# George Mason University

# DAEN 690

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# **Accure Autoencoder for denoising OCR**

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# Problem Definition

Optical Character Recognition (OCR) technology enables the extraction of text data from images. There are endless uses for this type of technology, from the digital processing of historical documents to the extraction of text in personal photos. It is designed to capture numbers, letters, and punctuation and transfer these characters into data that can be searched, processed, analyzed, and stored.

OCR technology is valuable in any instance where documents or images have text. This is especially useful as society moves away from physical documents and into the digital data space. Using OCR technology, entire document archives once relegated to file cabinets can instead be harvested for digital text. Doing so creates opportunities for non-digital text to be leveraged by other computer-enabled technologies.

This technology is not perfect, and it is difficult to translate character images into a digital text without some inaccuracies or errors. Image “noise,” which can occur if image resolution or coloring issues interfere with the characters, is one reason that OCR technology may have trouble reading character text.

This project aims to build a Convolutional Neural Network (CNN) auto-encoder that reduces image noise during the OCR process. We will evaluate the fidelity of our CNN by conducting OCR text extraction on a dataset before and after the implementation of our method.

# Assumptions

This project assumes the availability of compute resources through Google Colab and the instruction and guidance of commercial and academic stakeholders. Additionally, our ability to assess the usefulness of the constructed auto-encoder relies on the availability of training data considered to be ‘noisy’ regarding standard OCR methods.

# Scope

Our effort will develop and implement a CNN auto-encoder for application on OCR applications. The project will be based on the development and optimization of an autoencoder that will input a set of character images and classify the images.

The project will use K-means clustering, Python’s Tesseract library (i.e., PyTesseract), and denoise imager. We plan to leverage Google Colab computing resources. [1]; [2]; [3]; [4]; [5]; [6]; [7]

In addition to delivery of a prototype, the project team will evaluate our denoising model with respect to accuracy and performance.

# Risks

This project acknowledges the existence of facets that may negatively affect successful project completion. These include the unavailability of compute resources, internet access, or adequate means for team and stakeholder communication. We consider overall risk to be low.

**Risk Matrix**

A screenshot of a cell phone

Description automatically generated

# Data Acquisition

## Overview

This project will leverage the Ryerson Vision Lab Complex Document Information Processing (RVL-CDIP) dataset [8]. This dataset is the product of academic research by Adam W. Harley, Alex Ufkes, and Konstantinos G. Derpanis. Their 2015 paper, “Evaluation of Deep Convolutional Nets for Document Image Classification and Retrieval,” researched the ability of convolutional neural networks to conduct state-of-the-art document image classification and retrieval [9]. RVL-CDIP is a subset of the IIT-CDIP Test Collection, which was used for a 2006 conference paper titled “Building a test collection for complex document information processing [10].” The IIT-CDIP dataset is itself a subset of the Legacy Tobacco Document Library (TLDL), an archive of 14 million documents related to tobacco industry advertising, manufacturing, marketing, scientific research, and political activities. The full dataset is hosted by the University of California, San Francisco university library [11].

## Field Descriptions

The data consist of 400,000 grayscale images and 16 classes with 25,000 images per class. All images are unique. Data is classified using the following labels.

|  |  |
| --- | --- |
| 0 – letter | 8 – file folder |
| 1 – form | 9 – news article |
| 2 – email | 10 - budget |
| 3 - handwritten | 11 - invoice |
| 4 - advertisement | 12 - presentation |
| 5 – scientific report | 13 – questionnaire |
| 6 – scientific publication | 14 - resume |
| 7 - specification | 15 - memo |

## Data Context

This dataset was used by researchers at Carnegie Mellon University in 2015 to build a convolutional neural network focused on document image, classification, and retrieval.

## Data Conditioning

The data is stored as a downloadable file on Google Drive using a link provided on the dataset website. The data is zipped into a .tar file with two separate data sources, one for the images and one that provides information on labeling.

## Data Quality Assessment

The RVL-CDIP dataset is an academic creation that is designed to lend itself to computer vision and machine learning efforts. For each image, the largest dimension is not to exceed 1000 pixels. All are image formats and are classified by type of document as well as a predefined train, test, and validation set.

The raw dataset has several outstanding issues that need to be mitigated before final analysis can occur. The first issue is that each image in the dataset is separated into individual file folders making it difficult to extract the image into a tidy corpus for analysis. The second issue is that the data is currently in .TIF format (Tagged Image File) and may be insufficient for analysis in further steps. The third issue presented is the sheer size of the dataset corresponding with the preferred data storage on Google Drive. Google Drive uploads the information slowly and either the data needs to be scaled down for analysis only or another tool needs to be research for proper uploading. Finally, the dataset contains a few “bad” images for our analysis. These images contain little or no text and almost all noise and need to be eliminated from our purposes.

