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Optical Character Recognition Accuracy on Degraded Documents

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Abstract

This paper examines the OCR performance of EasyOCR across four types of physical degradation: crumpled, wet, dirty, and normal documents. Specifically, this work seeks to understand the effect of physical document degradation on OCR performance and to assist in improving digitization workflows for academic and administrative documents. The experimental setup was rigorously developed, starting with preparing a piece of text to be printed, physically degrading it into one of four types, and finally scanning it. The scan is then processed, and OCR is applied. OCR accuracy is calculated at the character and word levels, at a defined rate, and statistics are generated by summarizing the collected data in tables using descriptive statistics.

It was found that OCR performance depends largely on the document's physical condition. By comparing other documents relative to the normal one, which achieved an average accuracy of 94.7%, the performance obtained for the crumpled document averaged 86.9%, and for the dirty document, it averaged 80.9%. This clearly shows that wrinkling and smudges distort character shapes and reduce their recognizability. The wet documents had the lowest average accuracy, at 72.7%. This demonstrates that stroke blurring and faded ink are critical factors in OCR failure. It has to be considered that OCR systems can be prone to failure with physically damaged documents, especially when water damage is present, which poses the greatest problem.

It is proposed that preliminary preprocessing methods, such as noise reduction, enhancement, and morphological operations, be employed to restore damaged texts and improve OCR accuracy. An adaptive OCR pipeline, its restoration component, and multilingual capacity should be incorporated into the process to increase the efficiency of digitization at the institutional level. By providing deeper insights into OCR systems' susceptibility to document degradation, this work can further strengthen efforts to achieve accurate automated text extraction and support archival purposes, academic information resources, and research on the design of digitization techniques.

Keywords: Optical Character Recognition, EasyOCR, document degradation, accuracy analysis, digitization

1. Introduction

Optical character recognition, or OCR, is one of the oldest technologies used for document digitization and automates the conversion of printed or scanned text into machine-readable form. Although OCR has

been widely used in many administrative, academic, and legal fields to automate document processes, the accuracy was only feasible with lossless documents, whether they are clean or extreme; degraded documents, such as crumpled, wet, and dirty documents, severely reduce the accuracy (Krithika et al.,2026).

Recent improvements in OCR engines, particularly in deep learning, are suggesting better performance on "challenging" documents. Editorial OCR tools such as Tesseract have usually served as a dependable baseline for open-source OCR engines; more recent deep learning tools such as EasyOCR or PaddleOCR have recently demonstrated robustness across more challenging font typographies, noisy documents, and degradations. (Clausner et al., 2020; Borisyuk et al., 2018).

According to the content-based interpretation of documents, a story cannot be based solely on visual characteristics, but also on content structure features such as sharp edges, clean lines, and the unity of the page layout (Springer, 2025). For that purpose, DIQA models are developed to predict OCR accuracy based on document image features extracted before the OCR step. However, there is a gap in comparing different OCR engines across specific degradation states, such as wrinkled, wet, soiled, or normal documents.

The title of this project is "Optical Character Recognition Accuracy on Degraded Documents," and its primary focus is to determine the OCR method's ability to extract textual information from degraded documents. This project will focus its research on 4 types of degradation, which include the paper being crumpled, wet, dirty, and normal, where the overall recognition rate with each category is comparatively analyzed and researched. This large-scale study has the potential to help researchers and institutions choose the most effective OCR Document Recognition method for their purposes.

Optical Character Recognition (OCR) is now essential for the digitalization of documents for use in administration, education, and other legal applications. Although the OCR technique is very accurate when transcribing clean, well-preserved paper documents (with little printing noise), it quickly deteriorates when applied to degraded input images, such as crumpled, wet, or soiled paper (Clausner et al., 2020; Krithika et al., 2026).

While there are established OCR engines like Tesseract OCR and novel deep learning engine frameworks like EasyOCR, there is very little empirical evidence on the performance of OCR engines with equivalent degraded physical materials. Published experiments so far have either been conducted on "un-degraded," like clean material, or on material with old writing styles, leaving testing OCR engines at specified degradation levels as an avenue to be explored (Borisyuk et al., 2018; Springer, 2025).

