

# Development of a New Image-to-text Conversion System for Pashto, Farsi and Traditional Chinese

## Machine Learning and Big Data Approach

Marek Rychlik\*, Dwight Nwaigwe†, Yan Han‡, Dylan Murphy§

April 28, 2020

### Abstract

We report upon the results of a research and prototype building project *Worldly OCR* dedicated to developing new, more accurate image-to-text conversion software for several languages and writing systems. These include the cursive scripts Farsi and Pashto, and Latin cursive scripts. We also describe approaches geared towards Traditional Chinese, which is non-cursive, but features an extremely large character set of 65,000 characters. Our methodology is based on Machine Learning, especially Deep Learning, and Data Science, and is directed towards vast quantities of original documents, exceeding a billion pages. The target audience of this paper is a general audience with interest in Digital Humanities or in retrieval of accurate full-text and metadata from digital images.

## Contents

<b>1 Background</b>	<b>3</b>
1.1 Prologue . . . . .	3
1.2 Our main objective — building an Open Source OCR system . . . . .	3
1.3 The definition of OCR and its advantages . . . . .	4
1.4 Artificial Intelligence, Machine Learning and Data Science . . . . .	4
1.5 Recent successes with cursive scripts . . . . .	5
1.6 An overview of the OCR technology . . . . .	5
1.7 Rationale for building a new OCR system . . . . .	6
1.8 A review of prior OCR related research . . . . .	6
1.9 MATLAB as a development platform . . . . .	8
1.10 MATLAB as a software delivery system . . . . .	8
1.11 Other platforms . . . . .	8
1.12 Collaboration with our project . . . . .	9

---

\*University of Arizona, Department of Mathematics

†University of Arizona, Department of Mathematics

‡University of Arizona, Library Sciences

§University of Arizona, School of Information

<b>2 Results</b>	<b>11</b>
2.1 OCR on 1023 lines of text in Farsi with 97% accuracy . . . . .	11
2.2 OCR on Latin cursive script Bromello . . . . .	12
2.3 Cursive scripts . . . . .	12
2.4 Traditional and Simplified Chinese . . . . .	14
2.5 Steps to developing OCR for the Bromello font . . . . .	15
2.6 Steps to developing OCR for Farsi and DejaVu Sans font . . . . .	16
<b>3 Our methods and algorithmic basis</b>	<b>17</b>
3.1 Cursive scripts and the video processing pipeline . . . . .	17
3.2 Blob outline analysis . . . . .	17
3.3 The binary color model . . . . .	19
3.4 Blobs and their outlines . . . . .	19
3.5 Skeletonization . . . . .	21
3.6 Connectionist Temporal Classification (CTC) . . . . .	21
<b>4 A brief overview of existing software and its limitations</b>	<b>24</b>
<b>5 Evaluation of other OCR software</b>	<b>25</b>
5.1 Issues with reported OCR accuracy . . . . .	25
5.2 A list of tested OCR systems . . . . .	26
5.2.1 Tesseract . . . . .	26
5.2.2 Google Cloud and Google Drive . . . . .	26
5.2.3 ABBYY . . . . .	27
5.2.4 Convertio . . . . .	27
5.2.5 NovoVerus . . . . .	27
5.2.6 Sakhr . . . . .	27
5.2.7 Kraken . . . . .	27
5.3 Testing on Traditional and Simplified Chinese . . . . .	27
<b>6 The Tests</b>	<b>28</b>
6.1 Traditional Chinese . . . . .	29
6.1.1 Tesseract . . . . .	29
6.1.2 Google Drive (Convert PDF and photo files to text) . . . . .	29
6.1.3 ABBYY . . . . .	29
6.1.4 Abbyy.cloud . . . . .	32
6.1.5 Adobe Acrobat Pro DC . . . . .	32
6.1.6 Convertio . . . . .	32
6.2 Testing on Arabic and Persian . . . . .	32
6.2.1 Adobe Acrobat Pro DC . . . . .	32
6.2.2 NovoVerus . . . . .	32
6.2.3 ABBYY . . . . .	32
6.2.4 Kraken . . . . .	33
6.3 Observations on evaluated OCR systems and services . . . . .	33
6.3.1 Tesseract 3.0 and 4.x . . . . .	34
6.3.2 Notes on Tesseract 4.11 . . . . .	35
6.4 Persian . . . . .	35
6.4.1 Readiris . . . . .	35
6.4.2 Pershyangar . . . . .	35
<b>A Videos on YouTube</b>	<b>36</b>

# Acknowledgment

This article has been made possible in part by the National Endowment for the Humanities: *Development of Image-to-text Conversion for Pashto and Traditional Chinese*.

Any views, findings, conclusions, or recommendations expressed in this article do not necessarily represent those of the National Endowment for the Humanities.

## 1 Background

### 1.1 Prologue

The world's documents use many writing scripts and mainly consist of Latin (4,900+ million pages), Chinese (1,340 million pages), Arabic(660+ million pages), Devanagari (600+ million pages), Cyrillic (250 million pages), Bengali (220 million pages), Kana (120 million pages) and others. Latin languages use an alphabet, which is a standard set of letters to form words. In contrast, the Chinese language is a logographic system, of which a single written character represents a complete grammatical word.

While developing OCR technology for printed Latin scripts is viewed as a solved problem, as character and word accuracies typically reach over 95%, the problem for other languages, including Traditional Chinese and Arabic scripts, is not yet completely solved. See section 1.8 for a detailed discussion. In regard to Traditional Chinese, for documents utilizing modern fonts OCR is generally a solved problem, but old Traditional Chinese documents are still a big obstacle for OCR technology. An East Asian studies librarian wrote to the author in 2019:

I am just back from the annual AAS (Association for Asian Studies) and CEAL (Council on East Asian Libraries) meetings. This year (2019), Prof. Peter Bol of Harvard hosted a 2-day digital tech expo there to promote digital humanities... I spent 1 day on the DH sessions, where scholars constantly mentioned Chinese OCR as a conspicuous and serious block on their path to assessing “digitized” textual collections. If you and your team succeed, it will surely help the EAS scholarly community a lot.

### 1.2 Our main objective — building an Open Source OCR system

The primary objective of this project is creation of a new, modern OCR system, which will serve users with various needs. This includes the individual users, such as a researcher who would like to perform OCR on a single page or book, and institutions who may have large collections with millions of pages, such as a university or a library. In order to satisfy such a diverse community, the software will be produced in several forms:

- (1) A standalone **desktop software application** with a Graphical User Interface, running on **all major operating systems**, including Windows, Mac OS, Linux.
- (2) A **Web application** accessible through a Web browser and running on a server; the power of the server will determine the processing speed and quantity of data that can be handled.
- (3) A **MATLAB application**, primary for programmers and scientists who participate in the development of the system.

The standalone application is ideal for individual users, with a relatively small quantity of data. Large projects may use either a Web application or the standalone application. Parallel processing will be supported in all forms, which allows for shortening of processing time by the use of higher end hardware (clusters, supercomputers, cloud).

This level of cross-platform support may seem like a tall order for a small, research oriented team. Therefore, it is worth explaining how this is accomplished. We leverage the features provided by the MATLAB commercial software [1], which allows us to deliver our application in all of the above forms without extra work. Furthermore, our prototype software **has been verified to work on those multiple platforms**.

In section 1.9 we provide further details about how MATLAB is used in the project, and how it will be used as a software delivery platform.

It should be noted that **the use of MATLAB does not make our software commercial**<sup>1</sup>. The relationship of our software to MATLAB is similar to an Open Source application running on a commercial operating system (Windows, MacOS). The availability of MATLAB Runtime (the portion of MATLAB used by our standalone application) and a clear license that allows free use, addresses this matter (<https://www.mathworks.com/products/compiler/matlab-runtime.html>).

### 1.3 The definition of OCR and its advantages

Image-to-text conversion, also called Optical Character Recognition (OCR), is a crucial technology for Digital Humanities, connecting historical documents written on traditional media (e.g., paper, cloth) to modern, digitized storage. The main problem of the field sounds deceptively simple: to take an image, e.g., a photograph of a page of printed or handwritten page of text, and retrieve the original text. More precisely, we essentially reproduce the **sequence of keystrokes** that would result in text **semantically equivalent** to the content of the original page of text. Of course, a human expert familiar with the writing system used, and capable of typing or other form of data entry, may perform this task. The challenge is to **teach a machine** to perform this task and scale up the speed and volume that can be handled, so that the billions of pages of historically important written records can be converted from image form to text.

The benefits of having the text are numerous. Foremost, the text can be searched and edited with standard computer software, such as Microsoft Word or Emacs (our favorite text editor). Furthermore, the text can be processed with *Natural Language Processing* (NLP) software to study it from the linguistics point of view.

There are additional benefits to society, such as reduction of disk space used to store a **document's meaning** rather than various artifacts of its processing, such as yellowing of pages, chipping of ink, warping of paper, etc. Easily, the savings of disk space may be a **thousand-fold**, which may be translated into similar saving of, say, power consumption.

In short, OCR facilitates access to and reduces the cost of storing of massive quantities of data that is used in Digital Humanities, and will be multiplied rapidly in the near future.

### 1.4 Artificial Intelligence, Machine Learning and Data Science

As hiring human experts is prohibitively expensive for the totality of records under consideration, the conversion has to be performed with software imbued with the expert knowledge required to perform image-to-text conversion. Artificial Intelligence (AI) is defined as constructing machines or software capable of performing tasks at a level of a competent human. Therefore, image-to-text conversion is considered a branch of AI, and makes the current project an AI project.

Recent rapid progress in AI is mainly due to advancements in many distinct areas. In particular, Machine Learning (ML) has become a feasible approach to many AI problems. The premise of ML is to build software by training rather than programming. The components of the software that learn and retain information from the training are called (Artificial) Neural Networks, and are inspired by the biological neural network: the brain. Thus, a human programmer (e.g., a member of the current team), builds software which trains a neural network to perform image-to-text conversion. Neural networks are typically trained using **supervised learning**, whereby a sequence of examples is presented to the network of a task at hand performed correctly, and the network generalizes the examples to a much larger body of problems. In image-to-text conversion the network may be presented with a few pages of correctly transcribed text, and the network is then capable of transcribing all similar texts.

---

<sup>1</sup>Some colleagues have been concerned about this aspect of our software.

## 1.5 Recent successes with cursive scripts

The significant recent progress in OCR of cursive scripts (e.g., Arabic, Farsi, Pashto, off-line handwriting) has been mainly achieved due to progress in Machine Learning (ML) and especially Deep Learning (DL). All modern OCR systems incorporate ML and DL components.

Without going into the technical details associated with this approach we hope to give the user a flavor of these techniques and explain the impact on real workflows associated with them, as it relates to practical image-to-text conversion. The particular aspect of ML is that the software needs to be trained in addition to being written. Training is a crucial phase of building a software system which will perform well on real data. The crucial part of this phase is **collecting and digitizing samples of documents** and **using human experts** to manually transcribe the documents to Unicode (Unicode is described in section 1.6), which makes it slow or expensive, or both. Also, training may involve running software for weeks to optimize hundreds of thousands of parameters, and any interruption of this process, or mistakes in software design often require starting from scratch. Hence, one of the important aspect of this project is **shortening the length of time required to train** by using better algorithms and training protocols.

## 1.6 An overview of the OCR technology

There are two major phases of converting a physical record, such as a book printed hundreds of years ago, to a full-text digital record, without actually having access to the physical record, but requiring the record's textural content:

- (1) Digital capture, such as scanning with a digital scanner or digital camera, and storing the results in the form of a digital image.
- (2) Extraction of textual information from the image and storing it as encoded text, typically Unicode , either along with the original image, or replacing the digital image.

Unicode, in simple terms, is numbering of the keys of a virtual computer keyboard capable of producing all characters used in all languages, also called **encoding**. The endeavor of creating such numbering requires a **standards body**, and the *Unicode Consortium* [34] is such a body. It should be mentioned that many (often incompatible) encoding standards have been created in the past, starting with the American Standard Code for Information Interexchange (ASCII) first published in 1963, and Unicode is designed to be “the last” standard, to be universally used in the foreseeable future.

Of the two steps to OCR, **digital capture has become easy** due to the development of inexpensive, miniaturized digital cameras of extremely high quality.

The difficult part is the second step: image-to-text conversion. It is paramount that this step be fully automated, as it must be applicable to the totality of documents representing the cultural heritage of entire nations. In principle, image-to-text conversion can be performed by a large team of human experts, who visually examine and recognize the text, and key-in the results using a computer keyboard. The degree of expertise required varies. For instance, texts in Traditional Chinese may be hundreds of years old, and may require linguistic and historical knowledge to perform accurately.

OCR systems evolved towards a consensus architecture that identifies several common phases. This happened over a period of more than 40 years since the digital scanner was invented and the first algorithms for performing OCR on Latin scripts were developed [16, 9]. OCR phases may include: image pre-processing; image segmentation; recognition proper; post-processing; linguistic analysis. A good review of the architecture of the Tesseract OCR system [32] can be found in an excellent blog article entitled “Breaking down Tesseract OCR” (<https://machinelearningmedium.com/2019/01/15/breaking-down-tesseract-ocr/>). Many themes of the article can be traced back to an earlier article by Ray Smith [28]. Tesseract OCR development started over 30 years ago as a commercial project at HP and it is still being developed by its original developer Ray Smith. Tesseract and various publications based on it represent both current and historical views of the art of OCR. Kraken is a *fork* of an older system, *Ocropus* [2], released in 2007. The project does not appear to be actively developed, based on GitHub activity statistics. Therefore, there is a

need for a new, agile platform for research and software development, and we hope that our platform will fulfill this role.

