## Ideation Phase

## Literature Survey

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| Date | 03 September 2022 |
| Team ID | PNT2022TMID45235 |
| Project Name | A Novel Method for Handwritten Digit Recognition System |

**Abstract:** Humans with the help of their brain can recognize the things that they see. Similarly, deep neural networks is developed for the computers to recognize what they see through the User Interface (UI). Handwritten digit recognition is the ability of a computer to receive and interpret intelligible handwritten digit input from sources such as paper documents, photographs, touch-screens and other devices. The applications of digit recognition include in postal mail sorting, bank check processing, form data entry, etc. The heart of the problem lies within the ability to develop an efficient algorithm that can recognize hand written digits and which is submitted by users by the way of a scanner, tablet, and other digital devices.

**Keywords:** CNN, Alex Net, Handwritten Digit Recognition, MNIST.

**Objectives:**

- Know fundamental concepts and techniques of the Artificial Neural Network and Convolution Neural Networks
- Gain a broad understanding of image data.
- Work with Sequential type of modelling
- Work with Keras capabilities
- Work with image processing techniques
- know how to build a web application using the Flask framework.

**Introduction:**

Handwritten digit recognition has recently been of very interest among the researchers because of the evolution of various Machine Learning, Deep Learning and Computer Vision algorithms. Human can visually sense the world around them by using their eyes and brains. Computer vision works on enabling computer and process images in the same way that human vision does. Several algorithms developed in the area of computer vision to recognise images. The goal of this work is to create a model to identify and determine the handwritten digits from its database with better accuracy and aim to complete this by using the concept of Convolutional Neural Network and MNIST dataset.

**Basic Terms:**

**Pre-processing**

Pre-processing is the basic phase of character recognition and it's crucial for good recognition rate. The main objective of pre-processing steps is to normalize strokes and remove variations that would otherwise complicate recognition and reduce the recognition rate.Pre-processing includes five common steps, namely, size normalization and centering, interpolating missing points, smoothing, slant correction and resampling of points.

**Segmentation**

Segmentation is done by separation of the individual characters of an image. Generally, document is processed in a hierarchical way. At first level lines are segmented using row histogram. From each row, words are extracted using column histogram and finally characters are extracted from words.

**Feature Extraction**

The main aim of feature extraction phase is to extract that pattern which is most pertinent for classification. Feature extraction techniques like Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), Chain Code (CC), Scale Invariant Feature Extraction (SIFT), zoning, Gradient based features, Histogram might be applied to extract the features of individual characters. These features are used to train the system

**Image Acquisition**

Digitized/Digital Image is initially taken as input. The most common of these devices is the electronic tablet or digitizer. These devices use a pen that is digital in nature. Input images for handwritten characters can also be taken by using other methods such as scanners, photographs or by directly writing in the computer by using a stylus.

**`Post Processing**

Post-processing refers to the procedure of correcting misclassified results by applying linguistic knowledge. Postprocessing is processing of the output from shape recognition. Language information can increase the accuracy obtained by pure shape recognition. For handwriting input, some shape recognizers yield a single string of characters, while others yield a number of alternatives for each character, often with a measure of confidence for each alternative.

**Devnagari numeral recognition by combining decision of multiple connectionist classifiers**
**Reena Bajaj, Lipika Dey, and S. Chaudhury [1]**

**Classifier combination**

The classifiers used in this approach are based upon different representations of the input pattern. These representations, since they encode different types of property – style dependent and style-invariant, cannot be combined into a single monolithic feature vector. Individual classifiers dealing with these representations output the class labels depending on the features used. These class labels have been combined using a meta-pi network because it can devise a combination scheme on the basis of consistency and accuracy of the individual classifiers. Each output unit of the meta-pi net modulates output of individual classifiers. The network is called the meta-pi network owing to the multiplicative function that its output units perform. This function serves to combine the outputs of sub-networks (or "modules"), independently trained to classify numerals based on different features. Hence, there are three output nodes in the present meta-pi net. The network has been trained with the samples used for training the individual nets along with newer examples. Through the training process the meta-pi net learns to choose any one of the valid classifier outputs or a combination of these valid outputs to produce the correct global output. The initial stage of the proposed architecture consists of connectionist modules for style based categorisation of the input. Since style groups are characteristic of each character, for each character there exists a style categorisation module which acquires knowledge about style categories of the corresponding character through unsupervised learning. Output of this stage would indicate similarity of an unknown input with style categories of the different characters (including the correct one). An interesting feature of this stage is that the classifiers are not forced to classify distinct looking samples of one character into one monolithic class. The classifiers can self-organise themselves to categorise them into distinct style categories. The novel feature of this work is the approach followed for identification and integration of style specific information in the recognition scheme. Use of multiple classifiers using the meta-pi network is another significant feature of this work. A complete hierarchical recognition architecture has been suggested in this work.