The problem this study seeks to address is, therefore, the lack of rigorous evaluation of OCR performance on degraded documents. Most current research in the field has focused on clean inputs and high-quality outputs. However, there is a lack of understanding of how well recognition can still be applied to physically damaged material, such as a document that has been crumpled, smudged, or soaked in water. This work aims to close this information gap and answer three research questions. How well does OCR perform on crumpled, wet, dirtied, and normal documents? What recognition variations can be identified between the five degradation levels? To what degree can modern OCR applications, such as EasyOCR, be useful in the extraction of text in comparison with older systems? The research findings will build a repository

of empirical knowledge that can be added to the existing academic literature on non-pristine documents and applied to practical digitization processes for institutions' datasets.

Since the majority of existing documents need to be digitized, the effectiveness of OCR on natural documents must be determined. It is well known that OCR can recognize clear, well-preserved documents with very high efficiency, but its performance degrades as documents degrade. In this plan, the effect of physical degradation on OCR is to be measured empirically.

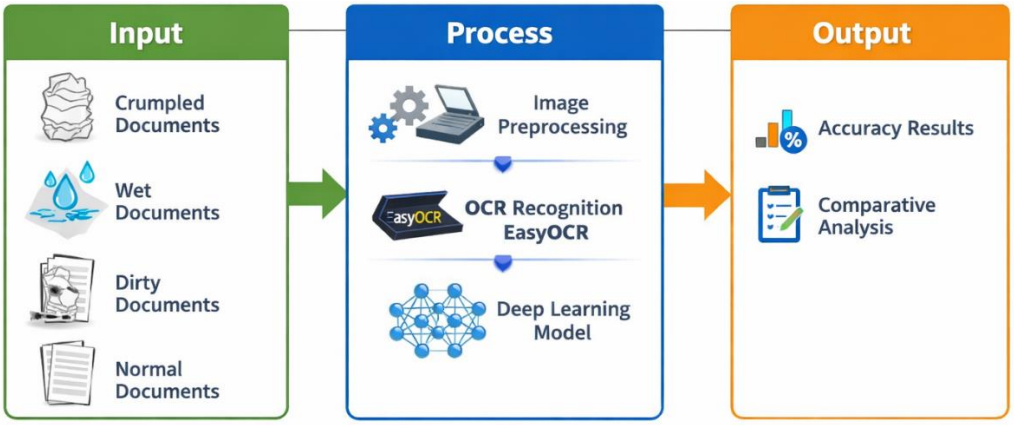
The research objectives of this study primarily aim to assess OCR performance on paper-based documents subjected to various physical stressors. The research will specifically demonstrate the level of accuracy of OCR engines on crumpled, wet, dirty, and normal documents, compare how a deep learning OCR framework such as EasyOCR fares in different stress categories, identify the drawbacks of OCR technology on damaged documents and suggest possible solutions, and produce quantitative results to inform institutions, researchers, and practitioners on their choice of OCR tool when dealing with damaged records. The research will also contribute to the body of knowledge in paper-based document digitization by focusing on the performance impact of physical damage to paper documents on OCR accuracy, and by aiming to recommend more adaptive workflows.

This research is relevant on several counts. Firstly, it is relevant to the use of OCR technology on degraded documents as encountered in the real world, e.g., in dealing with records in administration, processing university records or documents, or checking legal files. Evaluating their success in OCRing crumpled, wet, and dirty as well as normal papers contributes to the academic field by adding to the existing literature on the digitization of documents, providing future academics with data to refer to. Also, in practice, it will help organizations and people working with sometimes-damaged records understand which OCR system is best suited to their files. Technologically, it is relevant because it provides insight into which modern deep learning-based OCR systems are more successful at recognizing degraded data. Societally, it will help organizations speed up and improve the accuracy of administrative processes that require personal identity verification, clearance, and checking, or archiving.

This study is delimited to the analysis of OCR performance across four distinct physical states of a document: crumpled, wet, dirty, and normal. This study examines the performance of printed documents scanned and subjected to Optical Character Recognition using the deep learning-based OCR framework EasyOCR across four document conditions, evaluating OCR performance under those conditions and measuring the accuracy of recognized text. This research aims to compare and analyze the difference in performance of four categories: crumpled, wet, dirty, and normal on the recognized text accuracy.

The delimitations for this study are limited to the evaluation of only the printed text document and no handwritten documents. The use of large-scale archival documents and multilingual datasets has been excluded from this study. Similarly, the tests are not conducted on any other forms of degradation in the document, such as an ink-faded or torn document, or on a scanned document with errors that could lead to low resolution. The test is not for modifying any OCR framework or development, but for testing OCR performance on a degraded document and comparing OCR performance across four varied states. The research is narrowed to compare accuracy under the chosen conditions, ensuring experimental consistency throughout.