## 1.7 Rationale for building a new OCR system

Our project has as its goal building a superior OCR system, with higher accuracy and capacity to process huge quantities of data quickly. We aim to be able to achieve 90% accuracy, which is considered a threshold for the OCR results to be useful, on a much larger class of documents than currently possible. Increasing OCR accuracy is a particularly ambitious goal, as it involves advancing a field developed over a period of 40 years by extremely strong researchers. The strength of our team is its diverse yet complementary background in mathematics, statistics and scientific computing. The current focus of the project is **fundamental research and software prototyping**. The focus will gradually shift towards **software development**, while maintaining the ability to quickly prototype and do OCR research. We needed a software platform which allows this approach. The natural choice is MATLAB [1]. The pros and cons (mostly pros) of MATLAB as a development platform are further discussed in section 1.9.

We did look at other ways to structure our project. We quickly excluded commercial systems as they are essentially closed to modifications by non-commercial developers. Two open source domain projects *Tesseract* [32] and *Kraken* [15] are open to other developers, but they are primarily software development projects, not research platforms. This would hinder our ability to have a comprehensive look at the totality of OCR algorithms and bring in research results to bear on the problem.

## 1.8 A review of prior OCR related research

In the current section we briefly review mostly recent works devoted to the core OCR problems, and thus closely related to our own research, and software prototype development. Most of the problems discussed have already been solved in our software prototype. **We have not based our implementation on any particular work**, but designed our own algorithms. Naturally, our methods overlap with much other research in the field. Often, rather than working from scratch, we build our algorithms on top of the MATLAB framework, which provides a vast collection of high quality building blocks for a project such as ours.

*The reader may skip the remainder of this section upon first reading without loss of understanding.*

Tomaschek [33] identifies the following stages of processing in an OCR system: image acquisition, pre-processing, binarization, page segmentation, line, word, and character segmentation, recognition, and post-processing. In contrast, the dissertation [27] describes the process as having two major phases: preprocessing and recognition in a linear sequence. The preprocessing phase consists of noise removal, binarization, skew detection, page analysis, and segmentation, while recognition phase includes feature extraction and classification. The author suggests that context analysis and recognition are responsible for final output, i.e., an advanced OCR system shall be more than just text labeling.

In recent years new systems based on Deep Learning ideas merged various phases to reflect this new change in architecture. In the past various algorithms were proposed generally following the above design. These are relevant to this day, and they can be combined with the Deep Learning approach in various ways, and therefore are worth discussing. The new development in OCR technology is an application of Recurrent Neural Networks (RNN) which led to breakthroughs in OCR of cursive scripts, starting with Arabic. In the past, OCR systems performed poorly over complex scripts such as Indian and Arabic languages, and with RNNs the situation is greatly improved. The successes of RNN in this area can be traced back to the seminal research described in papers of Sepp Hochreiter, Jürgen Schmidhuber and Alex Graves [11, 7, 8]. The software system *Kraken* [15] referenced in other parts of this paper is perhaps the most pure implementation of this circle of ideas.

In the preprocessing stage, background and foreground segmentation occurs using mostly statistical modeling. The segmentation involves **blobs**, also called “objects”, which conceptually represent the contiguous

regions of a page covered by ink. Using various heuristics, one can combine blobs into larger entities: **lines of text, words, ligatures and characters**, without detailed knowledge about the the underlying languages, just on the basis of common principles used by most writing systems. One major distinction is between scripts which use separated characters (e.g., printed Latin scripts and the Chinese logographic system), and cursive scripts, in which characters are connected (e.g. handwritten Latin scripts, Pashto and Persian/Farsi).

Ciresan et. al. [5] proposed using a statistical *Gaussian mixture model*, and investigated simple training data preprocessing and focused on improving recognition rates using **committees of neural networks**. They suggested using committee-based classifiers as basic building blocks of any OCR system.

Dutta [6] proposed recognizing character  $n$ -gram images, which are groupings of consecutive character/component segments. They use the character  $n$ -grams as a primitive for recognition rather than for post-processing, resulting in a 15% decrease in word error rate on heavily degraded Indian language document images.

Shafii [27] presented methods for detecting skew angle and reviewed multiple methods proposed before. One method is based on geometrical features of a skewed document. The proposed algorithm and its implementation show 95% success rate on a certain set of documents.

Li, Zheng, and Doemann [37] proposed the use of a *Gaussian window* to detect text lines in handwritten documents.

Louloudis et.al [19] presented a 3-step method for text line detection. The first step includes image binarization and enhancement, connected component (blob) extraction, partitioning of the connected component domain into 3 spatial sub-domains and average character height estimation. The second step is to use Hough transform for the detection of potential text lines. The third step is to correct possible splitting and to detect text lines not found by the second step, and finally to separate vertically connected characters and assign them to text lines.

The dissertation [27] contains a literature review related to page segmentation, including top-down algorithms, bottom-up algorithm, and a combination of both. Shafii proposed a new segmentation technique based on image resampling methods. The method simply performs a downsampling (zoom-out) by upsampling with a calculated scaling factor. The sampling scale is calculated by utilizing a white gap transition algorithm and determining between the text row gaps. This process converts the image to blobs of segments. Each segment is identified as text or non-text using three criteria. Shafii concluded that many algorithms deemed to be successful for English do not apply to Persian (83,84). Citing previous research on this topic, Shafii proposed a hybrid feature extraction algorithm and 1st Nearest Neighbor classification for sub-word segmentation.

In the phase of post-processing, most popular approaches to handle degraded documents are to use post-processing methods such as character error models [13], dictionaries [17], statistical language models [20], and/or a combination as studied by Taghva and Sofsky [31].

In the phase of recognition, Sankaran and Jawahar [26] proposed BLSTM (Bidirectional Long-Short Term Memory) for the Indian script of Devanagari.

This approach does not require word to character segmentation, which is one of the most common reasons for high word error rate. They reported a 20% reduction in word error rate and 9% reduction in character error rate when comparing with the best available OCR system.

Paul and Chaudhuri [21] presented a OCR system using a single hidden BLSTM-CTC<sup>2</sup> architecture having 128 units. This architecture was trained by 47,720 text lines and tested over 20 different Bengali fonts, producing 99% character accuracy rate and 97% word accuracy. Using CNN-BLSTM-CTC architecture, the results show the superiority of this architecture over the simple architecture. They reported an 89% character accuracy on the degraded image simple.

The International Conference on Document Analysis and Recognition hosted a Chinese (simplified) handwriting competition in 2013 to gauge the effectiveness of various technologies. Almost all entrants used quadratic discriminant analysis or convolutional neural networks (CNN). The most accurate systems in terms of isolated character recognition were CNN-based, with accuracies of around 94%. This was closely followed by quadratic discriminant function-based methods which obtained accuracies of around 92% [38].

---

<sup>2</sup>BLSTM-CTC stands for “Bidirectional Long-Short Term Memory” and “Connectionist Temporal Analysis”.

## 1.9 MATLAB as a development platform

There is considerable interest in applying machine learning to a variety of problems of great importance to society. One well-known application is building a self-driving car. Another area is applications to medicine, in which a computer may look at images of lesions or tumors, and derive a diagnosis, which is now often more accurate than that of a human expert. Image-to-text conversion shares a great deal of technology and knowledge with these applications, as computer vision is an essential ingredient. Indeed, our software looks at digital images. Therefore, a significant effort has been devoted to providing platforms on which to build software supporting all these applications.

Our choice for implementing the *Wordly OCR* prototype software is MATLAB. This is commercial software with a generous academic license. The software is well-known to engineers as an essential tool in most engineering projects. MATLAB is also used extensively in the Mathematics Department and across the sciences. Perhaps to lesser degree it is a tool for humanities researchers, but is not unknown. Moreover, due to its excellent documentation and commercial support, it is easy to incorporate into humanities projects. Therefore MATLAB was a natural choice for the current project. Moreover, MATLAB features the Deep Learning Toolkit, which implements most of the components needed in the current project.

## 1.10 MATLAB as a software delivery system

**One important aspect of MATLAB is the ability to deliver free software to the end user.** This is because the core of MATLAB code is available as a collection of shared libraries called the *MATLAB Runtime* (<https://www.mathworks.com/products/compiler/matlab-runtime.html>) and freely distributable with an application built with MATLAB. This software distribution model is essentially the same as that of Microsoft products built with Visual Studio. Furthermore, **an application built with MATLAB is portable across all major OS platforms.** Also, it can be run as a **Web application**, utilizing the MATLAB server component. This means that a university or an organization is able to provide on-line access to the application running on a much more powerful computer than an average user can afford (a supercomputer or a large cluster), e.g., to support conversion of a large collection of documents quickly. Thus, in principle, MATLAB is an **ideal software delivery platform**. Some limitations are due to the fact that this is a relatively new addition to MATLAB.

As an example, we developed an application for breaking up a page of text into lines and characters. As indicated in other parts of the paper (e.g., Figure 19), complex layouts often lead to useless OCR results, and therefore it makes sense to interactively aid the software in determining the high-level document organization. Therefore, we developed a GUI application which quickly allows us to extract lines of text and characters from a page of text (an image). The basic look of the GUI is shown in Figure 1. So far, the application has been used internally by the project to:

- (1) extract lines from Pashto documents to build a training dataset similar to the OCR\_GS\_Data dataset in Farsi;
- (2) extract characters from Chinese newsprint (Figure 1).

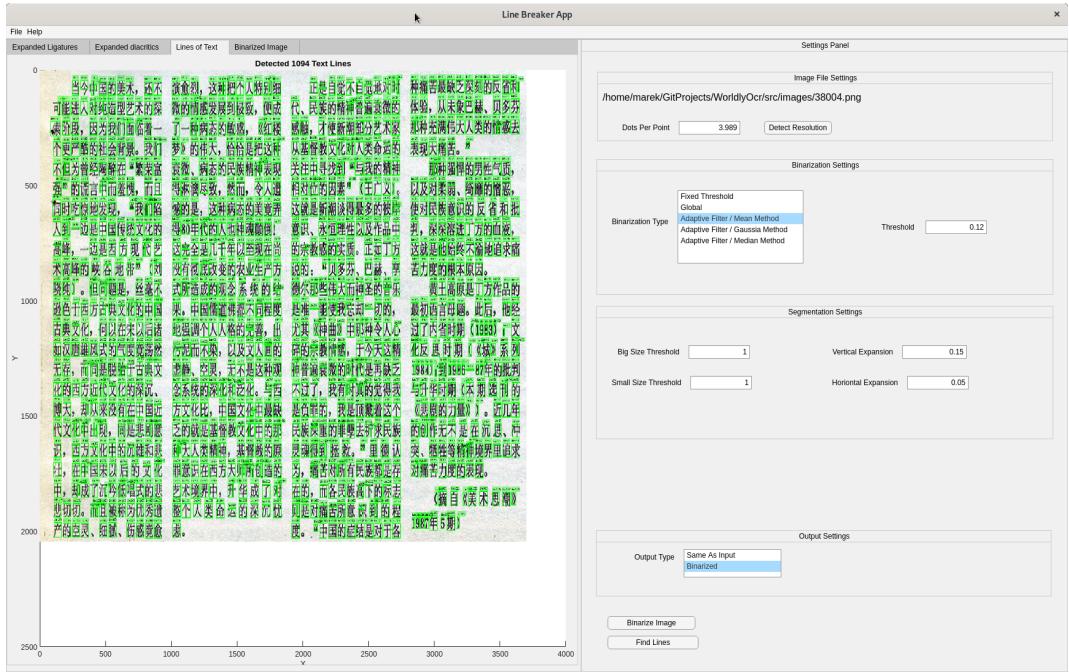
In the course of the project several GUI-based applications were constructed for various tasks, and it is expected that some of them will become a part of an integrated, GUI-based software package.

## 1.11 Other platforms

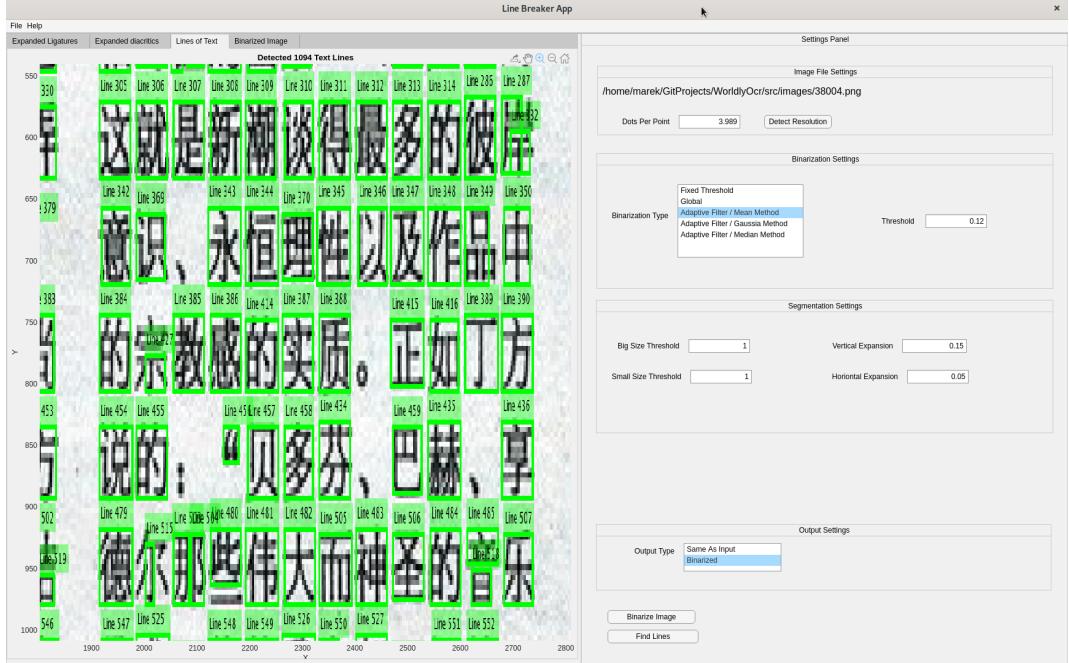
In the Data Science community there are many projects utilizing Python, and ML libraries such as PyTorch and TensorFlow. A part of their appeal is that they are Open Source, and are used to implement many of the newest research ideas in the field. However, this comes at a cost of lower stability, poorer documentation and a higher learning curve.

