

Assessing Google Vision and Tesseract OCRs for Different Font Styles

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Abstract. The development of fonts in typography has a long history that dates back to several centuries. Today, any text editing and processing tool has a large number of font types available, that allows the use of several font sizes and variations such as **bold-face**, *italic*, underlined texts and their combination. Different types of fonts are used for different purposes and may even be linked to the subject of the text it reports. This paper looks at the performance of the text transcription of Google Vision and Tesseract OCRs using printed texts with different font styles, size, and other font variations.

Keywords: Document engineering · Font-style · Font-size · OCR

1 Introduction

The first printed book in the, Gutenberg Bible, used a special typeface based on Textura and Schwabacher due to their condensed counters and increased spacing [1]. Such new type font would allow for more characters per line, and in turn, more information per page. Figure 1 presents part of a 1455-1456 page of Gutenberg's Bible.

Since Gutenberg's Bible, dozens on different typefaces or font styles were developed. Maximilien Vox in 1954 proposed the Vox-ATypI classification clustering typefaces into general classes. Vox proposed a nine-type classification which tends to group typefaces according to their main characteristics, often typical of a particular century (15th, 16th, 17th, 18th, 19th, 20th century), based on a number of formal criteria: downstroke and upstroke, forms of serifs, stroke axis, x-height, etc. Vox's classification, presented in figure 2, was adopted in 1962 by the Association Typographique Internationale (ATypI) and in 1967 as a British Standard, as British Standards Classification of Typefaces (BS 2961:1967),[1] which is a very basic interpretation and adaptation/modification of the earlier Vox-ATypI classification. On April 27, 2021, ATypI announced that they had de-adopted the system and that a working was building a new, larger system incorporating the different scripts of the world [1]. Although the Vox-ATypI classification defines archetypes of typefaces, many typefaces can exhibit the characteristics of more than one class.



Fig. 1: Part of a page of Gutenberg’s Bible, edition dating from ca. 1455-56.

The advent of digital technology has significantly influenced type design and legibility. For instance, when Lucida was created in the early 1980s as the first type family designed specifically for digital rendering on screens and laser printers, it was informed by scientific studies of reading and vision [2]. Historically, the perception of type size has significantly influenced human legibility studies. Early 20th-century research focused on determining the minimum human readable sizes for the different font types. Javal (1905) noted that the nine-point type was prevalent in French books and newspapers, with an x-height of 1.5 mm. Huey (1908) similarly recommended a minimum x-height of 1.5 mm for efficient human reading, a finding that Roethlein (1912) confirmed through tests of 10-point fonts with x-heights ranging from 1.4 to 1.5 mm. Miles Tinker’s comprehensive research in 1963 summarized that type sizes of 10 and 11 points were the most quickly read. By the early 1980s, many tested types were no longer common, but their x-heights averaged 1.5 mm, aligning with earlier findings. Legge et al. (1985, 2007) introduced the concept of “critical print size”, identifying a threshold below which human reading speed decreases but above which increases in size do not enhance reading speed. This critical size, approximately 0.20 degrees of visual angle, corresponds to a 1.4 mm x-height read at 40 cm [2]. Such considerations are particularly relevant in the context of Optical Character Recognition, where the recognition of fonts and their characteristics can significantly impact the accuracy of text transcription.

The focus of this paper is to analyze the effect of the choice of font style, size, and other features such as underline, **boldface**, *italics*, etc. in automatic font recognition (OCR) text transcription. The Vox-ATypI diagram lists 36 font styles, of which the Véronèse and Paris font styles were excluded from this study because they were not freely available. The excellent recent paper [13] explicitly says that no paper in the literature addressed the sensitivity of OCRs to font/size variation, amongst other issues.

2 Methodology

This paper shows that the accuracy of the OCR varies depending on the style and size of the font. A Python script was developed to automatically generate

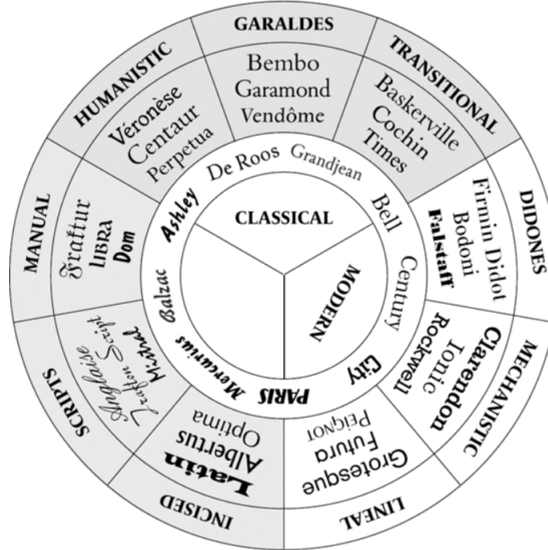


Fig. 2: Vox-ATypI diagram.