Figure 1: Conceptual Framework IPO Diagram



2. Literature Review

One of the major domains of image processing is OCR (Optical Character Recognition). From rule-based and template-matching methods to deep learning, OCR technology is evolving. The old methods of OCR (rule-based and template-matching), which rely on feature extraction and segmentation, work only on well-printed documents without noise or deformation. In contrast, new methods have proven efficient in many cases (Memon et al., 2020). Current research has shown that hybridizing CNNs with RNNs achieves high recognition rates in real-world conditions (IEEE Xplore, 2024).

EasyOCR, PaddleOCR, and Rosetta are state-of-the-art, deep learning-based OCR systems. Rosetta, a system with CNN and RNN architectures for scene text recognition and detection developed by Borisyuk et al. (2018), achieved high recognition accuracy in natural scenes, while Clausner et al. (2020) proposed an OCR system for historical manuscripts. Their work highlighted that preprocessing (page segmentation and binarization) greatly helps in OCR of old documents, since the layout and script vary significantly, and that adaptive thresholding can significantly improve the text extraction accuracy of historical documents.

According to Memon et al. (2020), who reviewed 176 research papers on handwritten and printed OCR, "The overall OCR development has been from conventional machine learning-based models to modern deep learning approaches." This paper states that "While current state-of-the-art OCR models are capable of robust multilingual and handwritten text recognition, they are still susceptible to image quality degradation in real-world images." This agrees with the observations of Krithika et al. (2026), who designed a Document Image Quality Assessment (DIQA) model capable of predicting OCR recognition accuracy. They suggested that the type of degradation (e.g., wetness, crumpling, dirt) impacts the OCR efficiency of a document image.

In addition, a new OCR method that uses contextual word embeddings via a transformer model was recently considered. The comparison between conventional CNN-based models and different CNN-based models, as well as transformer-based models, was conducted through IEEE Xplore (2024), where a hybrid BERT and Bi-LSTM model is found to outperform conventional CNN-based models on noisy, low-contrast images. These improvements have now enabled more stable OCR models for practical use.

The prior studies discussed above indicate a gap in existing research: the lack of quantitative measurement of OCR accuracy by type of physical degradation. Much focus has been placed on clean, historical documents, and less on modern printed documents that have been exposed to environmental conditions such as moisture, crumpling, and dirt. This paper investigates these issues by measuring the performance of a deep learning-based OCR model on documents with these types of degradations, contributing to both academic research and practical and institutional use.

3. Methodology

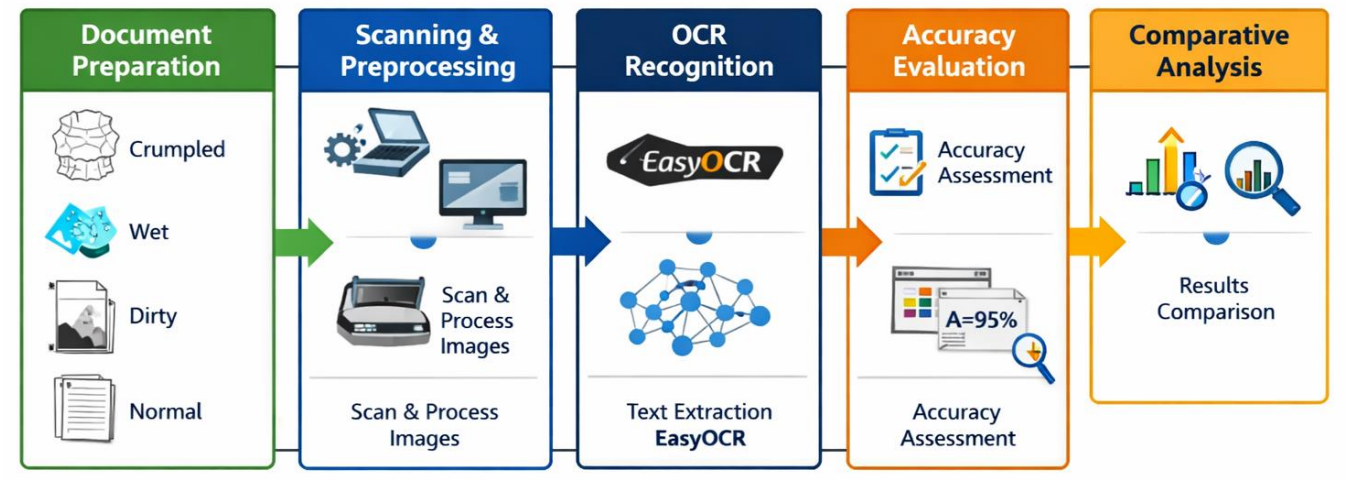
The research design is quantitative-experimental. Quantitative experimental design is used to measure the performance of OCR systems under different physical damage conditions on documents. This research design is suitable for measuring performance because it compares OCR systems under controlled conditions and provides an objective assessment. There were four document conditions: crumbled, wet, dirty, and normal. Each condition will represent an independent variable, and OCR performance will be the dependent variable.