## 1.12 Collaboration with our project

The potential user of our prototype software will find that it is relatively easy to modify and add to the *Worldly OCR* software with only minimal knowledge of the underlying science. It is fair to say that any scientist who has taken a course in Linear Algebra in which MATLAB was used, is prepared to modify and adapt the code of *Worldly OCR* for their projects.



(a) Basic view



(b) Blown-up view

Figure 1: A GUI-based program for breaking up pages into lines or characters. The GUI offers access to underlying parameters which can be interactively adjusted to parse new content and reused.

## 2 Results

To date the results of the project are preparatory in nature to producing a full-fledged software system. They generally fall into the following categories:

- (1) Fundamental OCR-related research, including original algorithms and examination of existing algorithms, for various phases of processing.
- (2) Prototyping parts of the system in MATLAB, ranging from small “throw-away” scripts, larger libraries of code, to complete applications with a Graphical User Interface (GUI).
- (3) Examination of existing and creation of new training datasets in Pashto, Farsi and Chinese.

Generally each of the results discussed below contains parts which belong to all of these categories.

### 2.1 OCR on 1023 lines of text in Farsi with 97% accuracy

Farsi is a stepping stone towards processing Pashto, which is the next major target for our software. There is no significant fundamental difference between the two languages in regard to the writing system. However, there is a logistical difference: the existence of verified training data (“the gold standard”) for Farsi. As creating a comparable standard for Pashto would be costly in time and resources, our prototype software is trained on existing Farsi data, to be later on applied to Pashto, when suitable training data becomes available or is created.

We trained our OCR software to decode 1023 lines of Farsi text achieving **approximately 97% accuracy** with 2 hours of training on a laptop computer. The input data was produced by using MATLAB Unicode text rendering in a specific font: DejaVu Sans. This font has good support for Arabic scripts and is typically present on Linux systems, but can be downloaded from the DejaVu font project as a True Type font (.ttf) file [23].

The full results of our experiment have been presented in the form of a video currently posted on YouTube [25]. One example is shown in Figure 2. It should be noted that an average line of text has 60+ characters, and thus one character error per line is roughly equivalent to a 1.6% error rate.



Figure 2: The OCR result obtained with our software, compared to the true label and the image input. This example features 1 error (1 omitted character). The number of errors is measured automatically using *edit distance*, i.e., the minimal number of single-character deletions, insertions and substitutions to change one string into another.



Figure 3: Our OCR results on samples utilizing the Bromello font. Accuracy is 100% **including whitespace**. Labels obtained with our OCR are atop of OCR’ed images picturing yellow-on-blue text.

## 2.2 OCR on Latin cursive script Bromello

In our research we used a Latin cursive script font, Bromello, as a stepping stone to handling non-Latin scripts, besides being of interest as an ML research problem. One standard line of Bromello looks like this:

*The quick brown fox jumped over the lazy dog.*

Bromello is not the only Latin script font. We also experimented with a font called Lunafreya, which is slanted:

*The quick brown fox jumped over the lazy dog.*

At this time we do not have results for Lunafreya to report.

Figure 3 shows several Bromello samples subjected to our OCR software. Latin cursive scripts are not used in normal typesetting, but are used in specialty printing, such as decorative documents (e.g. greeting cards). Latin script exhibits some features of non-Latin scripts, but it does not present the full range of difficulties, because it was designed for easy implementation along traditional typesetting systems for Latin script.

Our software attains **100% accuracy** on a great majority of texts typeset utilizing Bromello. The study of Bromello and Lunafreya Latin fonts is hoped to help with developing models of typed and handwritten text which are required to convert documents such as the one in Figure 6a.

## 2.3 Cursive scripts

One major theme of our project is image-to-text conversion of cursive scripts. The term OCR is used but is not quite correct in the context of cursive scripts, as no character recognition in isolation is actually performed, but groups of characters, typically lines of text, need to be recognized. Nevertheless, for convenience we will use the abbreviation OCR for the family of algorithms and softwares under consideration.

Of particular interest are cursive scripts used throughout Middle East and Western Asia, such as Arabic, Farsi and Pashto. This paper describes building an actual implementation of the algorithms under discussion as part of a project sponsored by the National Endowment for Humanities (NEH). The software will be applied to a large dataset [4] consisting of approximately 2 million pages of documents in Pashto and Farsi (sometimes mixed in the same document). Altogether, these documents represent a substantial portion of the cultural heritage of Afghanistan. The documents are a product of long term collaboration between the University of Arizona and Kabul University (ACKU), including digital scanning of the documents. We will refer to this collection as ACKU dataset. The experience acquired by working with these large datasets will allow us to develop strategies to be applied to other languages and large-to-huge datasets.

In the current phase of the project our focus has been on preprocessing of typical texts found in the ACKU dataset and similar data. A major part of the preprocessing is page segmentation, i.e., locating lines of text and separating large structures (ligatures and words). Another aspect is correct attachment of diacritics, which are a significant part of scripts based on the Arabic writing systems. An example of segmentation performed by our software is found in Figure 4. Another example of segmentation is in Figure 5, where lines of text are identified very precisely, with diacritics and punctuation properly identified.

**حُطّي» و «أكرمت حُطّي» و «نظرت إلى حُطّي» ، قال الشاعر :**  
**(الرجز)**

**لَمَّا رأيْتُ أَشْرَهَا فِي حُطّي أَخْدَلْتُ مِنْهَا يُقْرُونَ شِنْطَهُ<sup>(٤٨)</sup>**

قال الفراء : وإن شئت جعلت الياء الفاء في باب التسمية . فقلت : « هذا حُطّي » و « مررت بـ حُطّي » و « أكرمت حُطّي ». قال : وإن شئت شئت الياء في باب التسمية . فقلت : « هذا حُطّي » و « أكرمت حُطّي » ، و « مررت بـ حُطّي ». قال : فإذا سميت رجالاً بـ « كلمن » لم تجرب لعجمته ، وعزّزت النون ، فإن قلّ تقدير فعلول من أبنية العرب أجيبي . فإذا سميت رجالاً بـ « سعفاص » لم تجرب لانه أحجمي .

قال الفراء : وقد يحكى عن زكريا الأحمر<sup>(٤٩)</sup> أنه قال : ثقفت تسمى السكباجية : السعفاصة ، والسعفاص جمع : سعفاصة . فإذا سميت رجالاً بـ « سعفاص » وأنت تبني هذا المعنى أجيبي . وإن نويت أن تسميه بالكلمة التي يتعلّمها الناس لم تجرّها ، لأن الكلمة مؤثثة . قال : فإذا سميت رجالاً بـ « قرشت » أجيبي لانه يتعلّم تعلّمات ضئيلات وضريلات . قال : ويجوز أن لا تجريه إذا جعلته مجهولاً .

**باب الحذف في « أبي جاد » والاعتلال له  
وذكر ما فيه من الاختلاف**

أعلم أن حروف المد واللين تحذف كثيراً لأن ما قبلها يدل عليها . فلما كانت « أبو جاد » وأخواتها إنما تُقْبِدُ بها تعليم كتاب الحروف في الوصول لم تحتاج فيها إلى تكرير . فتحذف الواو من « أبي جاد » لأنها ثابتة في « هواز ». وتحذف الألف الثانية من « أبي جاد » لأنها ثابتة في أواه . فإن قال : فهل أثبتو الواو في « أبي جاد » لأنها أول الحروف ، فاكتفوا بها من الواو التي في « هواز » ؟ قيل : حروف « أبي جاد » كثيرة ، وحروف « هواز » قليلة ، فكان الحذف من الكثير أولى لتعتدل الكلمات . وحدفوا الألف من « هواز » لأنها ثابتة في « أبي جاد » وجاءت « حُطّي » سالمة الياء ، لأنها ليس قبلها مثل صورتها ، وحدفوا الواو من « كلمن » لأنها في « هواز ». فإن قال : لم كتبوا « صعفاص » صادين ، وقد قلت : إنه ليس من مذهبهم الجمع

٧٠

(a) A sample page



Figure 4: Arabic script segmentation. Large structures are enclosed in bounding boxes. Suspected punctuation and diacritics are detected.



Figure 5: Determining lines of text and attachment of diacritics. Skewed and warped lines of text are detected by performing regression analysis on each line, computing 3 auxillary lines (top — blue, bottom — green and middle — red) which allow precisely determining the vertical position of characters in a line of text.

## 2.4 Traditional and Simplified Chinese

Chinese scripts are the second script class that we focus on. We investigated several solutions to various sub-problems. This includes blob outline matching via correlations, dynamic time warping, and broken character fixing. We have been investigating the use of convolutional neural networks (CNN) in the recognition of isolated characters. As a proof of concept, one of the datasets we are working with is handwritten simplified Chinese characters. Our convolutional neural networks investigate several input formats:

- (1) grayscale image;
- (2) binarized image;
- (3) transformed image data obtained by constructing *blob outlines* (Figure 9 and Figure 10);
- (4) transformed image data obtained by *skeletonization* (Figure 11);

Generally, all methods tried work very well with Chinese characters. We have not yet studied skeletonization extensively, so this method will not be discussed extensively, but preliminary results and literature search indicates that the method is useful and will be studied further[18, 14].

Blob outlines are especially useful for large, historical Chinese texts (e.g., Figure 16), as they can be used for **unsupervised learning**, i.e., grouping characters into **clusters** (groups) of identical characters, only differing by damage due to noise. It should be noted that for ancient documents the fonts are unavailable; therefore clustering of characters can be used to re-create the fonts for these characters. Outlines are



(a) Chinese Qur'an in Sini with Chinese translation



(b) Random rotated Latin script found on Google

Figure 6: Two types of text written neither horizontally nor vertically. Chinese Qur'an source: [https://en.wikipedia.org/wiki/Islamic\\_calligraphy](https://en.wikipedia.org/wiki/Islamic_calligraphy); this document breaks many rules of typical Arabic texts.

somewhat sensitive to character damage, and thus should be used in conjunction with other techniques for superior accuracy.

We have positive (although considered preliminary) results with CNN as the neural network when applied to grayscales and binarized images, showing accuracies of up to 91% with almost no preprocessing of the images, when the class of characters is limited to 100. We also conducted an experiment of training a CNN on a set of 200 traditional characters which were rendered in 56 fonts. When tested on 14 other fonts, a 97% recognition rate was found. The CNN-based method is one of the most powerful methods known, and will be available in our software.

We are likely to use the *committee approach* to Chinese, whereby several methods are used to perform OCR, and the final decision will be obtained by properly weighing the “votes” supplied by different methods (committee members). The committee approach is especially useful for situations where the best method depends on the type of document, and this is clearly the situation for the diverse body of Chinese documents targeted by our project.

## 2.5 Steps to developing OCR for the Bromello font

This procedure has led to the development of an OCR system for a specific Latin cursive script: Bromello [12]. With small changes, the procedure was applied to Farsi, and may be used as a template to expanding

the scope of our OCR system to new languages and scripts.

We started by downloading and installing on our Linux systems the Bromello True Type Font (.ttf) file. Then we generated a basic training dataset consisting of the following sequences:

- (1) Unigrams, i.e., single letters, digits and punctuation characters.
  - (2) Bigrams, i.e., all combinations of two characters. For Bromello, these sequences contain crucial information about how the characters connect.
  - (3) Trigrams with a blank space in the middle. These sequences contain information about the inter-word space when words are close to each other.
  - (4) Selected other trigrams. These were selected as a subset of those trigrams which were not properly decoded by the system trained on the above three types of training data.

This resulted in approximately 12,000 short sequences. The results included in this paper were produced by software trained for about 1 hour on a laptop computer.

Notably, we did not use dictionary words or any other linguistic information (as many systems do). Thus, the system is unaware of the concepts such as word, sentence and grammar. Nevertheless, the system decodes the great majority of English sentences with 100% accuracy.

## 2.6 Steps to developing OCR for Farsi and DejaVu Sans font

By design, the procedure is very similar to the one in section 2.5. Thus, we will describe the differences. The alphabet consisted of all characters encountered in test data:

• ۱۲۳۵۶۷۸۹ • پژو کگی • ۱۲۳۴۰۶۷۸۹ • سش صنعتی خودرو شجاعی • [ ]

- (1) The Farsi alphabet was logically divided into 3 groups

  - alphabetic (letters)
  - numerals (digits); two sets of digits were identified in Unicode:
    - ◊ Persian: • ۱۲۳۴۵۶۷۸۹ (Unicode range: 0x6F0–0x6F9);
    - ◊ Eastern: • ۱۲۳۴۰۷۸۹ (Unicode range: 0x660–0x669)

as these are two different numeral systems encountered in test data;

  - diacritics: cow ↗ -

(2) We included all unigrams in the training data, except for diacritics.

(3) We included bigrams, excluding invalid ones (e.g., two diacritics).

(4) We pre-trained the system with the training data above.

(5) We included 1023 lines of Farsi from the OCR\_GS\_Data dataset.