PDF documents that included variations of text style whenever supported, such as regular, underlined, and **bold**. To demonstrate the variability in OCR performance, two different fonts from the Vox-ATypI taxonomy (see Figure 2) that exhibit significant differences in OCR performance, Balzac and Peignot, each representing a different typographic style, were selected. To provide a consistent basis for evaluating performance across these varied styles, **the same text was utilized throughout the experiment**. A sample of such a text is shown in Figure 3. Furthermore, the overall performance of two distinct groups, Scripts and Lineal, to provide a comprehensive analysis were also assessed.

The generated PDFs files were converted into 300 dpi PNG images, the most suitable resolution to OCR recognition [3]. The Tesseract OCR [4] was originally developed at Hewlett-Packard Laboratories Bristol UK and at Hewlett-Packard Co, Greeley Colorado USA between 1985 and 1994, with some more changes made in 1996 to port to Windows and C++ in 1998. In 2005 Tesseract was open sourced by HP. From 2006 until November 2018 it was further developed by Google.

Google Cloud Vision OCR is a cloud-based service that provides advanced text detection and extraction capabilities. Google announced the Cloud Vision API, including OCR capabilities, at the Google Cloud Platform Next event in 2015. The API was designed to bring Google’s image recognition and analysis capabilities to developers. The Cloud Vision API, including OCR, became generally available in 2016. Since then, Google has continuously improved its capabilities, increasing text detection accuracy and speed, and also expanding the support for additional languages and scripts. Google introduced advanced features such as document text detection and handwriting recognition, further

expanding the use cases for the OCR service. The integration with other Google Cloud services has also been deepened, providing a comprehensive suite of tools for developers.

The primary objective of the experiment performed here is to investigate and compare the impact of the different font types and sizes in the Vox-ATypI classification on the performance of both the Tesseract and Google Cloud Vision OCR engines. Eleven fonts with sizes ranging from 10 to 34 points were chosen to represent a wide spectrum of text sizes commonly encountered in printed and digital documents. Table 1 presents in blue the fonts selected in this study, while the fonts in red were not used for the reasons already discussed. This

Table 1: Fonts Accessed

Bembo	Garamond	Vendôme	Baskerville
Cochin	Times	Firmin Didot	Bodoni
Falstaff	Clarendon	Ionic	Rockwell
Grotesque	Futura	Peignot	Latin
Albertus	Optima	Anglaise	Traffon Script
Mistral	Fraktur	Libra	Dom
Véronèse	Centaur	Perpetua	Balzac
Ashley	De Roos	Grandjean	Bell
Century	City	Paris	Mercurius

work analyzes how font variations within each class affect OCR performance. Tesseract OCR version 4.1.1 was utilized. Levenshtein distance [5], also known as the edit distance, was used here to quantify the accuracy of the OCR output, counting the minimum number of single-character edits (insertions, deletions, or substitutions) required to transform an OCR output into the ground-truth text. The lower value of the Levenshtein distance corresponds to higher levels of OCR accuracy. The second author of this paper was possibly the first researcher to use Levenshtein distance to assess OCR performance [12].

*"To measure is to know" "If you cannot
measure it, you cannot improve it." "When you
can measure what you are speaking about, and
"To measure is to know: 'If you cannot measure it, you
cannot improve it. 'When you can measure what you are
speaking about, and express it in numbers, you can manage it."*

Fig. 3: Balzac font size 22 and Tesseract output. Accuracy: 70.4%.