**V.N. Manjunath Aradhya, G. Hemantha Kumar [2]**

In this paper, we propose a novel system based on radon transform for handwritten digit recognition. We have used a radon function which represents an image as a collection of projections along various directions. The resultant feature vector by applying this method is the input for the classification stage. A nearest neighbour classifier is used for the subsequent recognition purpose. A test performed on the MNIST handwritten numeral database and on Kannada handwritten numerals demonstrate the effectiveness and feasibility of the proposed method.

**A novel method for Handwritten Digit Recognition with Neural Networks – MALOTHU NAGU, N VIJAY SHANKAR, K. ANNAPURNA [3]**

Character recognition plays an important role in the modern world. It can solve more complex problems and makes humans' job easier. An example is handwritten character recognition. Pattern recognition system consists of two-stage process(Feature Extraction and Classification). Feature extraction is the measurement on a population of entities that will be classified. This assists the classification stage by looking for features that allows fairly easy to distinguish between the different classes. There are Several Pattern Recognition Methods, they are: Bayesian decision theory, Nearest Neighbour rule, Linear Classification Discrimination The Bayesian decision theory is a system that minimizes the classification error. This method is based on priority basis, it classifies using priority information about something that we would like to classify. We can use Baye's formula, which states the following: $P(wj |x) = p(x|wj ) P(wj )/p(x)$. The Nearest Neighbour (NN) rule is used to classify handwritten characters. The distance measured between the two-character images is needed in order to use this rule. The goal of Linear Classification is to assign observations into the classes. This can be used to establish a classifier rule so that it can assign a new observation into a class. In another words, the rule deals with assigning a new point in a vector space to a class separated by a boundary. Linear classification provides a mathematical formula to predict a binary result. This result is a true or false (positive or negative) result. The following is an equation that can be stated as the discriminator: $a1\ x1 + a2\ x2 + ... + an\ xn > x0$ Shape describes a spatial region. Most shapes are a 2-D space. Shape recognition works on the similarity measure so that it can determine that two shapes correspond to each other. The recognition needs to respect the properties of imperfect perception, for example: noise, rotation, shearing, etc. One of the techniques used in shape recognition is elastic matching distance. The difficult task is there are some handwritten digits that often run together or not fully connected. Numeral 5 is an example. But once these tasks have been carried out, the digits are available as individual items. But the digits are still in different sizes. Therefore, a normalization step has to be performed so we can have to have digits in equal sizes. After the digits are normalized, they are fed into the ANN. This is a feed-forward network with three hidden layers. The input is a 16 x 16 array that corresponds to the size of a normalized pixel image. The first hidden layer contains 12 groups of units with 64 units per group. Each unit in the group is connected to a 5 x 5 square in the input array and all 64 units in the group have the same 25 weight values. The second hidden layer consists of 12 groups of 16 units. This layer operates very similar to the first hidden layer, but now it seeks features in the first hidden layer. The third hidden layer consists of 30 units that are fully connected to the units in the previous layer. The output units are in turn fully connected to the third hidden layer.