(6) We continued training on the entire dataset.

We ran the training process for varying periods of time from 2 to 10 hours with various changes to the details. The 97% accuracy on training data was achieved with no more than 2 hours of training. Pre-training on the basic unigram/bigram dataset significantly shortened the training time.

The important factor in training on Farsi is the presence of samples that exhibit all frequent medial forms, which requires placing characters between two others, i.e. forming a trigram. As the number of trigrams is prohibitively expensive (hundreds of thousands are possible), the only medial forms that were seen by the system came from the OCR GS Data dataset.

In automatic validation we encountered an interesting detail: false negatives (errors that are not really errors), due to the fact that **identical character glyphs are represented by more than one Unicode**. For instance, the two numeral systems (see above) overlap in terms of the shape of the digits but two different Unicodes are assigned to them. It appears that even the human experts assigned the one of the two possible Unicode codes without a clear reason.

### 3 Our methods and algorithmic basis

As already mentioned, our approach is that of Machine Learning. Both for cursive scripts and for the logographic script of Traditional Chinese we use an Artificial Neural Network (ANN) consisting of many layers of artificial neurons (perceptrons). Generally, an ANN consisting of more than 2 layers is considered a *deep neural network* and the process of its training is known as Deep Learning (DL). For cursive scripts we use Recurrent Neural Networks (RNN) which look at the input as temporal data (time series). The timeline is created by scanning lines of text left-to-right (Latin scripts) or right-to-left (Arabic, Pashto and Farsi). In principle, the same approach can be applied to Chinese, and our results indicate that the accuracy is good. However, the main thrust of our effort on Chinese was based on non-recurrent RNN.

#### 3.1 Cursive scripts and the video processing pipeline

Cursive scripts are presented to machine learning software as sequences of *frames* which are several-pixel wide windows into the data. Typically, this is an image representing a line of text, obtained by preprocessing (cf. Figure 5). Thus, the sequence of frames is equivalent to a video sequence in which we produce a panoramic view of a line of text to be converted to Unicode.

The software needs to translate a long sequence of frames to a relatively short sequence of characters. For example, in Figure 12 the original image is 1416-by-93 pixels, the MATLAB-generated image is 750-by-53 pixels, and the Farsi Unicode is 59 characters long. The mapping of 750 pixel columns to 59 characters is accomplished using a machine learning algorithm known as Connectionist Temporal Classification (CTC) described by A. Graves in his dissertation [8] and has been subsequently applied in several text-to-image conversion programs, e.g., *Kraken* and *Tesseract* [15, 32]. A careful implementation of CTC in MATLAB has been important in our approach as well. In section 3.6 we provide further details on CTC.

While the overall strategy of DL is dominant in OCR of cursive scripts, the particular architectures differ in details. Figure 7 displays our architecture, as depicted by a MATLAB tool. The reader may note features typical of a video processing network. It is worth noting that:

- (1) The workflow implemented by the network is that of sequence-to-sequence mapping (e.g., as opposed to image classification).
- (2) There is an convolutional layer portion of the network, enclosed by the sequence folding/unfolding layer.

This architecture was chosen because it lends itself easily to modification and experimentation, and is relatively easy to implement in MATLAB. As OCR is performed on images of scanned pages, not on video, there are two preprocessing elements which are applied before submitting input to the DL network:

- (1) Images are segmented into lines of text. Several line-splitting algorithms have been produced by our project, and all of them have merits for specific types of content.
- (2) Lines of text are converted to video sequences using the sliding window approach, where a window of, say, 7 pixel columns is moved along the line of text, with a step of 1 pixel.

Thus, the sample video for a 750-by-53 pixel input of Figure 12 is converted to the video of 750 frames of 53-by-7 video frames. All frames are binary images, as the original image is binarized before processing, which is a customary step in OCR.

#### 3.2 Blob outline analysis

In the current section we present a method we have developed for OCR on a wide range of documents, with a substantial original research component. Among others, the method solves the following problems:

- (1) Extremely accurate classification of characters; e.g., near 100% accuracy on Latin and Chinese characters of high and medium quality.
- (2) OCR on rotated and scaled text (cf. Figure 6b).

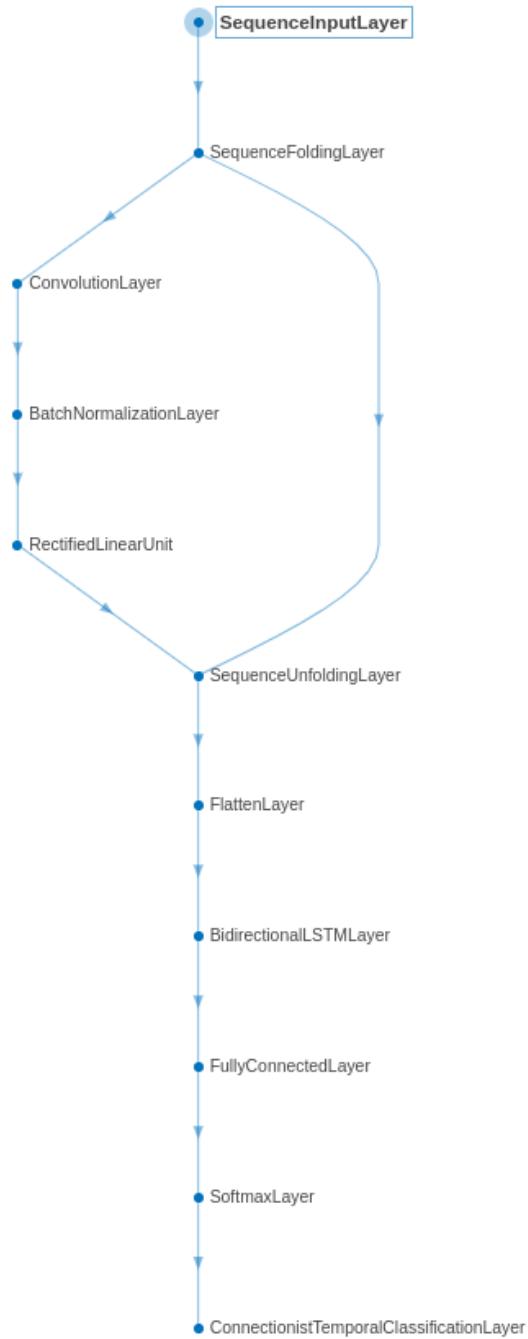


Figure 7: The layer graph of the DL network used in decoding cursive scripts.

- (3) Mapping one font to another, even if the fonts are quite distinct.
- (4) Accurate unsupervised classification of characters in an unknown font, e.g., grouping all 16,000 characters in an ancient Chinese book utilizing fonts non-existent in modern typography.

The University's decision to join the University Athletic Association is, at first glance, an exciting venture. It seems more appropriate for the U of C to compete athletically against universities they compete with intellectually. More meaningful rivalries can be built around schools with which the student body is already familiar. And if the concept of a rival athletic school catches on, the quality of student life on campus will be improved by this new diversion. More high school students will hear of the University of Chicago. This leads to more and better applicants to the college, and a larger class size. Alumni Associations will be able to show off a new crop of bright, promising student-athletes to alumni hungry for contact with their old college. This leads to more donations to the school. And with more students paying tuition and more donations...

The University's decision to join the University Athletic Association is, at first glance, an exciting venture. It seems more appropriate for the U of C to compete athletically against universities they compete with intellectually. More meaningful rivalries can be built around schools with which the student body is already familiar. And if the concept of a rival athletic school catches on, the quality of student life on campus will be improved by this new diversion. More high school students will hear of the University of Chicago. This leads to more and better applicants to the college, and a larger class size. Alumni Associations will be able to show off a new crop of bright, promising student-athletes to alumni hungry for contact with their old college. This leads to more donations to the school. And with more students paying tuition and more donations...

(a) A campus newspaper paragraph

(b) Outlines of all blobs

Figure 8: Blob outlines found for every character in an English newspaper paragraph.

### 3.3 The binary color model

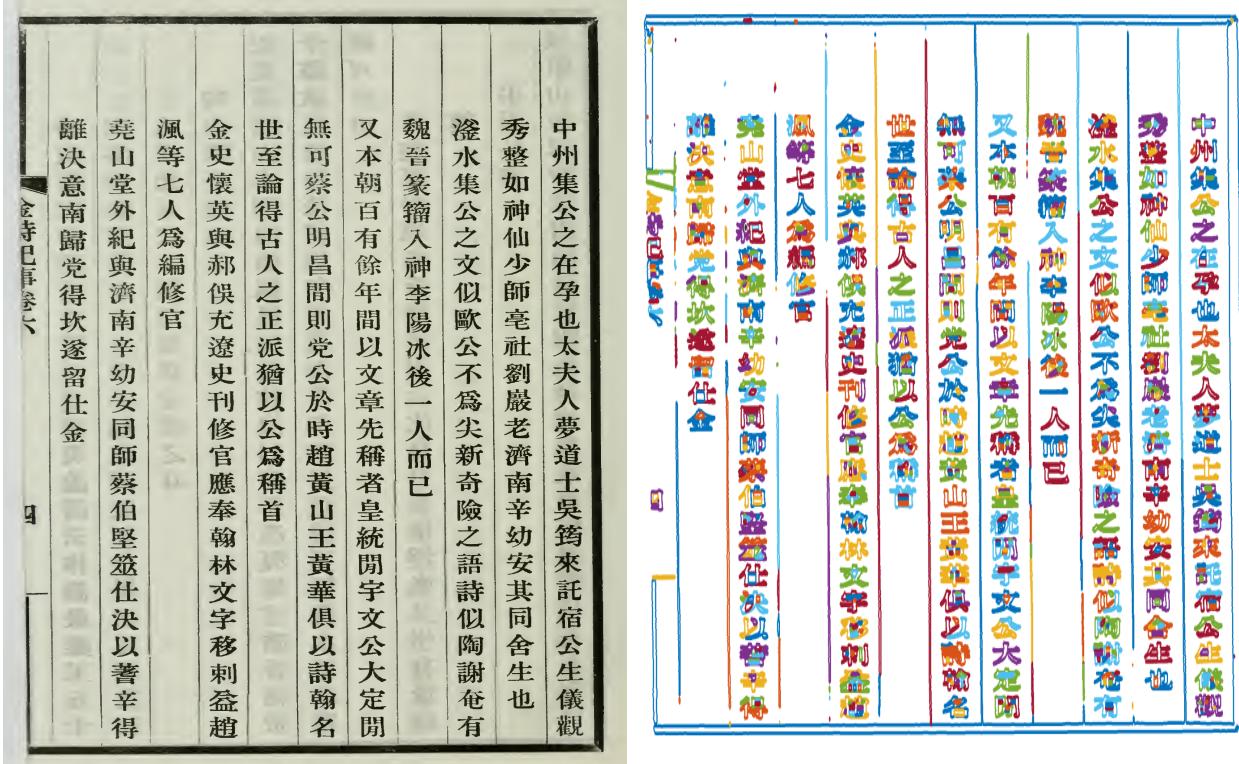
Scanned images for OCR are either grayscale or color. However, conceptually print is black and white. Therefore, the color model of image data for OCR uses only these two colors. Furthermore, traditionally background is considered black (zero pixel) and writing is considered white, or, more precisely saturated with maximum brightness. Digital scanners support this model, by lighting pages of documents being scanned with extremely strong light, and therefore the background is usually close to fully saturated, and characters are close to black. In particular, the images produced by a digital scanner are very different from images normally produced by a digital camera in a cell phone, which is tasked with capturing all intermediate brightness levels accurately.

The conversion of color or grayscale input to binary color is called binarization and is typically the first step in most OCR programs. After binarization we normally work with the negative, i.e., we place white characters on black background (cf. Figure 14). To avoid ambiguity the term *foreground color* will always refer to the color of the characters.

The software at this phase of processing has no idea of characters or other semantic constructs associated with text. It only sees contiguous areas of foreground referred to as ‘blobs’. Most Latin characters consist of a single blob, with exceptions such as ‘i’, but Chinese characters commonly consist of several blobs. For instance, in Figure 14 we can see that the characters consist of (counting from the left) 3, 2 and 2 blobs, respectively. It should be noted that (semantically) the same character may be represented by a different number of blobs, as a result of imperfections during the printing process. In Figure 10 we have an example from a Chinese book in which a character is either “whole” (consists of a single blob) or “broken” (consists of two blobs).

### 3.4 Blobs and their outlines

After conversion to black-and-white, a representation of a character image may be extracted in the form of the outlines of the foreground regions (the blobs). These outlines consist of one or more disconnected cyclical paths; for example, the Roman letter ‘f’ has a single outline cycle, whereas ‘e’ has two (one inside the other). A larger sample of Latin character outlines is seen in Figure 8. The approach also works well on Chinese characters, as seen in Figure 9.



(a) The original page

(b) Outlines of all blobs

Figure 9: Character outlines found for every character in a Chinese book page.

We extract these outlines as oriented paths, so that the outside boundary cycle can be distinguished from internal boundary cycles. We developed two fast methods of extracting those outlines:

- (1) a graph-based approach, which identifies boundary points and then searches for loops that can be traversed;
- (2) a potentially faster line-sweep algorithm that scans across the image and simultaneously detects boundary points and joins them into loops.

No information is lost in converting images to outlines—the image could be reconstructed from the outlines. Nonetheless, the volume of data is substantially reduced. Representing a character as a set of outlines is a form of *dimension reduction*, replacing the two-dimensional image by a set of one-dimensional paths. For typical pages of Latin or Chinese text, the volume of data is reduced by a factor of 50.