3 Analysis

The analysis here focuses on evaluating all fonts defined within the Vox-ATypI classification, examining their impact on the accuracy of Tesseract and Google Vision OCRs at various styles and font sizes. **The OCR data figures presented here were obtained in the first week of November/2025**

3.1 Consistently High-Performing Fonts

Certain fonts consistently perform well in both OCR engines, text sizes, and styles due to their clear character delineation, uniform spacing, and minimal embellishments: Ashley, Baskerville, Bell, Bembo, Bodoni, Franktur, Schibsted Grotesk, Ionic, Century, City, Claredon, Cochin, De Ross, Didot, Dom, Falstaff, Futura, Garamond, Mercurius, Optima, Rockwell, Vendome. Their simplicity ensures high readability, enabling accurate character extraction even under challenging conditions such as low resolution or varying text size. These fonts require no further attention in this study, as their performance remains consistently optimal.

3.2 Unique Performance Patterns

While many fonts perform consistently across different OCR systems, there are certain fonts that exhibit unique or unexpected behavior, highlighting the complexities of OCR text recognition. Such fonts present interesting challenges due to their distinctive design features, such as irregular spacing, intricate curves, or historical origins.

In some cases, specific OCR engines may handle such fonts better than others, showcasing differences in their underlying algorithms and ability to interpret non-standard text features. The performance variation may also stem from factors such as font style (serif vs. sans-serif), the presence of ligatures, or the extent of embellishments in certain characters. Examining such fonts offers valuable insights into the strengths and limitations of various OCR systems and how they cope with real-world scenarios that involve more complex typography.

Anglaise Anglaise is a style of cursive script rooted in the Copperplate tradition, known for its refined and ornamental appearance [6]. Anglaise design relies on the principles of Copperplate calligraphy, with its distinctive contrast between thick downstrokes and thin upstrokes, achieved through careful nib pressure. The Copperplate script, also referred to as English Roundhand, emphasizes graceful curves and a consistent 54-degree slant, making it popular for formal uses such as invitations, certificates, and legal documents. Figure 4 presents the performance of both Tesseract and Google Cloud OCR when processing text in the Anglaise font. The superiority of Google OCR is immediately apparent with this font. While Google OCR achieves a mean accuracy of 93%, Tesseract struggles significantly, with a mean accuracy of less than 30%. However, an unexpected

anomaly was observed in the case of Google OCR at 14pt in the regular style: its performance was surprisingly poor compared to other font sizes, marking a notable deviation from its overall strong results. This drop in accuracy may be attributed to the intricacies of the cursive style at smaller sizes, where the loops and delicate connections between characters can become more difficult for the OCR system to distinguish clearly, leading to misinterpretations of the text.

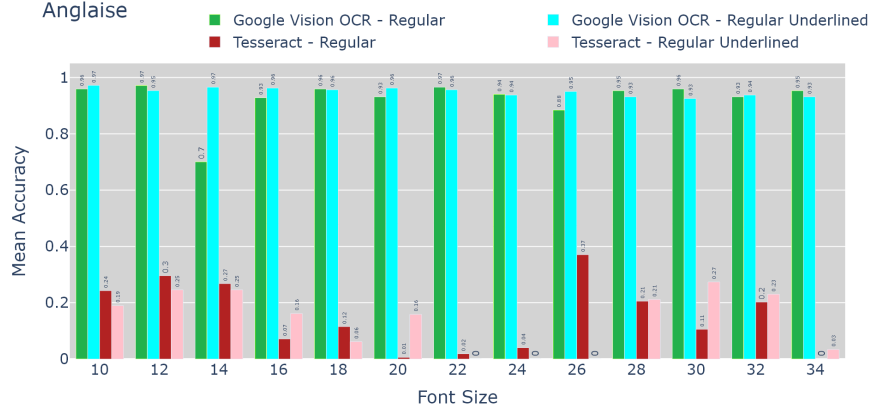


Fig. 4: Anglaise accuracy.

Balzac Named after Honoré de Balzac, the typeface reflects a literary elegance reminiscent of the 19th century [7]. Balzac comes in several styles, ranging from serif to script, often embodying characteristics such as rough texture and hand-drawn elements. Figure 3 shows the sample text formatted in the Balzac font, size 22, along with its transcription by Tesseract OCR. Figure 5 displays the

