

# Comparative Analysis of Handwritten Digit Recognition Investigation Using Deep Learning Model



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## 1 Introduction

A Convolutional Neural Network provides the convenience of extracting and using feature vectors over other ANN to evaluate the awareness of 2D form with a significantly lower degree of accuracy and no translation, balancing/manipulations. Initially, this research was addressed in their object. Convolutional Neural Networks was a control layer by the author to determine the digit and character [1]. CNN technology is simple, making it easy to install. We might well take the MNIST set of data for training and identification. This set of data aims primarily at characterising

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articles 1–10. Therefore, we have a total of 85,000 images for training and validation. Each digit is described by 32 grey image pixels [2]. The quantities are transferred to the Convolutional Neural Networks input layers, and afterwards, the hidden layers usually contain two sets of the convolutional layer. After this, it is visualised to the fully connected layers, and a SoftMax classification scheme is presented to dial the numbers. Researchers will use Python, OpenCV, Django, or TensorFlow to incorporate this classification [3]. To achieve accuracy with decreased operating uncertainty and costs, the Convolutional Neural Networks framework is proposed. To express the best learning parameters to set up a CNN, the complete innovative database identifies the investigator applying the review process for HDR and the mathematical collection of neural networks. The cohesive hybrid set of mathematical and geometric features aims to accomplish local and global sample numbers' characteristics [4]. The process utilises genetic modification algorithms to select the best attributes and a neighbour to evaluate the handwritten digit dataset's endurance. Regarding the purpose of isolated handwritten words [5], suggested a deep CNN. The proposed method is an excellent way of extracting practical visual attributes from an image frame. The approach assumes two handwritten datasets (IAM and RIMES) under several experiments to determine the model's optimal parameters [6].

## 1.1 Abbreviations and Acronyms

- CNN – Convolution Neural Network
- NN – Neural Network

### 1.1.1 Units

- *Fully Connected Multi-layer Neural Network:* The multi-layer CNN can label data points in the MNIST training dataset at a failure of less than 4.42% on the validation dataset with one or more neural networks [7]. This channel extracts the features that encompass the practical spatial domain of the image data, and therefore extraordinarily high dimensions are required. Such CNN is questionable because such networks' criteria are more than 200,000, which is unacceptable if complex and complicated faults have collaborated with large data sets [8].
- *Data Sets:* The classification of specific character recognition is investigated in this problem. The MNIST database provided an example of training. This research created a database of 50,000 training sets and 20,000 test results, including census responses extracted. The original images are  $64 \times 64$  standardised in size; however, they contain grey images because of the Graphical User Interface [9].

The image pixel resolution results are computed as  $-0.1$  in shadow (white) and  $1.275$  in the middle of the photo (black)—the actual outcomes in a measured input of  $0$  and a difference of roughly  $1$ . The decision variables are  $15$  grey images of  $15 \times 8$  digits developed by hand. But only data variables were used in this case [10]: the background and foreground ( $-1$ ) result in binary images. Such images were configured to provide adequate imbalance features for discriminatory practices in each ‘0’.

## 2 Related Works

HSD of minimal security has indeed formed significant improvements. Several papers were published with research and development of new handwritten numerals, characters, and English word categorisation [11]. The 3-layer Deep Belief Network (DBN) with a greedy algorithm for the MNIST dataset was evaluated, and a precision of  $98.75\%$  was described. In the aim of improving the efficiency of recurrent neural networks (RNN), the procedures and principles for deactivating were adapted in recognition of unpredictable handwriting. The reviewer significantly improved RNN efficiency, reducing the Character Error Rate (CER) and Word Error Rate (WER) [12]. The experiment explained that he might have been sufficient to attain an extremely high degree of precision using DL. The accuracy of the CNN with Keras and Theano was  $98.72\%$  [13]. Consequently, CNN operations that have used Tensorflow performance in an exceedingly better outcome of  $99.70\%$ . Even though the method and guidelines seem more complex and challenging than standard ML algorithms, precision becomes apparent. The investigator focuses on the various pre-processing methods used to recognise characters by respective classes of images, from easy, handwritten verification and information with a vibrantly coloured, cluttered background and wide-ranging complexity. This describes specific pre-processing methodologies, including skew detection and identification, stretching of the image, character recognition, deletion of noise, widespread acceptance and differentiation, and morphological diagnostic methods [14]. It was concluded that together we could process the image completely using a single pre-processing approach. However, a pre-processing module could not achieve complete precision even after implementing all these methodologies. CNN can be used for the acknowledgement of English character recognition. The features are considered from threshold mapping and its Fourier descriptors. The character is described by researching its template and attributing its attributes. To have access, a test was conducted to determine the number of hidden layer nodes to attain the network’s maximum performance. For handwritten English alphabets with a minor test set,  $94.13\%$  accuracy was mentioned [15].