After standardizing for position and character size, the geometric distance between corresponding points on a pair of cycles serves as a useful metric for comparing the cycles extracted from separate character images, allowing character matching and grouping.

A technique known as dynamic time warping (DTW) allows for matching these “corresponding points.” In DTW, we consider each cycle as a path traversed over time, and allow the traversing point on one cycle to “wait” until the traversing point on the other cycle is as near as possible before continuing to traverse. This reduces errors due to variation in starting position and minor noise or distortion of edges. Furthermore, outline analysis may be used to match points on a pair of cycles to points on a single cycle, allowing recognition of similarity between two characters when one has been damaged (either by breaking one boundary cycle into two, or merging two into one). Figure 10 shows an example of this process, where a character appears with a stroke either connected to the rest of the character or disconnected. The similarity of the outlines can be detected despite the different connectivity.

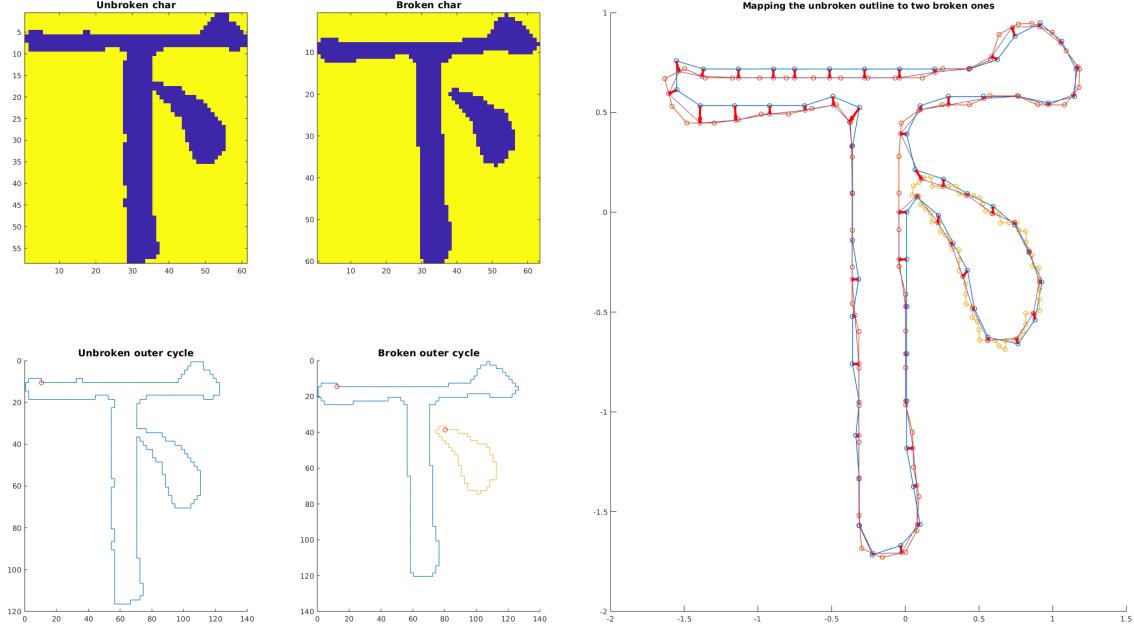


Figure 10: Matching outlines detects similarity between unbroken and broken versions of a Chinese character.

In addition to distance-based matching and clustering, the extracted outlines can be used as features for recognition by deep learning algorithms such as the convolutional neural networks referred to in the previous section.

### 3.5 Skeletonization

In the course of our research we researched skeletonization. This technique converts characters to one-dimensional objects. Like blob outlines (cf. section 3.2), it achieves significant data reduction. Examples for Latin, Chinese and Arabic scripts are found in Figure 11. The essence of the method can be described easily: characters occupying an area of an image are thinned out to be one pixel wide, yet preserving the shape of the original character. Our preliminary research of this method indicates that replacing characters with their skeletons does not lose the essential information needed to convert them to Unicode. The advantage of this method is that it opens new OCR approaches by bringing in a rich supply of methods from graph theory (a branch of mathematics). Skeletons are known to be useful in OCR. For example, Ning Lin [18] reported an implementation of a skeleton-based OCR system for Latin characters in 1991. Khorsheed [14] used skeletonization on his work on Arabic.

### 3.6 Connectionist Temporal Classification (CTC)

CTC applied along with RNN is considered the main advance in OCR of cursive scripts, including Arabic and Farsi. CTC has its origins in *speech recognition*. The original problem that it solves is the fact that speakers time speech differently. Even the same speaker sometimes speaks fast or slowly, or slurs certain vowels, etc. Therefore mapping spoken language to written text involves deciding the duration of various characters (or, more precisely, *phonemes*). Therefore, the software needs to have a component tantamount to a *variable speed clock* which will match the speed of the speaker with real time. CTC provides such a clock, thus automatically segmenting speech into its constituent elements.

It turns out that CTC can be applied to cursive scripts, to divide a continuous stream of characters, connected according to complex rules (or event without any discernible rules, as in handwritten text),

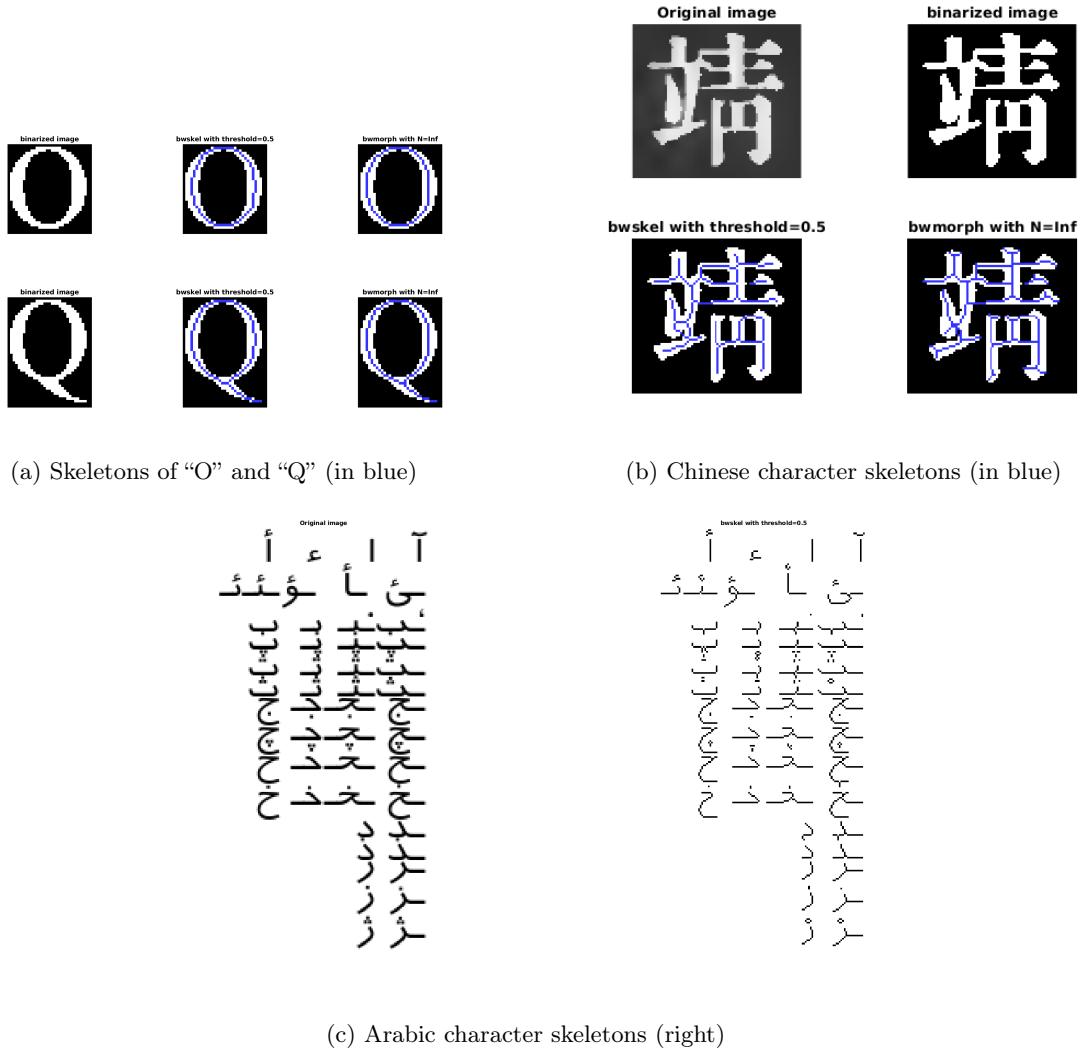


Figure 11: Character skeletons obtained with two distinct MATLAB algorithms: 'bwske' and 'bwmorph'.

into constituent characters. Hence, CTC solves one of the principal difficulties in using a neural network (especially, a recurrent neural network, or RNN) in OCR: the problem of **segmentation**.

The details of operation of CTC are beyond the scope of this paper, but excellent descriptions can be found in blogs, and in Alex Graves's Ph.D. dissertation [8]. Full understanding involves knowledge of mathematics, and especially probability theory, at the graduate level. However, to convey some more detailed understanding of CTC we offer the following explanation: let us imagine reading a line of text, viewing it through a narrow, vertical slit in a piece of paper. We slide the paper from left to right with uniform speed (or from right to left for Arabic) and try to read and understand the text using this information. Our brain plays the role of RNN in this case. Our memory allows us to remember a little bit of past information (accounting for the word "recurrent" in RNN). Our neural network is trained to assign a probability of seeing a specific character (or phoneme for speech) at any particular moment in time. CTC works in tandem with the neural network by computing *the most probable timeline* for seeing various characters, thus providing said variable speed clock.

It should be mentioned that in recent years the preferred neural network to work with CTC is an RNN but in the past a simpler model called a Hidden Markov Model (HMM) was used. RNN was demonstrated

to be superior.

CTC sidesteps the necessity for **manual segmentation** which was sometimes applied in the past with great effort and time expense. The segmentation problem was split between the neural network and CTC:

- (1) the neural network is focused on estimating the probability of each character as a function of time;
- (2) CTC is focused on adjusting the clock speed to produce the most probable sequence of characters.

We implemented CTC in MATLAB. Interestingly, no serious attempt at MATLAB implementation of CTC is known to us, but we have found several preliminary attempts, not good enough to be used in our system. One of the problems CTC encounters is a version of what is known as the **vanishing gradient problem** in Recurrent Neural Network Theory and first identified by Hochreiter [10]. The CTC version of this problem has to do with the necessity to **multiply thousands of extremely small probabilities** by each other. The problem is that we quickly run out of digits of precision, when doing so, which results in *underflow*, i.e., the computer rounds very small numbers to 0, although they are not 0. Unfortunately, we need to calculate with such small numbers.

We believe that our MATLAB system addresses the problem of vanishing gradients/underflow best of all CTC implementations known to us. It should be noted that making this claim was not an objective, but it was dictated by the demands of OCR on lines of Farsi. For example, the bottom image in Figure 12 has dimensions 750-by-53, which results in  $750 \times 53 = 43,500$  pixels, each pixel either black or white. Thus, this particular image has probability of occurring at random equivalent to obtaining **all heads** in 43,500 coin tosses! The probability of this is so tiny that no computer can natively store it with any precision (the reader is encouraged to calculate  $0.5^{43,500}$  with her favorite calculator). In principle, the solution to the problem is simple: substitute probabilities with their logarithms. The solution is hinted at by many authors, including Graves, but our solution differs in significant details. It is **guaranteed** not to produce underflow for even the longest lines of text, in practice.

عرا ف عارف این را گویند آورده‌اند که عالم به از صد زاهد و عالم به از صد زاهد  
عرا ف عارف این را گویند آورده‌اند که عالم به از صد زاهد و عالم به از صد زاهد

Figure 12: A line of Farsi from the OCR\_GS\_Data dataset. The top line is the original image. The bottom is an image rendered from the Unicode label of the image with MATLAB.

## 4 A brief overview of existing software and its limitations

There are several software systems, both open source and commercial, which potentially can perform text-to-image conversion on Farsi and Pashto [15, 32, 3, 29]. However, we have found that they are inadequate. Mainly, the accuracy of these systems is not adequate. As a rule of thumb, at least 90% of the characters of a document need to be recognized correctly in order for the OCR result to be useful, e.g., to be incorporated in high-quality library collections. While it has been reported that on some documents this target number is met, the overall fraction of the ACKU dataset which would meet the 90% rule would be minuscule. It is known that the success of OCR software on a particular document depends greatly on the quality of the document and other content characteristics:

- (1) The image resolution.
- (2) The quality of the underlying media, e.g., paper warping, yellowing, chipping of paint, etc., generally called “noise”.
- (3) Layout of the document. E.g., newsprint presents extra difficulty, due to its tabular nature, varying fonts and their sizes, and mixing of text and images.

Therefore, software author claims of, say, 99% rate of character recognition are highly misleading without specifying exactly the content on which the assessment was made. Despite the claim, a high quality text may produce accuracy of 85%. On the other hand, we will demonstrate that our software achieves 99% or 100% character recognition rate on selected texts.

We would like to mention the project Open Islamicate Texts Initiative (OpenITI) utilizing the program *Kraken* [15], which is similar in scope to our project. The project produced high quality reference data [22], and a white paper accurately summarizing the software performance on carefully curated test data [24]. In our current project we utilized the OpenITI dataset to test our own software. What is different about our project is the emphasis on research, including development of new algorithms and workflows, which will substantially expand the class of documents for which the 90% accuracy threshold is met.