Balzac Regular 10 pt	levenshtein: 74%
on "To measure is to know" "Sf you cannot measure tt, you cannot improve tt. When you can measure what you are speake feng about, and eapress tt in numbers, you know something about it; but when you cannot measure tt, cannot eapress tt in numbers, your knowledge is of a meagre and un actory hind." Lord Kelvin	
Balzac Regular 12pt	levenshtein: 27%
" 0 te Oe seh Ge i as "When about tt; bul when you canoe measure t, anhengou cannot rambers youn capress: tt	
Balzac Regular 16pt	levenshtein: 73%
"To is to know" "Gf you cannot measure tt, you cannot inprove tt, "When you can measure what you are speaking , and express it tn numbers, you know something about tt; but when you cannot measure tt, when you cannot eapress tt in numbers, your knowledge is of a meagre and unsatisfactory hind." Lord Kelvin	

Fig. 5: Tesseract output for font Balzac sizes 10, 12, and 16.

transcription results for the same text using the Balzac font in regular styles at sizes 10, 12, and 16pt. When analyzing the results for the Balzac font (Figure 6), Tesseract OCR demonstrated zero accuracy for most font sizes and styles, with the exception of regular fonts at 10pt, 12pt, 16pt, and 22pt. Interestingly, only

the 12pt size was successfully recognized when the text was underlined. Neither the bold nor italic styles of the Balzac font were recognized in any case. In contrast, Google Cloud OCR performed significantly better, achieving over 95% accuracy in most cases, regardless of font size or style. This highlights a marked difference in performance between the two OCR systems when processing the Balzac font. Bold version were not available.

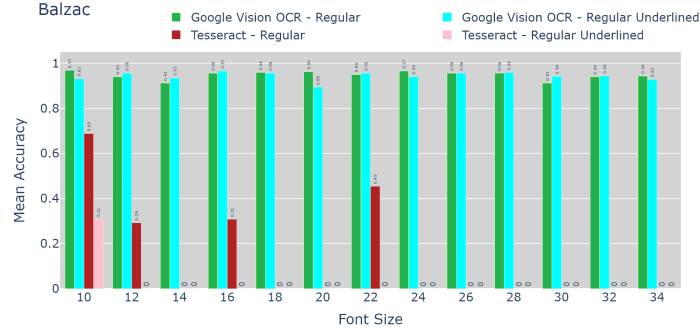


Fig. 6: Balzac accuracy.

Peignot a sans-serif typeface, has an innovative blend of uppercase, lowercase, and small caps, designed to be functional for publishing and advertising. Figure 7 presents the results for the Peignot font in both regular and underlined styles, with font sizes ranging from 10pt to 34pt, in increments of 2pt. The accuracy

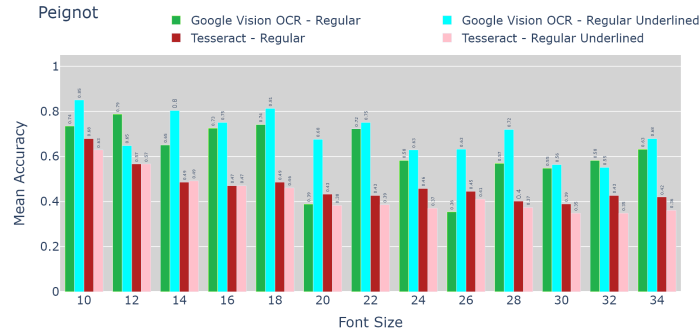


Fig. 7: Peignot accuracy.

of Tesseract OCR drops as the font size increases. At 10pt, the accuracy is 68% for regular and 63% for underlined text. However, by 34pt, the accuracy drops to 42% for regular and 36% for underlined, indicating a decrease of 26% and

27% respectively across the size range. In contrast, Google Cloud OCR consistently outperforms Tesseract, exhibiting higher accuracy across all font sizes and styles. Google OCR performs better with underlined Peignot text than with regular Peignot text, a result not typically seen with other fonts in this study. The performance of OCR systems with the bold version of the Peignot font

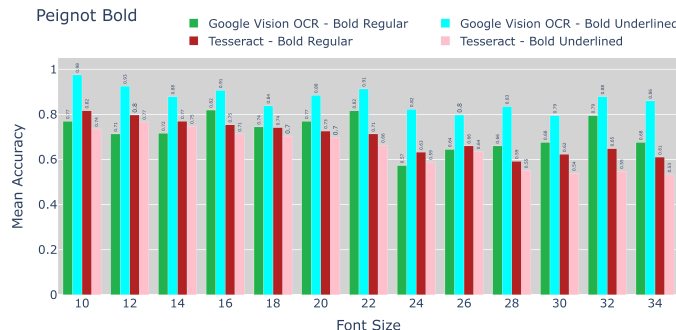


Fig. 8: Peignot bold accuracy.

