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HANDWRITTEN DIGIT RECOGNITION USING NEURAL NETWORK

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Abstract.

This research explores the application of Optical Character Recognition (OCR) in the realm of computer science, delving into the intersection of image processing, machine learning, and neural networks. The project comprises two main components: the training phase and the testing phase. In the training phase, a novel algorithm is employed to teach a neural network to recognize diverse characters by exposing it to various sets of similar but not identical characters. The testing phase involves evaluating the neural network's performance on a new dataset, akin to assessing a trained individual's ability to recognize characters. The project incorporates statistical modeling and optimization techniques, emphasizing the significance of statistical concepts, optimizer techniques, and filtering processes. Mathematical and predictive aspects underpin the algorithms, guiding the creation of a machine learning model. The research underscores the intricate interplay between prediction, programming, and the implementation of neural networks for character recognition.

Keywords: Optical Character Recognition, image processing, CNN

1. Introduction

In this research introduces Optical Character Recognition (OCR) as a technique encompassing various facets of computer science. The project aims to capture an image of a character and process it to recognize the character's image, akin to how the human brain identifies different digits. It delves into advanced Image Processing techniques and explores the extensive research field of machine learning, focusing on Neural Networks as a

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foundational component. The project comprises two distinct phases: the Training part and the Testing part.

The Training part involves the concept of instructing a neural network, likened to training a child with sets of similar characters, each slightly varied, and associating the correct output. This phase incorporates novel self-created algorithms tailored to the project's requirements. Subsequently, the Testing part entails evaluating a new dataset, occurring after the training phase. Initially, the system educates itself on character recognition, followed by assessments to validate the correctness of the acquired knowledge. In instances of errors, the system undergoes further training with new datasets and entries. This iterative process is mirrored in the testing of the algorithm's effectiveness.

The project integrates various aspects of statistical modeling and optimization techniques, necessitating a profound understanding of statistical concepts, optimizer techniques, and filtering processes. This involves an exploration of the mathematical foundations behind neural network implementation and prediction, drawing insights from notable works such as Peter Roelants (2016) on implementing neural networks and Kaiming He et al.'s contributions to prediction. Ultimately, the project aims to create a predictive model through machine learning algorithms, rooted in the fundamental concepts of prediction and programming.

2. Design/Methods/Modelling

THE NEURAL NETWORK MODEL

The neural network is fundamentally rooted in the realm of machine learning. Initially, it establishes a model resembling a brain unit, akin to a child, and subsequently trains this model with extensive datasets—specifically, for this project, focusing on digits. The neural network model consists of two pivotal phases:

Training Part

Testing Part

Before delving into the intricate details of these project-specific phases, it is essential to gain insights into the foundational elements and structural components of neural networks (C.C.Jay.Kuo – 2016, Adit Deshpande – 2016). Neural networks are composed of three fundamental segments:

Input Layer

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Hidden Layer

Output Layer

The amalgamation of these elements constructs a neural network by interconnecting numerous simple "neurons." This interconnection facilitates the transmission of output from one neuron to serve as input for another, creating a complex network. To illustrate, consider the representation of a basic neural network:

Input Layer→Hidden Layer→Output LayerInput Layer→Hidden Layer→Output Layer

This sequential arrangement encapsulates the core structure of a neural network, forming the basis for subsequent training and testing phases within the project.

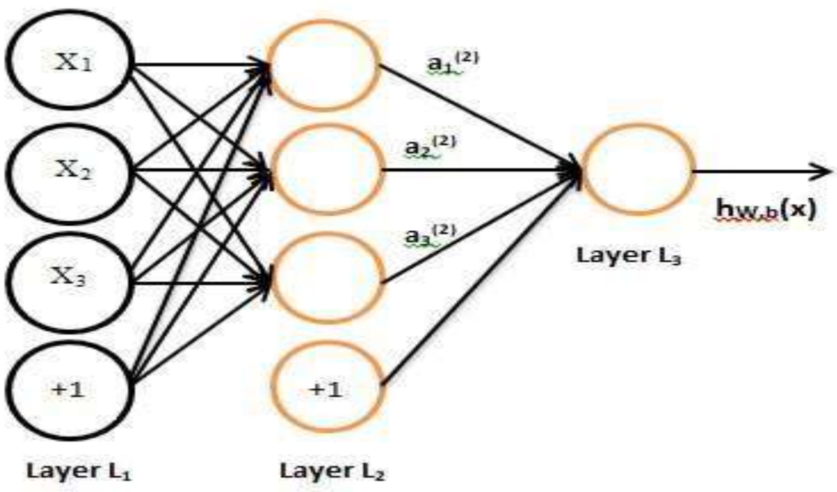

Fig-1 Neural Network Model

In Figure 1, the inputs to the network are represented by circles. The circles marked with "+1" denote bias units, signifying the intercept term. The input layer, situated on the leftmost side of the network, is where these circles are positioned. On the opposite side, we have the output layer, which, in this particular illustration, consists of only one node. The intermediary layer between them is referred to as the hidden layer, given that its values are not directly observed in the training set. For instance, let's consider a neural network in this example with 3 input units (excluding the bias unit), 3 hidden units, and 1 output unit.