## 5 Evaluation of other OCR software

We start with a disclaimer: a fair evaluation of complex software systems that OCR systems are is a nearly impossible task. We evaluated open source and commercial systems. Some systems were not available to us due to high cost. Open source systems are too complex to be completely understood. Moreover, software this complex is controlled by a myriad of parameters which affect its operation in often dramatic ways. Thus, **the accuracy can be greatly affected by the way we prepare data.** It would appear that a fair test would be to present the same document to two software systems, and see which produces more accurate results. However, this offers an unfair advantage to commercial systems which do not necessarily have better OCR algorithms, but devoted much more effort to coverage of different types of content.

Thus, our results are typical of what one would obtain from the respective software system with minimum intervention and tweaking of the parameters to produce better results.

In our studies, multiple commercial and open-source OCR systems and/or online services have been evaluated for their accuracy rates on three languages with four writing scripts (Simplified Chinese, Traditional Chinese, Persian, and Pashto) from 2017 to 2020 for several purposes. These purposes include:

- (1) to measure the accuracy of these systems, specifically for these languages;
- (2) to gain an understanding of their architecture and their underlying models;
- (3) to benchmark their performance;
- (4) to assess their trainability, using random testing data.

The primary focus of these tests is on character and word accuracy rates. Other factors such as pricing and running time are not important for the purpose of our research at this stage.

### 5.1 Issues with reported OCR accuracy

A recent evaluation by Tafti et.al. of multiple OCR systems concluded that Google Docs and ABBYY performed better than others [30].

Readers should be aware that there are underlying issues when evaluating these systems for their accuracy rate. Besides common factors such as quality of document images and background noise, there are other factors that affect the OCR quality greatly. Often we see reports showing very high accuracy rates for certain documents. We have observed another set of documents come with inconsistent OCR quality, given the difference in terms of retrospective publication dates and complex layout. As a result, the accuracy report might be subjective to a specific set of documents and languages. Our experience shows that there are several critical factors when evaluating accuracy rates:

**Language:** Typical OCR systems provide over 100+ languages support. However, one must understand that languages are complex subjects and there exists some fundamental differences in languages, from structure to writing order. For example,

- Retrospective Traditional Chinese is written vertically, in columns, from top-to-bottom, columns ordered right-to-left;
- Current Traditional Chinese is predominantly written horizontally, in rows, characters in each row ordered from left-to-right, and rows ordered from top-to-bottom.
- Sometimes vertical Traditional Chinese writing is still used in modern books.
- Arabic, Persian/Farsi, Pashto, and Urdu are written horizontally, in rows, with characters in each row order from right-to-left and rows ordered from top-to-bottom.

**Cursive and non-cursive:** Arabic alphabet and adaptations of the Arabic alphabet such as Persian and Pashto are written from right-to-left in a cursive style, and letters vary in shape depending on their position within a word. Letters can have up to 4 distinct forms corresponding to an initial, medial, final, or isolated position.

**Layout:** Documents with simple and straightforward layout tend to allow OCR systems to produce very high accuracy, while newspapers with complicated layout mixing figures in multiple irregular columns typically bring low-quality (and sometimes unusable) results.

**Fonts:** Documents with unusual fonts typically will receive bad OCR results. It is hopeful that a new generation of OCR with CNN or LSTM will produce better OCR results. Our effort is to evaluate OCR systems specific to languages. We have found that certain OCR systems work better for certain languages and certain OCR systems work better related to layout.

We favor open source systems over commercial systems, because these systems can be ported to multiple devices and can be trained for various applications. As an example, we have successfully conducted training of *Tesseract*, and we build simple applications based on the *Tesseract* API (Application Programmer’s Interface). Training *Kraken* is also straightforward, and the source code base is small and well-written, in Python. It is easy to understand and modify. The successes of open source systems are readily tracked by the community contributions to these systems by non-developers, in the form of **trained models** and **training data**, which extend the coverage of various languages. In addition, these systems come with pre-trained models for many languages and are shipped with training data.

Our testing datasets are available in the Github public repository.

## 5.2 A list of tested OCR systems

### 5.2.1 Tesseract

*Tesseract* is probably the most well known open-source OCR software. It was originally developed at HP Laboratories Bristol and HP at Greeley Colorado from 1985 to 1994. In 2005, *Tesseract* was open sourced by HP, and it has been sponsored by Google since 2006. The leading developer has been Ray Smith, starting from the inception at HP Labs in 1987, until today.

One of the most highly cited papers related to *Tesseract* was written by Ray Smith [28]. However, readers should be aware this paper was published in 2007, before RNNs and specifically LSTM, gained entrance into the OCR arena. Therefore, the paper does not cover the LSTM implementation in version 4.0. We have tested multiple versions of this system, including:

**Version 3.0:** First version 3.0 released in July 2015. The last patch release was 3.05.02, and was released on June 19, 2018. It added more language support than the previous version, including language models for traditional Chinese (chi\_tra and chi\_tra\_vert), Persian and Farsi (fas) and Pashto (pus).

**Version 4.00.00 alpha:** Released in Oct 2018. This was the first version implementing LSTM, and it is the same RNN as is used in *Kraken*.

**Version 4.1.1:** This version was released in Dec 2019. Version 4 adds an LSTM machine learning OCR engine. We have tested this in the official trained data version and the version with our own trained data. However, the result was still not satisfactory as compared to the leading systems.

### 5.2.2 Google Cloud and Google Drive

Google Cloud and Google Drive platforms offer OCR services. The documentation is available at <https://cloud.google.com/functions/docs/tutorials/ocr>. Given that Google has been supporting *Tesseract* since 2005, and *Tesseract* lead developer Ray Smith has been working at Google and Google Deepmind since 2005, it is reasonable to believe that Google uses *Tesseract*, but we cannot verify this. Walker compared Google Cloud and *Tesseract* in 2008, and showed that Google performed better than *Tesseract* in Arabic, English, Hindi, Japanese and Russian [35].

### 5.2.3 ABBYY

ABBYY has been in the OCR business since 1989 specializing in OCR technology. Its products have been licensed to many scanning and document solutions companies such as Fujitsu, plustek and Panasonic. Many universities have licensed its products.

- Finereader 11 (windows) and 12 (Mac).
- Abbyy.cloud: ABBYY's cloud service. It is straightforward to set up.

### 5.2.4 Convertio

An online service is provided by Softo Ltd. It has a 4.7/5 high overall conversion quality rating.

### 5.2.5 NovoVerus

The software provider is NovoDynamics; NovoVerus Professional is \$6,500 USD plus an annual \$1,300 USD license.

### 5.2.6 Sakhr

On its website, Sakhr states that it is a pioneer and market leader in Arabic language technology and solutions with 28+ years of research and development. It claims that its OCR technology (<http://www.sakhr.com/index.php/en/solutions/ocr>) was ranked #1 by U.S. government evaluators, but we cannot find any evidence to back this claim. With email exchanges with its sales representative, the company claimed to have up to 99% accuracy depending on the image quality (300 DPI) for Persian/Farsi and Pashto if their fonts are Arial or Simplified Arabic. Unfortunately, the company required us to pay \$1300 upfront without giving us a chance to evaluate their product.

### 5.2.7 Kraken

*Kraken* [15] is an OCR system written in Python. It features a small code base of approximately 8,000 lines of Python code<sup>3</sup>. However, the small line count may be misleading, as *Kraken* relies upon a vast code base available to a Python developer in a myriad of Python libraries. Some of the most critical libraries include *clstm* and *pyrnn* for RNNs, a massive ML library *torch*, a scientific computing and math library *scipy* which is meant to provide functionality similar to MATLAB. *Kraken* is currently focused on cursive scripts (mainly Arabic) and does not provide a model for Chinese.

## 5.3 Testing on Traditional and Simplified Chinese

Simplified Chinese characters 简体字 are standardized Chinese characters for official use in mainland China, Singapore and Malaysia. Professor Qian XuanTong, a linguist, proposed to simplify Chinese characters in 1920. With growing interests, the Republic of China Department of Education in August 1935 released the first table of simplified Chinese Characters containing a total of 324 characters, which have been used in the society for a long time. This act was retracted in February 1936 due to strong opinions from some government officials. In 1952, the government of People's Republic of China (mainland China) started to implement Simplified Chinese characters, and by 1964 the Table of General Standard Chinese Characters was released.

Traditional Chinese characters have over 3,000 years of history. They are still officially used in Hong Kong, Macau, and the Republic of China (Taiwan). As one of the major characters in the world, it has influences on other character sets such as Korean Hanja and Japanese Kanji. It is estimated that over 2,000 Traditional Chinese characters are still used in Kanji. Traditional Chinese Characters and simplified Chinese characters are one of the two standard character sets of the current Chinese written language system.

---

<sup>3</sup>An automated count of kraken, version 2.0.8, yields 7,091 lines of Python code.

In a broad sense, simplified Chinese characters are simplified versions of traditional Chinese characters in terms of “structure”, some of which have existed for thousands of years along with their regular (more complicated) forms. Simplified characters were created by reducing the number of strokes.



(a) Simplified Chinese Newspaper



(b) Simplified Chinese Book

Figure 13: Chinese Newspaper and Simplified Chinese Book

## 6 The Tests

### Simplified Chinese

#### Tesseract 3.0

- This version achieved 90%+ accuracy rate if the paper was simply a text layout without any images, columns or variation in background intensity.
- Fig. 13a and Fig. 13b: we recorded 30%-60% accuracy rates depending on the degree of complexity of the layout or background (Tested January 2020).

### ABBYY Fine reader 11 (Windows) and 12 (Mac)

- Fig. 13a and Fig. 13b: ABBYY generated accurate page segmentation as well as a higher accuracy rate of 86%+ (Tested May 2019).

# 進幾謂室齊學林庭嬌禮椒

Figure 14: : Eleven Traditional Chinese Samples



Figure 15: : Three Traditional Chinese Samples

## Adobe Acrobat Pro DC

- Fig. 13a: Page segmentation was not 100% correct. Character accuracy rate was 83% (Tested March 2020).
- Fig. 13b: Page segmentation was in order and the rate of character accuracy was 84%. (Tested March 2020)

### 6.1 Traditional Chinese

#### 6.1.1 Tesseract

- Version 4.00.00alpha: Fig. 14: We fed 11 randomly selected characters to the following OCR systems. Accuracy rates were very good. Tesseract and Convertio achieved 91% accuracy rate, while O2CR achieved 82% ( Tesseract the 4th character, O2CR the 9th and 10th character, Convertio the 9th character) (Tested May 2019)
- Version 4.11: Fig. 15: We fed 100 random characters (selected from our GitHub repository, see Fig. 16 for samples) and recorded 60% accuracy rate (version 4.11) vs. 36% (version 3.0) (note: version 4.11 with pre-trained data). After training using our 100 pic dataset, the result improved, but not as much as we wanted. (Tested Feb 2020)  
There might be two reasons for this result.
  - (1) A larger training dataset may be necessary.
  - (2) Characters might need better quality. We will run more tests for this version

#### 6.1.2 Google Drive (Convert PDF and photo files to text)

- Fig. 16: The result was good. It was very time consuming compared to a local system. We have to wait 30 minutes to get one page of PDF to be converted. (Tested March 2020)
- Fig. 17: No result was returned after a four hour wait time for the page to open in Google Doc. (Tested March 2020)

#### 6.1.3 ABBYY

FineReader 11 (Windows) and 12 (Mac):

- Fig 16: The result was very disappointing. Page segmentation was wrong. (Tested May 2019)
- Fig 17: The result was disappointing. (Test May 2019)

給移助災區方異愈多愈妙浙江旣經稟請則江南士子亦必聞風而起請以折價撥充賑務而  
豈知若此二百文者實三倍而不止前年以之欺士子而今歲以之欺災民推士子好善之心彼  
司供給者留此倍半之盈餘得無清夜自思有惄焉不安者耶吾故願兩省大吏旣允士子之請  
尤必嚴飭供給各官照例定銀數實提而足解也倘以余爲多言彼人聞而深惡之則以災民之  
故亦不遑辭謗矣

勸戒纏足

抱拙子

夫纏足之俗各國皆無惟中國獨有然亦非舉國皆然惟漢人大半有之推其原由歷朝史冊並  
無言及僅見於後唐李後主愛妃窅娘善歌舞得寵幸後主乃作金蓮花命窅娘以白綿纏足作  
新月狀歌舞其上由是作俑而後人相沿成風愈久愈熾牢不可破想其時窅娘始纏之足如現  
在同邑鄉間婦女式大而曲故能舞於金蓮中若今時城市女人式尖而小詎能跳舞哉但後主  
所爲大非正道是故其國不久寢衰爲晉所滅可見纏足乃傾家敗國之兆也無如俗人習焉不  
察以纏足爲美觀以愈小爲艷羨由是苦其足而不辭而我信主之人見是則遷知非則改豈可  
效此治容之惡俗而干正道者哉或謂纏足之事始於紂王愛妃妲己他乃妖狐化身其足有毛  
故纏帛以飾之欲紂王觀其嬌嬈體態庶可蠱惑寵然此乃耳食相傳經史並無此說也縱使  
果由妲己之倡益明爲惡俗矣夫妲己乃敗國之婦依野史所載又是獸類吾人爲萬物之靈可  
效彼獸類所行乎然世人愚昧執迷難曉我教會有受真理之光照射名稱正教斷不可從此惡俗  
也且人愛子女之心稟自天性由生育以至長成就不盡心繫懷拊蓄顧復願其強健爽俐或有  
偶染微疾則急爲問藥調治如其身患瘡瘍則尋方敷施不忍坐視其疾痛之苦如孔子云父母