is generally acceptable, with accuracy levels mostly ranging between 60% and 70%. As illustrated in Figure 8, both Tesseract and Google Cloud OCR exhibit similar behavior with this variant of Peignot, though Google Cloud OCR consistently achieves slightly higher accuracy than Tesseract across all font sizes. A noteworthy distinction occurs in the Bold Underlined style, where Google Cloud OCR significantly outperforms Tesseract. While both OCR systems demonstrate a gradual decrease in accuracy as font size increases, the gap between the two widens in this particular style. This performance divergence is not seen in the Bold Regular style, where the systems remain closely matched. This result suggests that the bold and underlined variant of Peignot presents unique challenges to Tesseract, particularly at larger sizes, whereas Google Cloud OCR maintains more robust performance. Despite the overall acceptable results, there remains potential for improvement in both systems, especially in handling the bold and underlined text at varying font sizes.

Interestingly, the overall behavior of OCR systems with Peignot regular and bold is quite close, with OCRs performing slightly better with Peignot Bold. This contrasts with initial expectations of a more significant variation between the two styles. The results indicate only a marginal improvement in accuracy with the bold version, suggesting that the visual distinction between regular and bold does not drastically impact OCR performance.

Grandjean is characterized by its mathematical proportions and geometric regularity, combining artistry with a mechanical, measured approach to typography [11]. OCR systems show poor performance when recognizing this typeface. As depicted in Figure 9, both Google Cloud OCR and Tesseract struggle with Grandjean in both regular and underlined styles. Across various font sizes, the

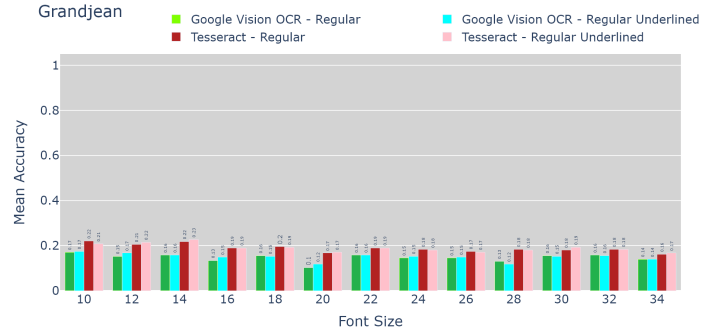


Fig. 9: Grandjean accuracy.

accuracy remains consistently low, with no result exceeding 22%. In fact, the worst accuracy observed is just 10%, indicating severe difficulties in character recognition. Such outcome was unexpected, given that its design is based on mathematical proportions and a grid system, was anticipated to align well with the requirements of OCR systems. However, both Google Cloud OCR and Tesseract fail to interpret the characters effectively, possibly due to the historical or ornamental qualities of the font that differ from modern, more OCR-friendly designs. Bold style is not available.

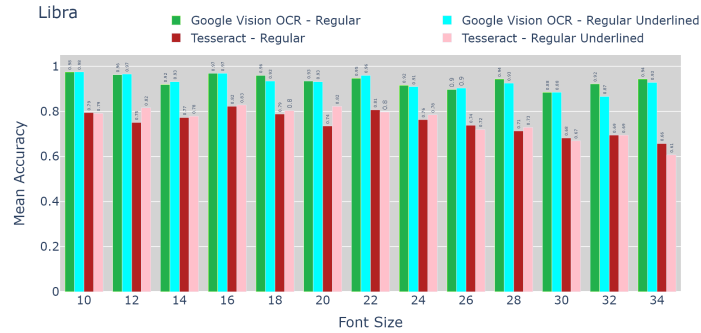


Fig. 10: Libra accuracy.

Libra was designed by the Dutch type designer Sjoerd Hendrik de Roos in 1938, as a geometric display typeface that embodied the modernist ideals of clarity and functionality. Libra design is characterized by clean, simple lines and geometric forms, making it suitable for bold headlines and large-scale designs, such as posters and advertisements [10]. The performance of OCR systems with the Libra font shows a distinct disparity between the two main tools evaluated. As illus-

trated in Figure 10, Google Cloud OCR performs exceptionally well with Libra, achieving no accuracy below 90%. This high level of performance underscores the font clear geometric forms, which facilitate effective character recognition.