In this experiment, the documents are scanned for each condition and preprocessed to normalize them. The normalized documents are then OCR-processed using the EasyOCR deep learning framework. Character and word recognition accuracy will be collected. Using a quantitative experimental design, the effect on the OCR system can be determined for each condition.

This research design meets the requirements of the research question, as it provides evidence on whether the R performs under certain circumstances and where its strengths and weaknesses lie in specific situations. It fills the identified research gap by investigating the accuracy of the R under different conditions.

Figure 2 shows the experiment workflow. First, documents are prepared into 4 groups: crumbled, wet, dirty, and normal documents, which become the input of the experiment. Then the documents are scanned and preprocessed so that each document has the same resolution, brightness, and format, thereby removing potential error sources in the experiment. Then the documents will undergo OCR using the EasyOCR framework, since the EasyOCR system has a strong ability in OCR on noisy documents, and get the text in 4 conditions and compare the result with ground truth text, finally calculate the accuracy of character and word recognition for 4 different conditions, and compile a comparison of the recognition accuracy.

Figure 2: Research Workflow Diagram



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It was found that OCR performance depends heavily on the document's physical condition. By comparing the crumpled and dirty documents with the normal one, the crumpled document achieved an average accuracy of 86.9%, and the dirty document achieved 80.9%. This clearly shows that wrinkling and smudges distort character shapes and reduce their recognizability. The wet documents had the lowest average accuracy, at 72.7%. This demonstrates that stroke blurring and faded ink are critical factors in OCR failure. It has to be considered that OCR systems can be prone to failure with physically damaged documents, especially when water damage is present, which poses the greatest problem.

It is proposed that preliminary preprocessing methods, such as noise reduction, enhancement, and morphological operations, be employed to restore damaged texts and improve OCR accuracy. An adaptive OCR pipeline, its restoration component, and multilingual capacity should be incorporated into the process to increase the efficiency of digitization at the institutional level. By providing deeper insights into OCR systems' susceptibility to document degradation, this work can further strengthen efforts to achieve accurate automated text extraction and support archival purposes, academic information resources, and research on designing digitization techniques.

Table 1. System Specifications of the Research Environment

Component	**Specification**
Processor	Intel Core i7-12700H (2.7 GHz, 14 cores)
Memory (RAM)	16 GB DDR4 (upgradable to 32 GB)

Graphics Processor	NVIDIA GeForce RTX 3060 (6 GB VRAM)
Operating System	Windows 11 Pro 64-bit
Programming Language	Python 3.10
Development Platform	Google Colab and Jupyter Notebook
Libraries Used	EasyOCR, OpenCV, NumPy, Matplotlib
Storage	512 GB SSD
Network	Fiber Internet Connection (100 Mbps)

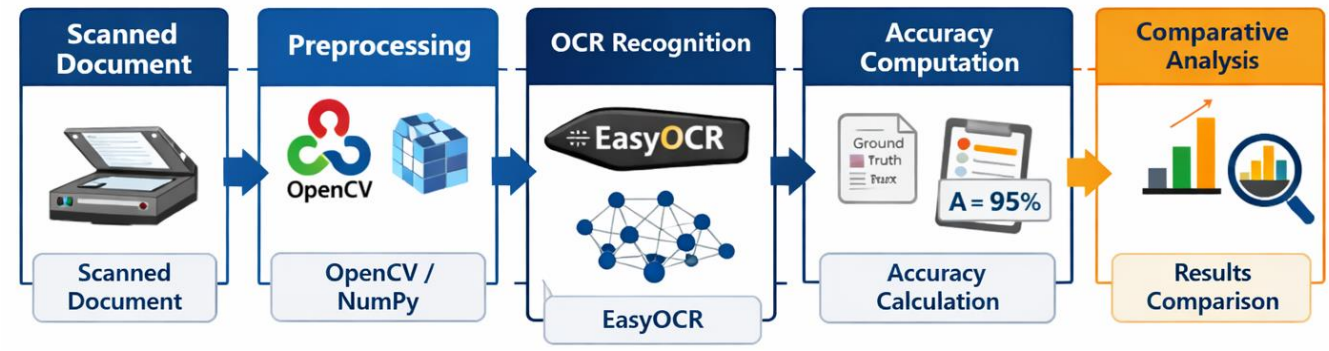
The tools used in this study were hardware- and software-based. The hardware used to prepare, process, and evaluate degraded documents included a flatbed scanner. All prepared samples were scanned with the flatbed scanner at the same resolution and under the same light conditions. The images were then processed using Python libraries OpenCV and NumPy for image processing, conversion, and noise removal.