Figure 16: A Traditional Chinese Monograph

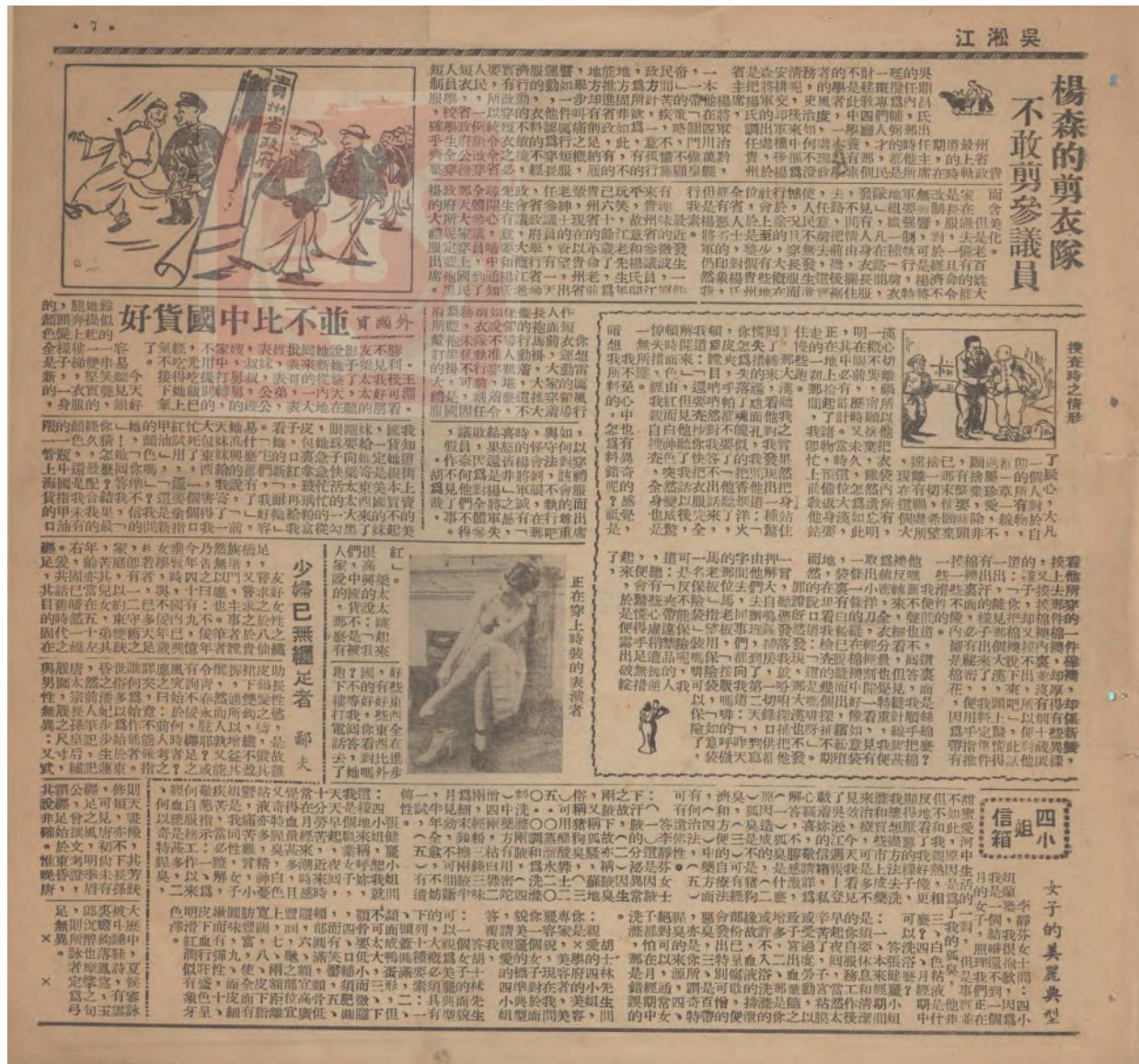


Figure 17: A Traditional Chinese Newspaper. This sample features a complex layout for which no software succeeded at producing good OCR results.

#### 6.1.4 Abbyy.cloud

- Fig 3: It produced a high accuracy rate of 91%. (Tested March 2020)
- Fig. 16: High accuracy rate of 90% (Tested April 2020). It is slightly better than Adobe Acrobat Pro DC (see below), but produced different errors including punctuation. Please note that old Traditional Chinese materials typically does not have punctuation.
- Fig. 17: No output was produced and an incorrect error message was issued. (note: The website returned message “was not processed: the recognized document contains errors”). (Tested March 2020)

#### 6.1.5 Adobe Acrobat Pro DC

- Fig. 16: We have the same PDF file digitized from the original monograph in color, and generated three file formats: A PNG file (exported from Acrobat Pro DC from page 1 of the PDF with 600 DPI in color), A TIFF file (exported from Acrobat Pro DC from page 1 of the PDF with 600 DPI in color) and a PDF file (screenshot of page 1 of the original PDF with estimated 88 DPI from a 49 inch 4K Monitor). We received different results with the same software. The PDF generated a good accuracy rate of 83%, while Acrobat Pro DC displayed “Acrobat could not perform Text Recognition on this page because: Unknown error” for both the PNG file and the TIFF file generated. We reduced both PNG and TIFF images to its 33% and re-ran OCR. We received different OCR results. The lower resolution of screenshot had slightly better results (Tested March 2020) and both PNG and TIFF images had the same OCR outputs.
- Fig. 17: Output was not recognizable and page segmentation was faulty. (Tested March 2020)

#### 6.1.6 Convertio

Online service (<https://convertio.co/ocr/>)

- Fig. 16: We uploaded two file formats. A PNG file (page 1) and a PDF file (page 1) from the same PDF file. It was odd that the service produced different page segmentation and different accuracy results. The OCR result from the PDF file recorded 90% accuracy rate, while the OCR result from the PNG file missed 40% of characters (i.e. accuracy dropped to 50%). For both OCR results, the service returned acceptable page segmentations, but they were different. The online service time to get the file uploaded and converted to OCR text was about 5 minutes. (Tested April 2020)
- Fig. 17: It took us 10 minutes to upload and analyze the PDF of size 303 kb. It displayed an error message “Analyze error”. (Tested March 2020)

## 6.2 Testing on Arabic and Persian

### 6.2.1 Adobe Acrobat Pro DC

- Does not support OCR for Arabic, Persian or Pashto languages.

### 6.2.2 NovoVerus

We received OCR tests from the company for three Arabic and Persian documents. The company does not offer an evaluation version, but they were kind enough to send us OCRed results back. Generally speaking, the overall results were the best.

- Fig. 18: Accuracy was 85%+ (Tested Feb 2020). See Persian Sample Page with OCR text
- Note: Red - error, Purple - shall split; **س** should be **س**

### 6.2.3 ABBYY

FineReader 12 Professional:

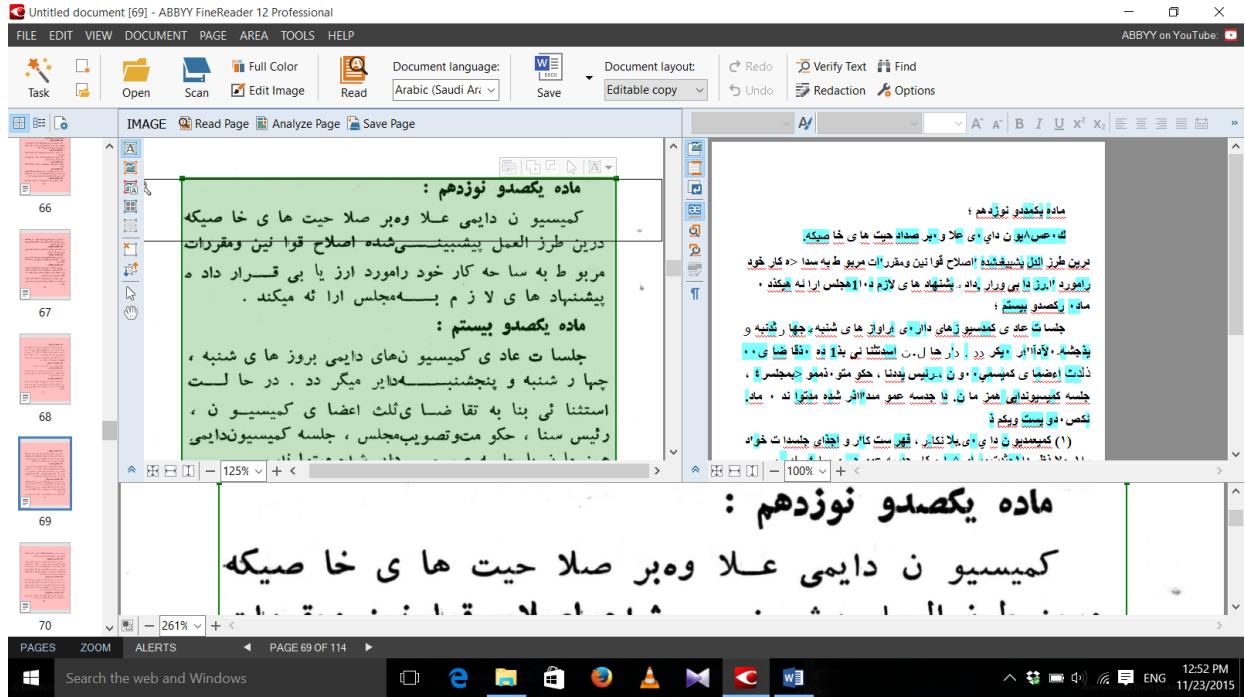


Figure 18: Original Arabic text (simple layout) and OCR result

- Fig. 18: Many characters were misread or replaced. Accuracy was not satisfactory. (Tested Nov 2015).

#### 6.2.4 Kraken

In September 2017, Mohamad Moussa of our team evaluated Kraken for Arabic language. The sample text has 261 words and 44 of them were wrong, meaning 83% word accuracy and 95% character accuracy, because most of these errors are one character error.

### 6.3 Observations on evaluated OCR systems and services

We conducted limited tests on Chinese materials, including contemporary materials in both Simplified Chinese characters (images from current online newspapers) and Traditional Chinese characters (images from current Taiwan newspapers), and retrospective materials from the 1600s to 1940s whose images were obtained by digitization. The contemporary materials typically have modern writing (left-to-right first, and then top-to-down order) with current fonts, while retrospective materials have old writing methods (top-to-down first, and then right-to-left) and are either on old fonts or handwriting.

The evaluation results show that the accuracy rates for Traditional Chinese characters vary, depending on the source of traditional Chinese characters. We processed some samples from a contemporary Traditional Chinese newspaper. In this case, for the current materials (simple layout and current fonts) the accuracy rate was as high as 90-95%.

Based on the experiments we carried out, we can make these general conclusions:

- (1) Achieving accurate page segmentation for complex layouts is the first priority, as failure at this stage is predictive of very poor overall results; the problem is better solved by some commercial systems.
- (2) Line and character segmentation has secondary priority; most systems appear to divide text into lines, and for non-cursive scripts reliably identify.

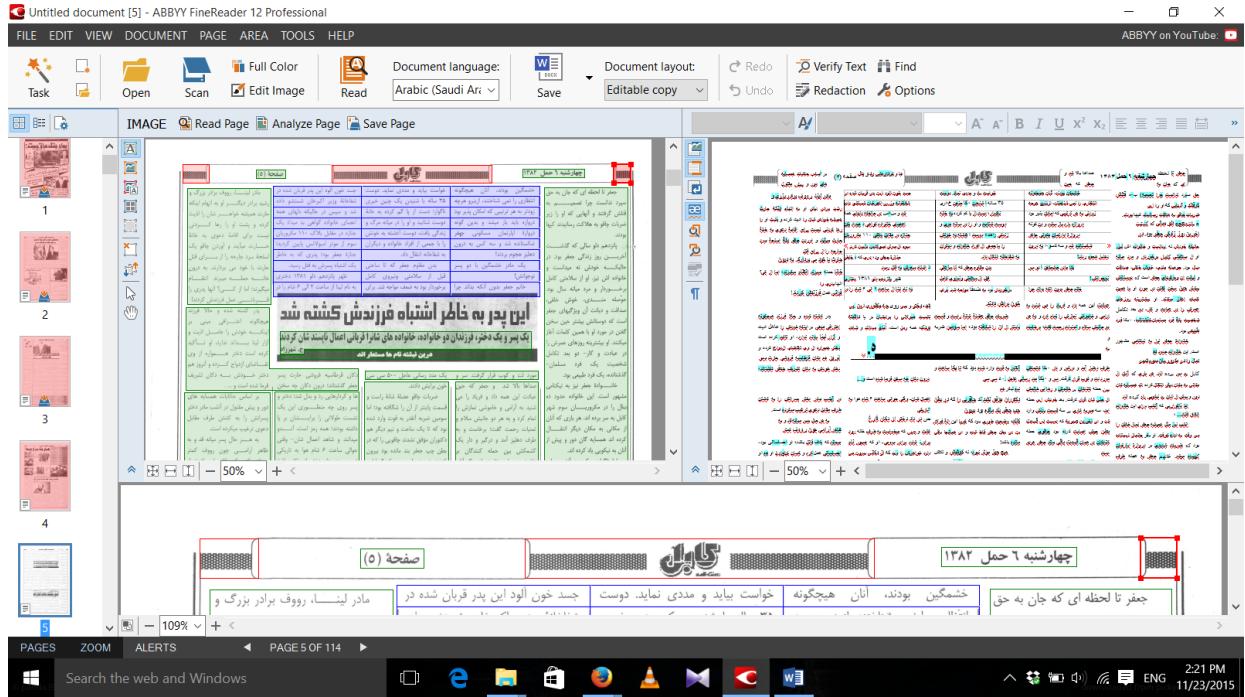


Figure 19: : Original Arabic text (complex layout) and OCR result

- (3) Using more training data does improve accuracy; thus the performance of OCR systems can be improved without changing their source code, if user-trained models are supported (e.g., for *Kraken* and *Tesseract*).