### 3 Proposed CNN Image Classification

Classified images are not a simple problem that can be managed to achieve by various methods. Nevertheless, many ML systems have been effectively implemented in recent times. Researchers consequently recommended dramatic CNNs to direct and evaluate our handwritten figures throughout that work. Building Convolutional Neural Networks plays an essential role in effectiveness and cost factors. So, after thoroughly reading its boundary conditions, we have established a chic CNN in our execution. Usually, critical elements described below have included Convolutional Neural Networks for HDR: Prepare patterns before feeding CNN. Before actually accessing the network, all images are pre-processed [16–18]. CNN is constructed for the size of  $64 \times 64$  pixels in our experimental tests. Subsequently, all images were cut to the same size to feed the model. They are provided to the deep model to prepare images to retrieve characteristics. As relatively recently shown, a clear CNN is used throughout the experiment to extract powerful features used in the ultimate decision to support their classification [54–56]. The last layer, SoftMax, minimises the variance at the highest possible CNN level [19, 20].

#### 3.1 PReLU

A Parametric Rectified Linear Unit (PReLU) is an intuitionistic fuzzy rectified unit with a curve for zero value. Lawfully:  $f(B_i) = B_i$  if  $B_i \geq 0$   $f(B_i) = A_i B_i$  if  $B_i \leq 0$ .

- Feature Extraction: LR Image
- *CNN Layer 1*: 56 Filters of  $1 \times 5 \times 5$  Image Size Extraction
- *Activation Function*: ReLU
- *Result*: 56 Map Feature Set
- *Limits*:  $1 \times 5 \times 5 \times 56$

#### 3.2 Shrinking

Reduces the function vectors' size (by limiting parameters) using reduced filters (compared to the number of filters used for image feature extraction).

- *Conv. Layer 2*: Shrinking 12 filters of size  $56 \times 2 \times 2$
- *Activation Function*: PReLU
- *Result*: 12 Feature Maps
- *Limits*:  $56 \times 2 \times 2 \times 12$

### 3.3 *Non-linear Mapping*

Maps the LR to HR patches image features. This procedure is performed with many map-based layers relatively small than SCRNN (Fig. 1).

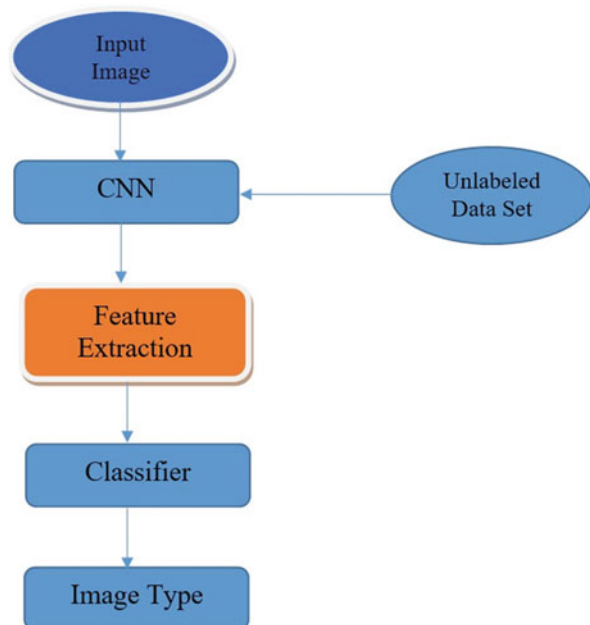
- *Conv. Layers 3–6:*
- Mapping
- $4 \times 12$  Filters of Size  $12 \times 4 \times 4$
- *Activation Function:* PReLU
- *Result:* HR Feature Maps
- *Limits:*  $4 \times 12 \times 4 \times 4 \times 12$