The types of layers in a neural network can be summarized as follows:

Input Layer

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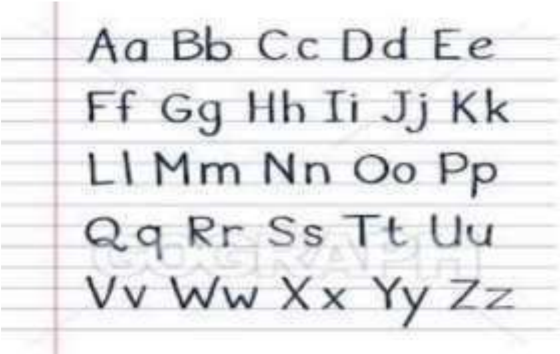
Input variables, sometimes called the visible layer.This layer can be of features or the direct input from the dataset.



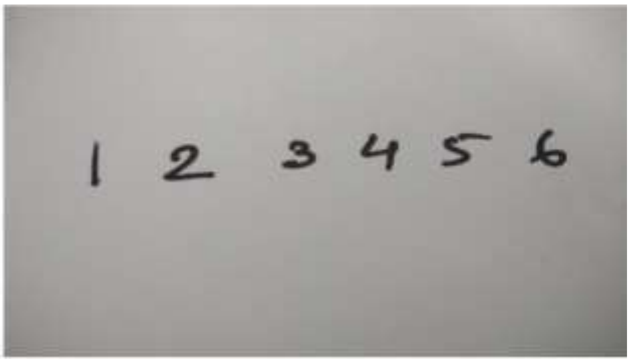


Fig -4.2 Handwritten Margin pic Input

Fig -4.3 Handwritten Plain paper Input

Fig-4.4 MNIST dataset Input

Hidden Layer The hidden layer constitutes the stratum of nodes positioned between the input and output layers. There could be one or multiple hidden layers, and the augmentation of hidden layers intensifies the network's operations, increases the number of weights, and subsequently mitigates the impact of variations in this layer's values. This layer holds paramount significance within the neural network, as it is where weight adjustments occur, influenced by the returning input.

Output Layer The output layer encompasses nodes responsible for generating output variables, subsequently facilitating iterative processes based on the predefined targets. Additionally, several terms are employed to characterize the structure and capabilities of a neural network, including:

Size: Denotes the total number of nodes in the model.

Width: Indicates the number of nodes within a specific layer.

Depth: Signifies the count of layers in a neural network.

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Capacity: Refers to the type or structure of functions that a network configuration can learn, often termed "representational capacity."

Architecture: Describes the specific arrangement of layers and nodes in the network.

In this research, the utilization of max relu and softmax has been employed due to their consistently superior performance, as evidenced in Figure 4.2. The experimental approach is solely result-driven, with no additional theoretical application, emphasizing the convergence of the sigmoid and tangential curves to the verified output scenario.

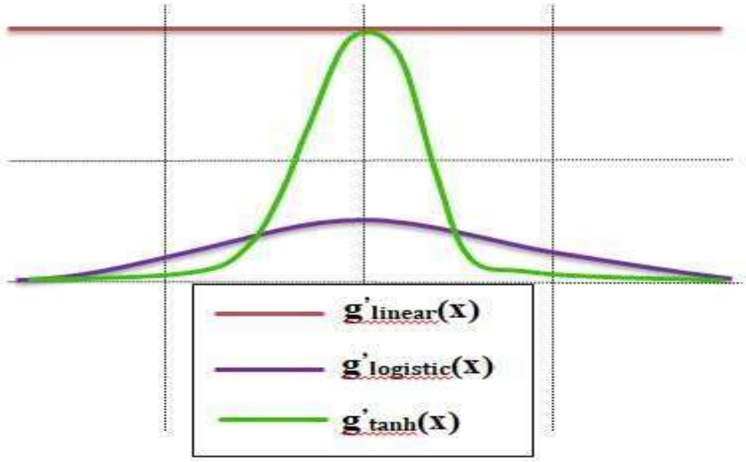

Fig – 4.2 Types of activation functions over graph

Given the substantial deflection of linear, logistic (sigmoid), and tangential functions for static inputs, where they promptly reach 1 or 0 and do not practically revert, these three options have been dismissed. While sigmoid yields commendable results, in practical terms, max relu and softmax prove more effective for handwritten digit recognition.

Moreover, bias inputs are excluded to preserve the genuine structure of data derived from the primary flattened and sequential data. To enhance the model's effectiveness, a deliberately low learning rate of 0.002 has been assigned.

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