Tesseract demonstrates significantly lower performance, with a mean accuracy of approximately 80%. While this result is still respectable, it highlights the differences in how each OCR system interprets and processes the Libra font. The geometric simplicity and clean design of Libra should ideally lend itself to high recognition rates; however, There is no bold version of Libra available, which may impact the analysis of its performance in different styles.

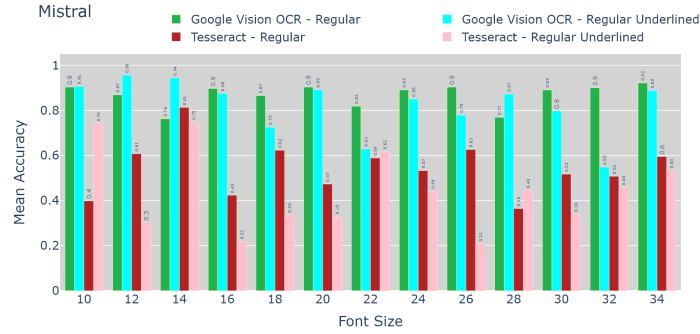


Fig. 11: Mistral accuracy.

Mistral was one of the first typefaces to successfully mimic informal handwriting and it became highly popular in graphic design and advertising. Its use of fluid, flowing letterforms made it ideal for applications requiring a personal or artistic touch, such as posters, invitations, and branding materials. This typeface is still widely used today for its unique combination of elegance and casual charm, remaining a prominent choice in various design contexts. The performance of OCR systems with the Mistral font reveals notable differences between the two tools, particularly in terms of accuracy and font size. As illustrated in Figure 11, Google Cloud OCR performs well overall, with accuracies ranging from a high of 92% to a low of 55%. Interestingly, the results indicate that the legibility of the regular style may surpass that of the underlined style at certain font sizes, while in other cases, the underlined version performs better. This variance highlights the significant influence of font size and style on recognition accuracy, suggesting that optimal performance may depend on the specific context of use.

Conversely, Tesseract exhibits significantly poorer performance when recognizing Mistral, with accuracy levels lower than those achieved by Google OCR. However, Tesseract also reflects similar disparities between font sizes and styles, indicating that while it struggles overall, the characteristics of size and style still affect its performance in a comparable manner. There is no bold version of Mistral available.

Perpetua was designed by Eric Gill between 1928 and 1930 for the Monotype Corporation, is a classic serif font influenced by Roman inscriptions and modern typography. It bridges traditional and modern typography, remaining popular for diverse applications, from literature to advertisements [8]. The performance

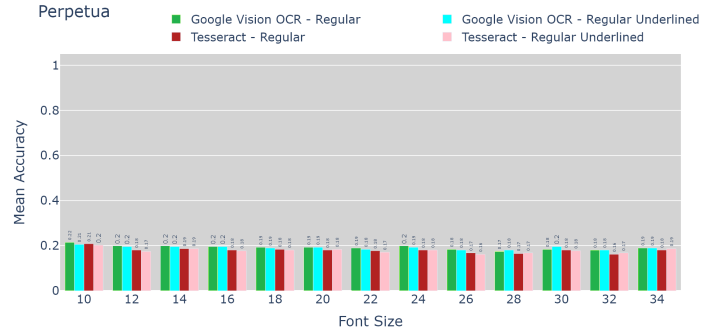


Fig. 12: Perpetua accuracy.

of OCR systems with the Perpetua font is illustrated in Figure 12, both Google Cloud OCR and Tesseract struggle significantly with Perpetua, with neither system achieving accuracies above 22%. This outcome is particularly disappointing given its geometric regularity and design, which one might expect to enhance legibility and recognition rates. The accuracy rates highlight a consistent pattern between the two fonts, reinforcing the challenges posed by their respective characteristics. Despite the elegant design of Perpetua, both OCR systems demonstrated a failure to effectively recognize the letterforms, with accuracies falling as low as 16%. This similarity in performance with Grandjean suggests that certain design elements inherent to both typefaces may hinder the OCR ability to accurately interpret them.