### 6.3.1 Tesseract 3.0 and 4.x

We reviewed the code and architecture and did a few tests in Oct 2017. Our evaluation of this version shows that:

- The system is very big with approximately 150,000 lines of C++ code<sup>4</sup>. We surmise that some lines of C++ code are not necessary. It seems some part of the code is for version 3 and could be removed for version 4.
- Tesseract appears to have its own implementation of LSTM in C++.
- There is a training script “tesstrain.sh” in folder “training”. This is a nice feature that allows users to train the software via their own data.
- The production version comes with pre-trained data, and un-trained data having 300MB space which is significant.
- Overall, Tesseract seems to be more open than Kraken.
- The bottleneck of all systems include:
  - Line and page segmentation:** If this version can read the first character, then most likely it can read the following characters.
  - Fo**nts: Current fonts are very likely to be recognized by the system. Traditional ones or hand-writing fonts are not.

<sup>4</sup>An automated count on recent version tesseract 4.1.0-rc1-188-gd49c6 yields 149,482 lines of C++ code in the src folder and 60,490 lines in header files, for a total of 209,972 lines of code.

### 6.3.2 Notes on Tesseract 4.11

We examined this version closer and observed that OCR accuracy is better with feeding the program a whole page rather than individual lines, words or characters. Further details of the tests conducted:

- Testing before training:
  - Use Tesseract-ocr to generate a box file containing character strings and their positions in the image.
  - Use jTessBoxEditor to double-check and correct data in the box file.
  - Generate dictionary data and trained data according to the box file.
  - Move the trained data to the working space of Tesseract-ocr.
- Training tesseract-ocr:
  - Use Tesseract-ocr to generate a box file containing character strings and their positions in the image.
  - Use jTessBoxEditor to double-check and correct data in the box file.
  - Generate dictionary data and trained data according to the box file.
  - Move the trained data to the working space of Tesseract-ocr.
- Testing after training:
  - It cannot recognize the character if it not in the dictionary.
  - For the character image that the dictionary includes, the accuracy is around 16%.
- Traditional Chinese characters from current traditional Chinese websites from Hong Kong and/or Taiwan: the accuracy rate is more than 90%+.
- Traditional Chinese characters from Siku QuanSu and Newspaper published in the 20<sup>th</sup> century (Fig. 13a and 13b). The accuracy rate is relatively low.
- Testing steps:
  - Picked 100 one-character, png format, black background and white character images from the project GitHub repository [36] as testing data.
  - Picked a one-page, pdf format image from “Great Qing Legal Code”.
  - The accuracy of Tesseract OCR v. 3.0 is around 36% for one-character, PNG format images, and around 70% for the one-page PDF format image.

## 6.4 Persian

Since 2017, we have tested multiple OCR software systems for Persian.

### 6.4.1 Readiris

### 6.4.2 Pershyangar

Farsiocr <http://farsiocr.ir/> Tesseract official trained data: (<https://github.com/tesseract-ocr/tessdata>) Wordly-ocr: (<https://github.com/mrychlik/worldly-ocr>)

## A Videos on YouTube

Most of the progress achieved by our project is illustrated in a series of videos posted on YouTube. In Table 1 one finds a list of the videos, including the Web links. Brief summaries accompany the content, but the videos should be mostly self-explanatory. Loosely, we will present the videos in antichronological order.

Table 1

Video Title	Link
Image-to-text conversion for Farsi	<a href="https://youtu.be/-TTZ7w3ujEE">https://youtu.be/-TTZ7w3ujEE</a>
Comparing Chinese Characters Ignoring Damage	<a href="https://youtu.be/03FPrgrPbhA">https://youtu.be/03FPrgrPbhA</a>
Comparing two Chinese Characters in the Presence of Damage	<a href="https://youtu.be/f6aQdm4hgX0">https://youtu.be/f6aQdm4hgX0</a>
OCR on Latin Characters - Clustering	<a href="https://youtu.be/1bKyYMoC8Zs">https://youtu.be/1bKyYMoC8Zs</a>
Chinese OCR - Nearest Neighbors	<a href="https://youtu.be/srVzYrVg4zI">https://youtu.be/srVzYrVg4zI</a>
Dynamic Time Warping	<a href="https://youtu.be/XcbZL4KECRQ">https://youtu.be/XcbZL4KECRQ</a>
Arabic/Persian OCR - baseline	<a href="https://youtu.be/PGMQI-N41oo">https://youtu.be/PGMQI-N41oo</a>
OCR on Rotated and Reflected Numbers	<a href="https://youtu.be/ZmhUdBv4bLE">https://youtu.be/ZmhUdBv4bLE</a>
Chinese character OCR with scale bound	<a href="https://youtu.be/ft30kJEh5fQ">https://youtu.be/ft30kJEh5fQ</a>
Rotated Text to Helvetica	<a href="https://youtu.be/LV3bu8U2b9E">https://youtu.be/LV3bu8U2b9E</a>
OCR on Traditional Chinese characters	<a href="https://youtu.be/hws9uVjISsw">https://youtu.be/hws9uVjISsw</a>
OCR On Rotated Text	<a href="https://youtu.be/1icnxxl2cKU">https://youtu.be/1icnxxl2cKU</a>
Converting Newsprint to Times New Roman	<a href="https://youtu.be/TogD1_JU1-0">https://youtu.be/TogD1_JU1-0</a>
Chinese OCR - clustering of characters in 7 pages	<a href="https://youtu.be/Qgn0aRDvD3o">https://youtu.be/Qgn0aRDvD3o</a>
English Clusters	<a href="https://youtu.be/URz0uHpsN-g">https://youtu.be/URz0uHpsN-g</a>
OCR Test Content	<a href="https://youtu.be/9SHi9057F7A">https://youtu.be/9SHi9057F7A</a>
Newsprint to Times New Roman - OCR	<a href="https://youtu.be/YenxuIBAU-g">https://youtu.be/YenxuIBAU-g</a>
Traditional Chinese OCR - Two books	<a href="https://youtu.be/-_cD2VAsyW8">https://youtu.be/-_cD2VAsyW8</a>
Mapping Times New Roman to Helvetica	<a href="https://youtu.be/gEiHhoJ9HzU">https://youtu.be/gEiHhoJ9HzU</a>
ChineseOCRMovie	<a href="https://youtu.be/2VHX5HnZHaY">https://youtu.be/2VHX5HnZHaY</a>
A "Catscan" of an Artificial Neural Network	<a href="https://youtu.be/tEyRGVuEgh4">https://youtu.be/tEyRGVuEgh4</a>
A "Catscan" of an Artificial Neural Network	<a href="https://youtu.be/ej8sNN3YrAM">https://youtu.be/ej8sNN3YrAM</a>
OCR on a document in Persian	<a href="https://youtu.be/T4sALF10gUs">https://youtu.be/T4sALF10gUs</a>
ChinesePageSegmentation	<a href="https://youtu.be/eC08IVx4lCk">https://youtu.be/eC08IVx4lCk</a>
Chinese Character Search	<a href="https://youtu.be/L2YxqLnzATg">https://youtu.be/L2YxqLnzATg</a>

## References

- [1] **MATLAB**. URL: <https://www.mathworks.com/products/matlab.html>.
- [2] Ocropolis. URL: <https://github.com/tmbarchive/ocropy>, 2020.
- [3] ABBYY. FineReader 14, April 2019.
- [4] **Afghanistan Digital Collections**. URL: <http://www.afghandata.org/>.
- [5] Dan Claudiu Ciresan, Ueli Meier, Luca Maria Gambardella, and Jurgen Schmidhuber. Convolutional Neural Network Committees for Handwritten Character Classification. In *2011 International Conference on Document Analysis and Recognition*, pages 1135–1139, September 2011.
- [6] Shrey Dutta, Naveen Sankaran, K. Pramod Sankar, and C. V. Jawahar. Robust Recognition of Degraded Documents Using Character N-Grams. In *Proceedings of the 2012 10th IAPR International Workshop on Document Analysis Systems*, DAS ’12, pages 130–134, USA, March 2012. IEEE Computer Society.
- [7] Alex Graves, Marcus Liwicki, S. Fernandez, Roman Bertolami, Horst Bunke, and Jürgen Schmidhuber. A Novel Connectionist System for Unconstrained Handwriting Recognition. *IEEE Trans. Pattern Anal. Mach. Intell.*, 31(5):855–868, 2009.
- [8] Alex Graves and Jürgen Schmidhuber. Offline Handwriting Recognition with Multidimensional Recurrent Neural Networks. In Daphne Koller, Dale Schuurmans, Yoshua Bengio, and Léon Bottou, editors, *NIPS*, pages 545–552. Curran Associates, Inc., 2008.
- [9] OCR history ABBYY. **Technology**. URL: <http://www.abbyy.co.il/?categoryId=72050&itemId=168963>, 2018.
- [10] Sepp Hochreiter. The vanishing gradient problem during learning recurrent neural nets and problem solutions. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 6(02):107–116, 1998.
- [11] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. 1997.
- [12] <https://alitdesign.net>. Bromello Font, March 2020.
- [13] S. Kahan, T. Pavlidis, and H. S. Baird. *On the Recognition of Printed Characters of Any Font and Size*. IEEE Computer Society, February 1987.
- [14] M.S. Khorsheed. Recognising handwritten arabic manuscripts using a single hidden markov model. *Pattern Recognition Letters*, 24(14):2235–2242, oct 2003.
- [15] **Kraken**. URL: <http://kraken.re/>, 2018.
- [16] **Kurzweil Technologies**. URL: <http://www.kurzweiltech.com/kcp.html>, 2018.
- [17] G.S. Lehal, C. Singh, and R. Lehal. A shape based post processor for Gurmukhi OCR. In *Proceedings of Sixth International Conference on Document Analysis and Recognition*, pages 1105–1109, September 2001.
- [18] Ning Li. An implementation of ocr system based on skeleton matching. 1993. Publisher: University of Kent, Computing Laboratory.
- [19] G Louloudis, B Gatos, I Pratikakis, and K Halatsis. A block-based hough transform mapping for text line detection in handwritten documents. 2006.

- [20] Prem Natarajan, Ehry MacRostie, and Michael Decerbo. The BBN Byblos Hindi OCR System. In Venu Govindaraju and Srirangaraj (Ranga) Setlur, editors, *Guide to OCR for Indic Scripts: Document Recognition and Retrieval*, Advances in Pattern Recognition, pages 173–180. Springer, London, 2010.
- [21] Debabrata Paul and Bidyut Baran Chaudhuri. A BLSTM Network for Printed Bengali OCR System with High Accuracy. *arXiv:1908.08674 [cs]*, August 2019.
- [22] OpenITI Project. OCR GS Data, March 2020.
- [23] Project DejaVu. DejaVu, March 2020.
- [24] Maxim Romanov, Matthew Thomas Miller, Sarah Bowen Savant, and Benjamin Kiessling. Important new developments in arabographic optical character recognition (ocr), 2017.
- [25] Marek Rychlik. Image-to-text conversion for Farsi — a YouTube video.
- [26] Naveen Sankaran and C. V Jawahar. Recognition of printed Devanagari text using BLSTM Neural Network. In *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*, pages 322–325, November 2012.
- [27] Mahnaz Shafii. Optical Character Recognition of Printed Persian/Arabic Documents. *Electronic Theses and Dissertations*, January 2014.
- [28] Ray Smith. An overview of the Tesseract OCR engine. In *Ninth International Conference on Document Analysis and Recognition (ICDAR 2007)*, volume 2, pages 629–633. IEEE, 2007.
- [29] Sakhr Software. *Arabic language technology*. March 2020.
- [30] Ahmad P. Tafti, Ahmadreza Baghaie, Mehdi Assefi, Hamid R. Arabnia, Zeyun Yu, and Peggy Peissig. OCR as a service: an experimental evaluation of Google Docs OCR, Tesseract, ABBYY FineReader, and Transym. In *International Symposium on Visual Computing*, pages 735–746. Springer, 2016.
- [31] Kazem Taghva and Eric Stofsky. OCRSpell: an interactive spelling correction system for OCR errors in text. *International Journal on Document Analysis and Recognition*, 3(3):125–137, March 2001.
- [32] Tesseract Open Source OCR Engine (main repository). URL: <https://github.com/tesseract-ocr/tesseract>, 2018.
- [33] Martin Tomaschek. *Evaluation of off-the-shelf OCR technologies*. PhD Thesis, Masaryk University, 2018.
- [34] Unicode Consortium. URL: <https://unicode.org/>, 2018.
- [35] Jake Walker, Yasuhisa Fujii, and Ashok C. Popat. A web-based ocr service for documents. In *Proceedings of the 13th IAPR International Workshop on Document Analysis Systems (DAS), Vienna, Austria*, volume 1, 2018.
- [36] Worldly-OCR GitHub repository. <https://github.com/mrychlik/worldly-ocr>, December 2018.
- [37] Yi Li, Yefeng Zheng, and D. Doermann. Detecting Text Lines in Handwritten Documents. In *18th International Conference on Pattern Recognition (ICPR'06)*, volume 2, pages 1030–1033, August 2006.
- [38] F. Yin, Q. Wang, X. Zhang, and C. Liu. ICDAR 2013 Chinese Handwriting Recognition Competition. In *2013 12th International Conference on Document Analysis and Recognition*, pages 1464–1470, 2013.