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# Recognizing Handwritten Digits Using Multi-Dimensional Recurrent Neural Networks Intelligent Character Recognition (ICR) with Improved F-Score Measures

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**Abstract** The goal of this study is to create a model that can recognize digits using Novel Recurrent Neural Networks (RNN) with LSTM cells and provide an F score comparison for optical character recognition versus Support Vector Machines (SVM) with Linear Kernel on the MNIST dataset. The sample estimation is done using the GPower statistical software with a pre-power test of 80%. The type-I error rate (alpha error rate) of 0.05 is considered. The dataset has 70K samples of handwritten digits, of which 60K are used as training samples and the remaining 10,000 are used as testing samples. In this research work, the digits are classified using RNN and linear SVM algorithms. The RNN attains an accuracy of 99% with a significance value of 0.171 (p 0.05), whereas the Linear SVM attains an accuracy of 87.75%. The results proved that optical character recognition using Novel RNN with LSTM cells performed much better than Linear SVM.

**Keywords.** Novel Recurrent Neural Network, Linear SVM, Machine learning, Deep Learning, Handwriting Recognition, Optical Character Recognition.

## 1. Introduction

Digit detection is a significant initial stage for visual character identification and document understanding. Handwriting digit recognition (HDR) is a process of recognizing handwritten digits using training and testing sets of labeled data. This research work develops a model that can recognize the digits using Novel Recurrent Neural Networks using LSTM cells [1]. An RNN[2] is a feed-forward type that has a memory associated with it. It is recurrent because it computes the same function for all the inputs and the output of the current input is dependent on the output of the previous input. Linear SVM [3] is used for separating data into two classes by using a straight line. Hence data is termed linearly separable data, and the classifier is called Linear SVM. This type of system can be used in scanning number plates of vehicles [4],

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scanning passbook details, cheque reading, etc. This system can find its application in the government offices for their paperwork.

The most vital feature of RNN is the hidden layer, which remembers some information as a few sequences. The RNN is composed of Long Short Term Memory (LSTM) cells which act as a memory for the entire LSTM network. A standard LSTM unit consists of a cell and gates for input, output, and forget. This LSTM can remember values at random intervals of time. SVM is employed to classify data into two classes.

## 2. Related works

The authors discussed the real-time application of the deep learning architecture [5]. It also goes over hidden layers and activation functions like Relu, Softmax, Sigmoid, and Adam optimizer in depth.[6] gives a detailed explanation of how to use recurrent transfer deep architecture to recognize handwritten digits.

A residual learning framework was discussed to ease the training of neural networks [7] and to reduce the complexity of training models. [8] proposed the diminishing gradient predicament while learning recurrent networks and problem solutions. The poor accuracy in recognition of handwritten digits using RNN [9] and Linear SVM [10]. A wide portfolio of research has translated into publications in numerous interdisciplinary projects. [11–15].

## 3. Materials and Methods

The study was conducted at the premises of Saveetha School of Engineering, SIMATS, Chennai. In the study, there were two groups, namely Recurrent Neural Network (RNN) and Linear SVM. The sample estimation is done using the GPower statistical software with an 80% pre-power test. The alpha error rate (type-I error) of 0.05 gives the differences between the two algorithms and the enrolment ratio of 1. The samples for Group 1 and Group 2 are taken from previous studies [9] and [10] respectively. The dataset was collected from http://yann.lecun.com/exdb/mnist/. The dataset has 70k samples of handwritten digits, of which 60000 are used as training samples and the remaining 10000 are used as testing samples. Each image in the dataset is of the dimension of 28 x 28. The output of recurrent neural nets depends on previous input. The pseudo-code for recurrent neural networks is depicted in Table 1.

### *3.1. Testing Procedure*

The following steps give details on the test procedure adopted to evaluate the model. The Pseudo Code for novel RNN is given in Table 1, and Table 2 gives the Pseudo Code for Linear SVM.

**Table 1.** Pseudo Code for Novel Recurrent Neural Network

| **Recurrent Neural Network (epoch, batch_size, nb_classes)** |
| --- |
| **Input:** Training dataset (MNIST)<br>**Output**: Accuracy |
| 1. The necessary classes, namely LSTM, sequential, and dense, were imported from the Keras library. |
| 2. The dataset was loaded and split into training and testing samples, followed by reshaping. |
| 3. The Hyper parameters were set to nb_clsses = 10, epochs = 20, and batch_size = 128. |
| 4. The LSTM-based model is built with three LSTM layers, each having relu as an activation function and followed by a dropout of 20%. |
| 5. The model is trained and tested for accuracy. |

**Table 2.** Pseudo Code for Linear SVM

| **Linear SVM** |
| --- |
| **Input:** Training dataset (MNIST)<br>**Output**: Accuracy |
| 1. The necessary libraries, NumPy, pandas, and skLearn are imported. |
| 2. The dataset was loaded and split into training and testing samples, followed by reshaping. |
| 3. The Linear SVM model is built by using the SVC class of the skLearn module and by setting the kernel parameter as linear. |
| 4. The model is trained and tested for accuracy. |

### *3.2. Data Collections*

The accuracy data collected for the RNN algorithm is given in Table 4. The accuracy data collected for the Linear SVM algorithm is given in Table 5.