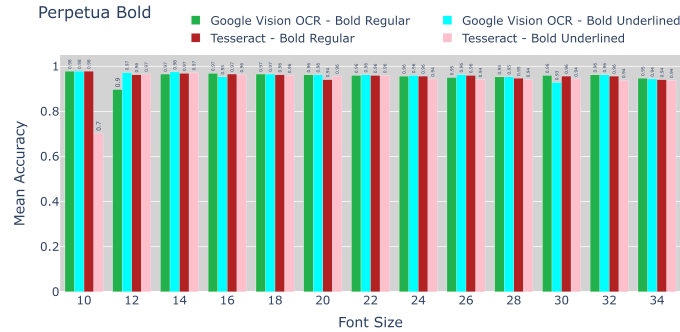


Fig. 13: Perpetua bold accuracy.

The results for Perpetua Bold present a stark contrast to those observed with Perpetua Regular. As shown in Figure 13, both Google Cloud OCR and Tesseract perform flawlessly with Perpetua Bold, achieving an impressive mean accuracy of approximately 96%. This is in direct opposition to the poor recognition rates recorded for Perpetua Regular, where accuracies did not exceed 22%. The significant difference in OCR performance between the regular and bold styles of the same typeface underscores the importance of font style in OCR technology. Perpetua Bold heavier strokes and increased contrast appear to make the letterforms much more legible for the OCR systems, highlighting how subtle changes in typeface design can dramatically affect recognition accuracy. Such a behavior demonstrates that even minor stylistic variations, such as switching from a regular to a bold style, can play a crucial role in how effectively OCR systems interpret text. The remarkable ease with which Perpetua Bold is recognized further emphasizes the need to consider font style when optimizing OCR accuracy.

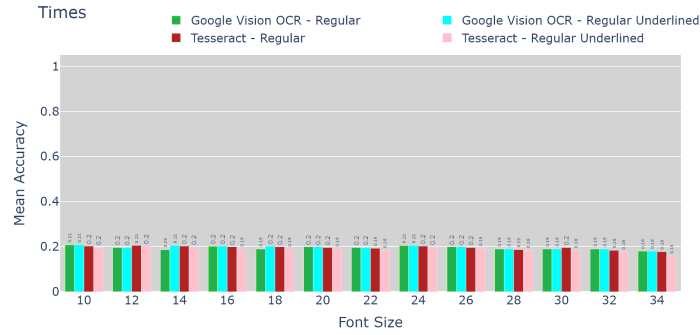


Fig. 14: Times Regular accuracy.

Times is originally known as Times New Roman, is one of the most iconic serif typefaces. It was created to enhance readability and optimize space in newspaper columns, Times features moderate contrast, compact letterforms, and functional aesthetics [9]. Its legibility and versatility quickly established it as the standard for newspaper typography and print media. Over the decades, Times has influenced numerous designs, cementing its status as a classic, enduringly popular for its balance of elegance and practicality [9].

The performance of OCR systems with the Times font for regular style presents unexpected results, as both Google Cloud OCR and Tesseract exhibit notably poor accuracy rates. As illustrated in Figure 14, this widely used typeface, which has long been regarded as a standard in typography, fails to deliver satisfactory recognition results across both platforms. Despite Times reputation for clarity and legibility, the OCR systems struggle to accurately interpret its let-

ter formats, resulting in lower performance than anticipated. This contradiction raises questions about the effectiveness of current OCR technologies when processing such a commonly employed typeface. The findings highlight a significant disparity between the established font design principles and the practical capabilities of existing OCR systems. The poor performance of Times in this context emphasizes the need for further advancements in OCR technology, particularly in improving recognition accuracy for typefaces that are staples in the publishing industry. Just like Perpetua, the Times Bold font exhibits drastically better

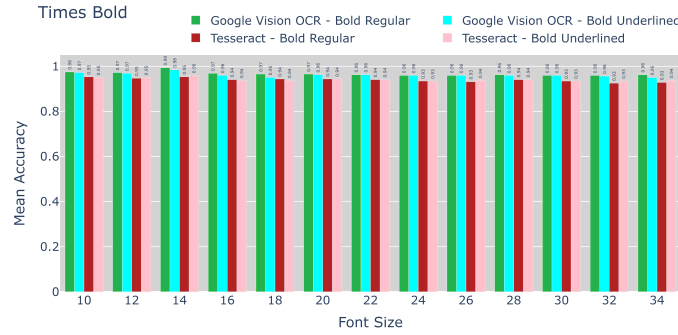


Fig. 15: Times Bold accuracy.