**Cheng-Lin Liu, K. Nakashima, H. Sako, H. Fujisawa [4]**

This paper presents the latest results of handwritten digit recognition on well-known image databases using the state of-the-art feature extraction and classification techniques. The tested databases are CENPARMI, CEDAR, and MNIST. On the test dataset of each database, 56 recognition accuracies are given by combining 7 classifiers with 8 feature vectors. All the classifiers and feature vectors give high accuracies. Among the features, the chain-code feature and gradient feature show advantages, and the profile structure feature shows efficiency as a complementary feature. In comparison of classifiers, the support vector classifier with RBF kernel gives the highest accuracy but is extremely expensive in storage and computation. Among the non-SV classifiers, the polynomial classifier performs best, followed by a learning quadratic discriminant function classifier. The results are competitive compared to previous ones and they provide a baseline for evaluation of future works.

**M. Revow, C.K.I. Williams, G.E [5]**

Hinton describes a method of recognizing handwritten digits by fitting generative models that are built from deformable B-splines with Gaussian "ink generators" spaced along the length of the spline. The splines are adjusted using a novel elastic matching procedure based on the expectation maximization algorithm that maximizes the likelihood of the model generating the data. This approach has many advantages: 1) the system not only produces a classification of the digit but also a rich description of the instantiation parameters which can yield information such as the writing style; 2) the generative models can perform recognition driven segmentation; 3) the method involves a relatively small number of parameters and hence training is relatively easy and fast; and 4) unlike many other recognition schemes, it does not rely on some form of pre-normalization of input images, but can handle arbitrary scaling, translations and a limited degree of image rotation. We have demonstrated that our method of fitting models to images does not get trapped in poor local minima. The main disadvantage of the method is that it requires much more computation than more standard OCR techniques

**L.S. Oliveira, R. Sabourin, F. Bortolozzi, C.Y [6]**

Suen discusses the use of genetic algorithms for feature selection for handwriting recognition. Its novelty lies in the use of multi-objective genetic algorithms where sensitivity analysis and neural networks are employed to allow the use of a representative database to evaluate fitness and the use of a validation database to identify the subsets of selected features that provide a good generalization. Comprehensive experiments on the NIST database confirm the effectiveness of the proposed strategy

**U. Ravi Babu, Y. Venkateswarlu, Aneel Kumar Chintha [7]**

This paper presents a new approach to off-line handwritten digit recognition based on structural features which does not require thinning operation and size normalization technique. This paper uses four different types of structural features namely, number of holes, water reservoirs in four directions, maximum profile distances in four directions, and fill-hole density for the recognition of digits. The digit recognition system mainly depends on which kinds of features are used. The main objective of this paper is to provide efficient and reliable techniques for recognition of handwritten digits. A Euclidean minimum distance criterion is used to find minimum distances and k-nearest neighbour classifier is used to classify the digits. A MNIST database is used for both training and testing the system. 5000 images are used to test the proposed method a total 5000 numeral images are tested and get 96.94% recognition rate.

**Savita Ahlawat, Amit Choudhary [8]**

This paper is to develop a hybrid model of a powerful Convolutional Neural Networks (CNN) and Support Vector Machine (SVM) for recognition of handwritten digits from MNIST dataset. The proposed hybrid model combines the key properties of both the classifiers. In the proposed hybrid model, CNN works as an automatic feature extractor and SVM works as a binary classifier. The MNIST dataset of handwritten digits is used for training and testing the algorithm adopted in the proposed model. The MNIST dataset consists of handwritten digits images which are diverse and highly distorted. The receptive field of CNN helps in automatically extracting the most distinguishable features from these handwritten digits. The experimental results demonstrate the effectiveness of the proposed framework by achieving a recognition accuracy of 99.28% over MNIST handwritten digits dataset.

## DISCUSSION & CONCLUSION

The paper discusses in detail all advances in the area of handwritten character recognition. The most accurate solution provided in this area directly or indirectly depends upon the quality as well as the nature of the material to be read. Various techniques have been described in this paper for character recognition in handwriting recognition system. Studies in the paper reveals that there is still scope of enhancing the algorithms as well as enhancing the rate of recognition of characters.

**Reference:**

[1] Devnagari numeral recognition by combining decision of multiple connectionist classifiers - Reena Bajaj, Lipika Dey, and S. Chaudhury

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[5] Hand-printed digit recognition using deformable models - M. Revow, C.K.I. Williams, G.E

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