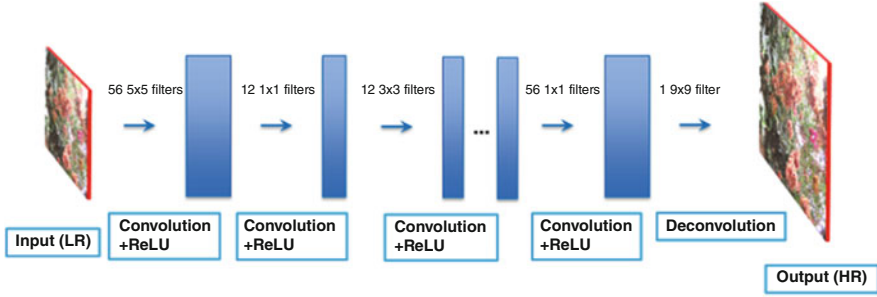
### 3.4 *Expanding*

Determines the complexity of the feature vector. The whole procedure performs the complete reverse function as the decreasing layers produce the HR image more reliably.

- *Conv. Layer 7:*
  - Increasing
  - 56 Filters of Size  $12 \times 2 \times 2$

**Fig. 1** Process of image function extraction





**Fig. 2** Image processing

- *Activation Function:* PReLU
- *Result:* 12 Feature Maps
- *Limits:*  $12 \times 2 \times 2 \times 56$

### 3.5 Deconvolution

Produces the HR image from HR features

- *DeConv Layer 8:*
  - Deconvolution
  - One filter of size  $56 \times 8 \times 9$
- *Activation Function:* PReLU
- *Output:* 13 Feature Maps
- *Parameters:*  $56 \times 8 \times 9 \times 1$

The down-sampling layer might be another layer and is often hidden (Fig. 2).

## 4 Mathematical Model

### 4.1 Subsampling Layer

The sub-sampling function applies a sampling technique on the input maps. The input and output visualisations do not alter in this interface. For instance, if there are  $N$  input maps, there are  $N$  output maps exactly [21–29]. The test operation reduces the size of the feature maps based on the size of the mask [30–34]. The two different shows are used in this investigation as Eq. (1).

$$\text{Image}_j^i = \text{MapFunction} \left[ \beta_j^i \text{DownSampling} \left( \text{Image}_j^{i-1} \right) + B_j^i \right] \quad (1)$$

where  $(\cdot)$  is a sub-sampling feature. This predominant source encapsulates the estimated value or  $n$  to block the actual accuracy of the input image maps [35–41]. Therefore, the map output dimension significantly decreases to  $n$  periods for both feature vector components. The output maps are ultimately triggered as linear/non-linear [42–47].

## 5 Result and Discussion

In this case, the digital image of the handwritten digit is the pattern  $x$ , and  $0-9$  is the category  $y$ . We use 1500 of  $64 \times 64$  gray scaled images as a dataset, and we separate this dataset into 1200 for training data and 300 for testing data. For pattern  $x$ , we reshape  $64 \times 64$  gray scaled images to 4096-dimension vectors [48–53]. Therefore, we apply LDA on a Gaussian model with 4096-dimension Gaussian distribution (Figs. 3, 4, 5, 6, 7, 8 and 9).

## 6 Conclusion

The proposed Handwritten Digital Recognition has shown us that traditional neural networks training can distribute comparatively more minor fault rates that aren't too far from several other trailing results that focus on deep Convolutional Neural Networks. Convolutional Neural Networks has the advantage of being able to extract and use feature data. This research's significance would address all the Convolutional Neural Networks model features that deliver the best precise

