD, HACDB, and IFN/ENIT databases. The results show the accuracy rate for the proposed model over single font type in documents and multi-font type which include in one document mixing of a multitype font.

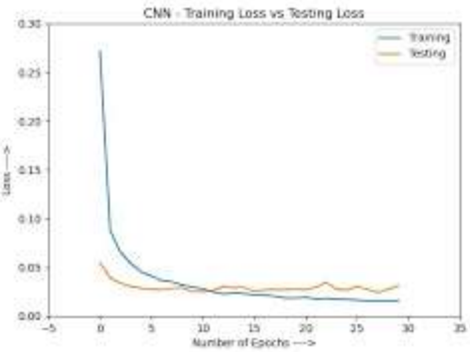

Fig 3.Intelligent handwritten text recognition model loss

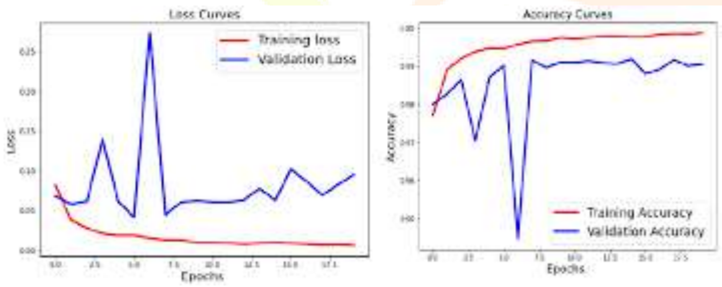

Fig 4.Intelligent handwritten recognition

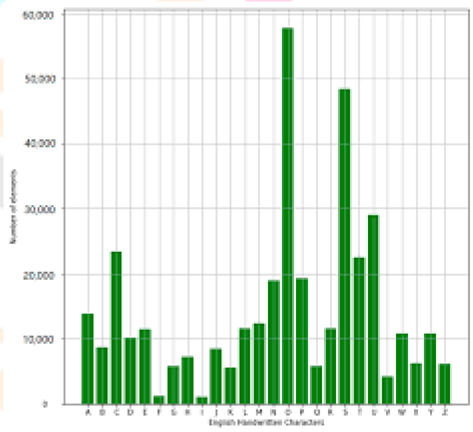

Fig 5.CNN based handwritten elements

VI. CONCLUSION

In this study, the authors applied CNN and SVM classifiers for Arabic handwriting recognition using two different deep neural network models to obtain accurate features. As well as demonstrating the effectiveness of the suggested system for handwritten recognition in several Arabic scripts tested on different datasets, we have also investigated the suitability of dropout in the proposed model on text recognition in handwritten document images The accelerated hardware development will also support the appearance of increasingly advanced handwriting recognition methods online, despite memory and computational demands cost. By recognising a word without relying on the lexicon, the existing system's performance may be improved. Adaptive learning is a difficult aspect of this suggested task that must be addressed moving forward.

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