**Table 4.** Accuracy value for various epoch for Novel RNN

| S. NO | Accuracy |
| --- | --- |
| 1 | .97 |
| 2 | .98 |
| 3 | .96 |
| 4 | .99 |
| 5 | .98 |
| 6 | .99 |
| 7 | .98 |
| 8 | .99 |
| 9 | .99 |
| 10 | .98 |

**Table 5.** Accuracy value for various epochs for Linear SVM.

| S. NO | Accuracy |
| --- | --- |
| 1 | .89 |
| 2 | .88 |
| 3 | .91 |
| 4 | .92 |
| 5 | .90 |
| 6 | .94 |
| 7 | .88 |
| 8 | .90 |
| 9 | .93 |
| 10 | .91 |

### *3.3. Statistical Analysis*

A software tool called IBM SPSS is used for statistical analysis. The independent variables are handwritten digits and the dependent variable is accuracy. Analysis was done for mean, standard deviation, and independent T-test.

## 4. Results

The configuration of the RNN and linear models during the training phase with hardware and software requirements is discussed. The improved accuracy of 99% for RNN compared to 90.4% for the Linear SVM algorithm is shown in Figure.1. This proves that RNN is the best model for optical character recognition in comparison to the Linear SVM algorithm. Even though there is a slight increase in the standard mean error of 0.1478, it can be improved by optimising the model parameters. According to the group statistics, the mean accuracy for RNN was 98.97, with a standard deviation of 0.04285 and a standard error mean of 0.1478, whereas the accuracy for SVM with linear kernel function is 0.91 with a standard mean error of 0.1520.

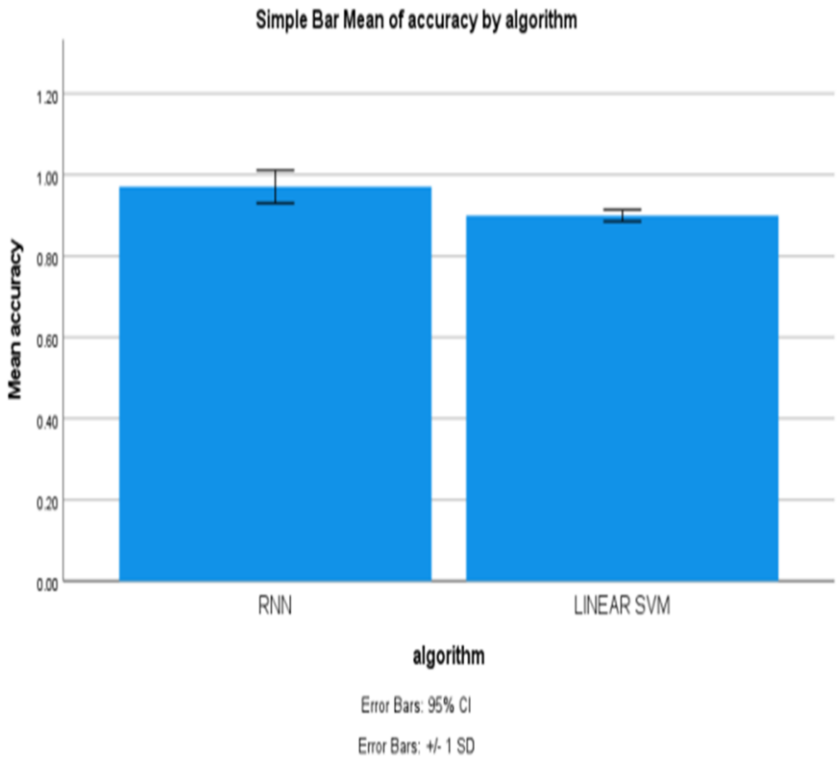


**Figure 1.** Comparison of the mean accuracy of the novel RNN and linear SVM algorithms. RNN and Linear SVM on the X-axis; mean accuracy on the Y-axis. SD + 1.

**Table 6.** Accuracy of Novel Recurrent Neural Network(RNN) and Linear SVM algorithm using Statistics (Mean, Standard Deviation, and Standard Error). There is a significant statistical difference in accuracy, with the highest accuracy of 99% for RNN.

| | **Algorithm** | **Mean** | **N** | **Standard deviation** | **Standard .error mean** |
|---|---|---|---|---|---|
| **Accuracy** | Recurrent Neural Network | 98.7905 | 10 | 0.04285 | .01428 |
| | Linear SVM | 90.4000 | 10 | 0.01647 | .01520 |

**Table 7.** Comparison of significance levels for recurrent neural networks and linear SVM with value X = 0.15. The significance level is less than 0.131 for both logistic regression and linear regression.

| | Levene's test for equality of variances | | T-Test for equality of means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | F | Sig. | t | df | sig. (2-tailed) | Mean difference | Std. error difference | 95% confidence interval of the difference | |
| | | | | | | | | Lower | Upper |
| Equal Variances assumed | 2.045 | 0.171 | 4.601 | 17 | .000 | 6.71100 | .01458 | 3.63424 | 9.78823 |
| Equal variances not assumed | | | 4.414 | 10.109 | .001 | 6.71100 | .01520 | 3.32910 | 10.09432 |

## 5. Discussion

This study reveals that RNN has much higher accuracy for RNN compared to linear SVM accuracy evaluation. Table 7 shows the significance value of 0.00 (p 0.05) in the 2-tailed test for RNN, which confirms that there is a significant difference in the accuracy of the 2 algorithms for optical character recognition (OCR). The limitation of the study is that this model is more suitable for digit recognition, but the model can be designed to recognize letters and multiple scripts, viz., Devanagari scripts.

## 6. Conclusion and Future work

It is observed from the study that the precision and accuracy increase as the epoch increases for RNN, and RNN attains the highest accuracy of 99%. This indicates that the model is working fine and is neither underfitting nor overfitting, whereas, for the Linear Support Vector Machine (SVM), the accuracy (94%) and precision were much less in comparison to RNN.

The researchers can try to improve the architecture of the model in the future by adding extra layers of LSTM cells, manipulating the optimization function, or using different combinations of activation functions. The researcher can also try to train the model for various other datasets for Latin and Devanagari scripts.

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