* Completeness: The RVL-CDIP dataset includes 400,000 grayscale images in 16 classes, with 25,000 images per class. Also, it is split into 320,000 training images, 40,000 validation images, and 40,000 test images.
* Uniqueness: The dataset consists 16 different classes, and each image in each class is unique.
* Consistency – Images are sized so not exceed 1000 pixels for largest dimension.
* Integrity – All images are .tif (Tagged Image File), which may be challengeable for analysis in further steps.
* Conformity – All images are stored in a standard format.
* Accuracy – Data appears to be accurately managed given the quality of the source.
* Overall Quality: The quality of the dataset is high.

## Other Data Sources

We have identified several additional datasets that may also be used for our project. These datasets vary in quality, volume of data, and usefulness toward our defined project scope.

# Algorithm & Analytics

## Convolutional Neural Network

This autoencoder model will be built using a Convolutional Neural Network (CNN) with unsupervised learning to reduce noise in various text images. A regular neural network contains three layers: an input layer, a hidden layer, and an output layer. The input layer is simply a vector of data that is passed through a series of hidden layers to produce a result in the output layer. A traditional neural network is show below:

A close up of a logo

Description automatically generated

Figure 1: A Neural Network

Source: Adapted from [12]

A Convolution Neural Network has a similar structure but differs by having three distinct layers: the convolutional layer, the pooling layer, and the fully connected layer. CNN’s also almost always include images so spatial information and their relation to each other at the pixel level is important. This is the key aspect of the convolutional layer which reduces the image to smaller pixel vectors while retaining the relationship of those pixels to each other. This process is called filtering and the more filters used in the model the longer the model takes to produce a result. The next layer is called the pooling layer which takes information from the convolutional layer and reduces the pixels even further. The process by which it reduces the image is by using max pooling by looking for which pixels have the highest value between them. The higher the value is, the more important the pixel is to the image. The convolution and pooling layers continue until finally being flattened into one vector called the fully connected layer [12]. An example of a basic CNN is below:

A picture containing clock, drawing

Description automatically generated

Figure 2: A Convolutional Neural Network (Layers)

Source: Adapted from [12]

## Noisy Autoencoder

The autoencoder will use CNN’s to train and reduce image noise by reconstructing the image into an improved version. This means there are two steps in the training process. The first step is shrinking the images down into flattened vectors with the most important features remaining. This step is the encoder step. The second step, or decoding step, is to take the flattened vectors from the encoding step as an input. These inputs are then reshaped and ran through the convolutional and pooling layers to recreate an improved image. The pooling layers in the decoder instead of reducing pixels by max pooling increase the size of the image using Up sampling. This process produces an output of the improved original image. An example of the Autoencoder process is below:

A close up of text on a white background

Description automatically generated

Figure 3: Autoencoder Overview

Source: Adapted from [13]

## Convolution

The Digital Image - - - - TBD



Figure 4: Digital Image Data Structure [14]

Kernel Convolution is the process of applying a matrix of numbers to portions of the image, transforming it as you go based on the values in the matrix. This creates a feature map of the image by using the below formula (see Figure 5). The imput image (f) and the matrix, known as a kernel (h), are applied to the pixel vector space rows and columns (m and n). As the function steps through the pre-defined row-column space each time, the pixel values are matrix multiplied with the kernel value and the resulting number is added to the now-reduced feature map (see Figure 6). This process is considered one convolution. [14]

Figure 5: Convolution equation

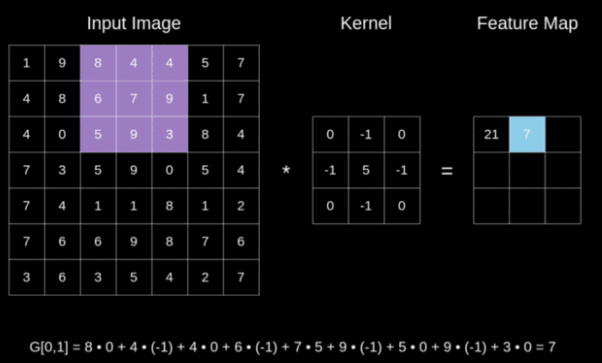


Figure 6: Digital Image Data Structure [14]

Next, in order to make use of the new feature map, we need to apply an activation function. The role of the activation function is to turn the summed feature map into an output for that node. There are several activation functions used in CNNs. We chose to use the rectified Linear activation function (ReL), which is a nonlinear function that uses stochastic gradient descent with backpropagation. ReL is popular because of it’s built-in gradient descent/backpropagation learning methods, but also because it acts both linear and nonlinear in nature. For values greater than 0, the function performs linearly, making it easier to understand and optimize. However, it also acts nonlinear for values less than 0 by creating a resulting output of 0. The simple statement, “If input > 0, Return input; else Return 0” sums up the idea behind ReL. A convolutional node that uses the ReL function is known as a Rectified Linear Unit (ReLU). Neural networks that leverage RELU are often called Rectified Networks. [15]

Each convolution in a neural network follows the same process, but each additional convolution does not have to use the same rules. These tunable features, or hyperparameters, are used to refine and direct the convolutional process based on need. One such parameter, Step length, or Stride, sets the rules for how many pixels the kernel will shift for each calculation. This will effectively set the spatial dimensions of the feature map for that convolution. The filter size, or Kernel size, is also considered a hyperparameter. [14]

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