OCR performance compared to its regular counterpart. As shown in Figure 15, both Google Cloud OCR and Tesseract handle Times Bold with remarkable precision, achieving near-perfect accuracy across all sizes. This stands in stark contrast to the poor performance recorded for Times Regular, where OCR struggled to achieve reliable results. This disparity underscores a critical point: style and size matter in OCR. The shift from a regular to a bold style significantly enhances the legibility of letter formats, making them easier for OCR systems to process. Larger font sizes also contribute to an OCR performance improvement, further demonstrating that even subtle changes in typeface weight or size can dramatically impact recognition accuracy. The example of Times illustrates that despite being a widely used and highly legible typeface, the regular version poses challenges for OCR, while the bold version performs flawlessly. This phenomenon reinforces the importance of considering font style and size when optimizing text for OCR systems, as the right combination can vastly improve the accuracy and reliability of text recognition.

Trafton font was a popular choice for American school yearbooks in the 1940s and 1950s. The Trafton Script font data (Figure 16) reveals an intriguing anomaly at 10-point font size, where each OCR engine exhibits an unusual performance pattern. Google Vision OCR achieves higher accuracy with underlined text than with regular text, while Tesseract OCR demonstrates the opposite, performing

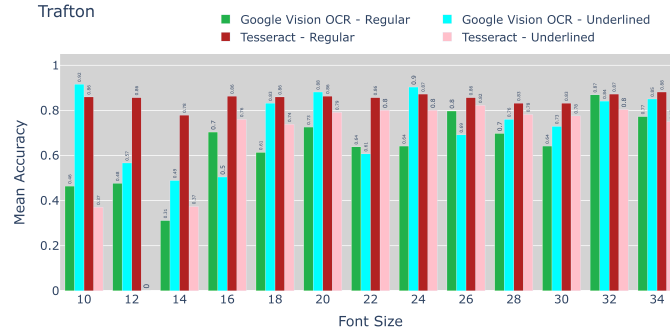


Fig. 16: Trafton accuracy.

better with regular text than with underlined. This behavior diverges from the trends typically observed in our dataset, where underlined text generally does not significantly enhance the accuracy figures. One possible explanation for Google Vision OCR superior performance with underlined text may lie in Trafton script style. As a connected, flowing typeface, the underline may serve as a stabilizing feature, providing a baseline or visual “guide” for Google Vision OCR to follow, thereby aiding character recognition. This guiding effect could help counteract the natural variability and complexity of the script letter formats, which are generally more challenging for OCR engines to interpret accurately. In contrast, Tesseract OCR appears to struggle with the underline in this context, potentially perceiving it as additional noise or a distraction that interferes with text clarity. Overall, the data suggests that Google Vision OCR architecture may better accommodate underlined script fonts, particularly in smaller sizes, potentially due to the role of the underline as a guiding stroke in the recognition process. This insight into underline interaction with script fonts such as Trafton presents a promising direction for future research on OCR accuracy with decorative and stylized typefaces. No bold version is available for Trafton Script.

4 Conclusions

This paper investigated the influence of font size and styles in the accuracy performance of the Tesseract open-source Optical Character Recognition (OCR) systems. Experiments showed how variations in font style and size affect the OCR performance, with particular emphasis on fonts categorized according to the Vox-ATypI taxonomy. The experiments reported here were made with 33 different font styles from the 36 fonts in the Vox-ATypI classification. This paper reports on the performance of the Tesseract OCR and Google Vision OCR on two of the fonts that presented more drastic behaviour with font size and style variation, which were from different groups in the Vox-ATypI font classification. The study of the OCR performance of each font category, one can gain deeper insights into the factors influencing recognition accuracy.

In further works, the authors plan to comparatively assess the performance of other OCR engines, such as ABBYY FineReader and Adobe Acrobat OCR, and to investigate potential strategies for enhancing OCR accuracy. This expanded analysis will include a wider range of fonts and explore the effects of both regular and italic styles across various typefaces. One possible unfolding is to determine whether font-specific training or preprocessing techniques—such as image enhancement, binarization, or style adaptation can improve OCR performance, particularly in cases where certain fonts or styles challenge OCR accuracy. Such a broader approach seeks to identify practical methods to achieve higher transcription accuracy and adaptability across diverse typefaces and stylings.

5 Acknowledgments

Rafael Dueire Lins holds a Senior Researcher Grant of CNPq - Brazil.

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