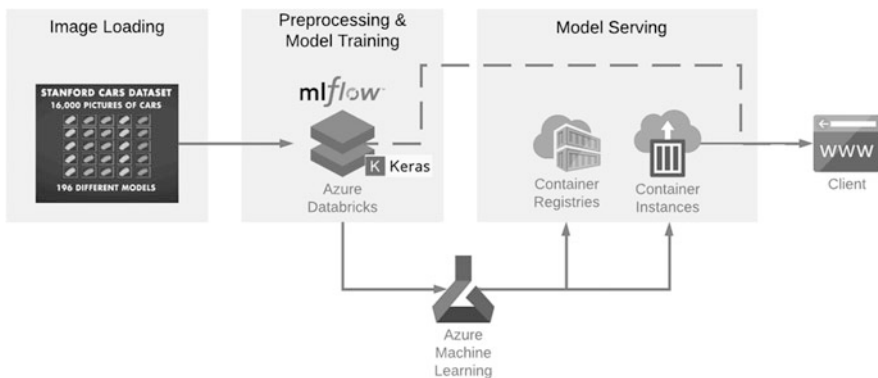


Fig. 3 Convolution Neural Framework

Fig. 4 Input Image and the function

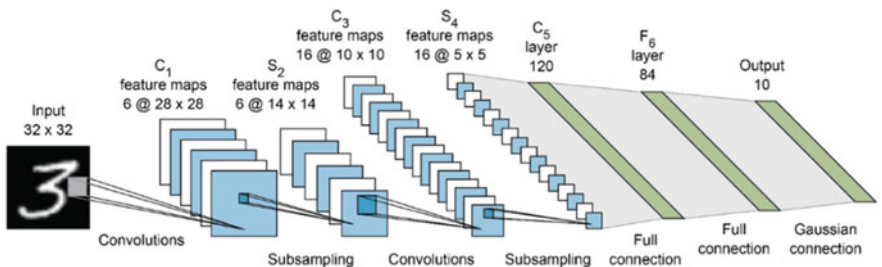
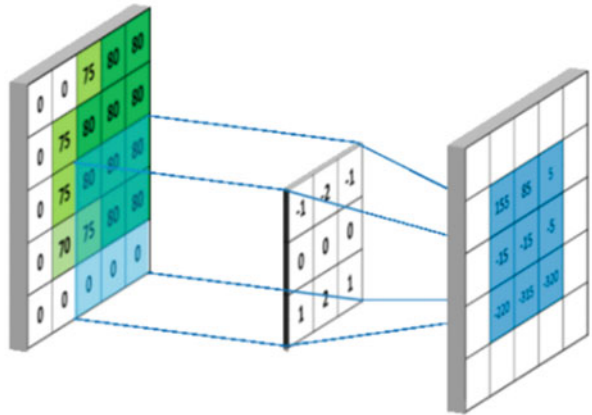


Fig. 5 The use of six images increases the final image size

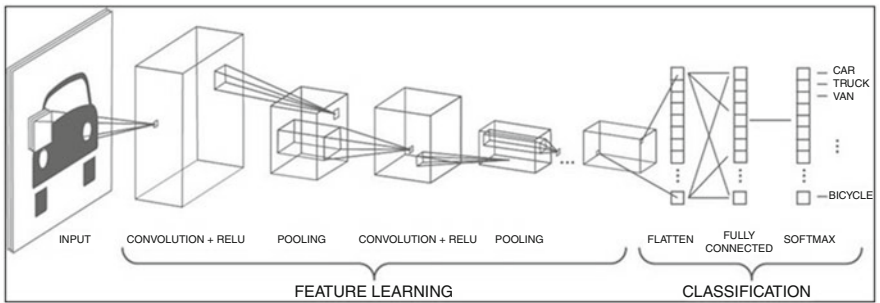


Fig. 6 Fully connected layer



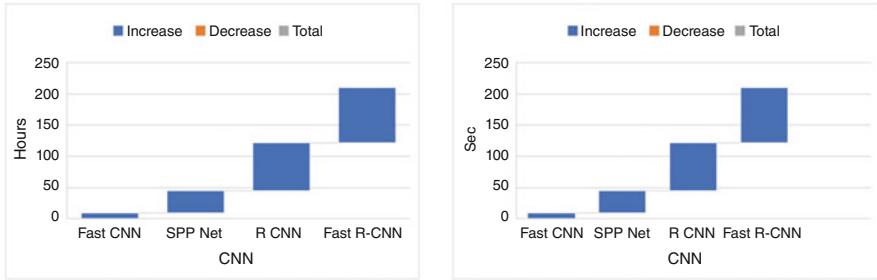


Fig. 7 Accuracy Rate at each level

Fig. 8 Tensorflow using CNN



Fig. 9 Open CV using Django



assessment for an MNIST dataset. The model’s metadata of dissimilar methodologies and error frequency is ordered as follows: (a) Random Forest Classifier is 1.32%, (b) K-Nearest Neighbours is 4.34%, (c) Support Vector Machine is 4.134%, (d) Convolutional Neural Networks is 5.28%, (e) TensorFlow is appropriate and provides a maximum 100% presentation similar to OpenCV.

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