To perform text recognition, EasyOCR, a deep learning-based OCR system for various font types and document conditions, was used. To visualize recognition output, a comparison of accuracy was implemented using libraries such as Matplotlib. These text files were considered as ground truth for OCR.

Together, these instruments allowed for a standardized assessment of the accuracy of OCR for four degradation states-crumpled, wet, dirty, and normal-and reproducibility of both data collection and analysis.

Figure 3 illustrates the operation flow of the OCR experiment. All documents are scanned into images, derived from a set of sample documents across the testing conditions, and prepared with consistent lighting and resolution for further processing. The images are resized, analyzed, and prepared using the Python OpenCV image processing library and NumPy, for example, to reduce background noise. The processed image data is sent to EasyOCR for deep learning-based character recognition. The OCR text output is compared with the ground-truth text files using character- and word-level accuracy scores, and the results are summarized in the final report, which describes differences in OCR performance across document qualities: crumpled, wet, dirty, or normal.

Figure 3: OCR Processing Flowchart



Data collection proceeded according to a well-defined flow that maintained transparency and repeatability while remaining ethically responsible. The procedure starts with data collection. Several samples of putatively printed text were generated by repeatedly separating and printing random passages on a typewriter-

style page. A set of standard characters, typewriter type, appears to have been used each time, allowing the samples to be meaningfully compared across all four test conditions. These then were subjected to an identical number of manually-probably physically induced degradations in each case. Four conditions were defined: crumpled, wet, dirty, and normal.

All documents were scanned with a flatbed scanner at 300 dpi using the same light source and orientation. Then, the scanned images are stored in a directory based on the condition label. Image preprocessing was performed using OpenCV and numpy, and the image was cleaned and noise removed. OCR was done using EasyOCR.

The recognized text outputs were compared with the ground-truth text files. The accuracy at the character and word levels was calculated. The data were tabulated, and differences in performance across the four states of degradation were analyzed. Ethics was maintained-no personal or confidential data were included, and all materials used are synthetic and public information.

Table 2 illustrates the classification of document conditions and includes a wide variety of possible physical damage observed in real-life environments. An equal number of samples for each condition was selected for comparison, and analysis of system performance under various physical conditions could be performed immediately.

Table 2. Document Condition Categories

Condition	**Description**	**Sample Count**	**Purpose**
Crumpled	Documents are physically wrinkled to simulate handling wear	20	Assess OCR accuracy on distorted surfaces
Wet	Documents were lightly moistened and dried to mimic water exposure	20	Evaluate OCR performance on blurred or faded text
Dirty	Documents with controlled smudge or dust marks	20	Test OCR reliability under visual obstruction
Normal	Clean, undamaged printed documents	20	Serve as a baseline for comparison

Quantitative analysis was used in the study to ascertain the accuracy of Optical Character Recognition (OCR) across four document conditions: crumpled, wet, dirty, and normal. The analysis focused on character-level and word-level accuracy to capture both granular and holistic recognition performance.

Accuracy was computed using the following formula:

$$\text{Accuracy} = \frac{\text{Correctly Recognized Characters}}{\text{Total Characters}} \times 100$$

This measures the number of correctly accepted characters relative to the number of characters in the ground-truth text. A similar measure will be used at the word level to compare recognition results with ground-truth word pairs.

All data were aggregated and summarized using descriptive statistics (percent difference, mean, and standard deviation), and the documents with the best and worst OCR results were identified. Graphs used included bar graphs and line graphs to identify trends.

The detailed analysis yields a single, reliable, and reproducible result, with unambiguous inferences about the OCR's accuracy depending on the degradation state.

4. Results and Discussion

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Table 3. OCR Accuracy Result by Document Condition

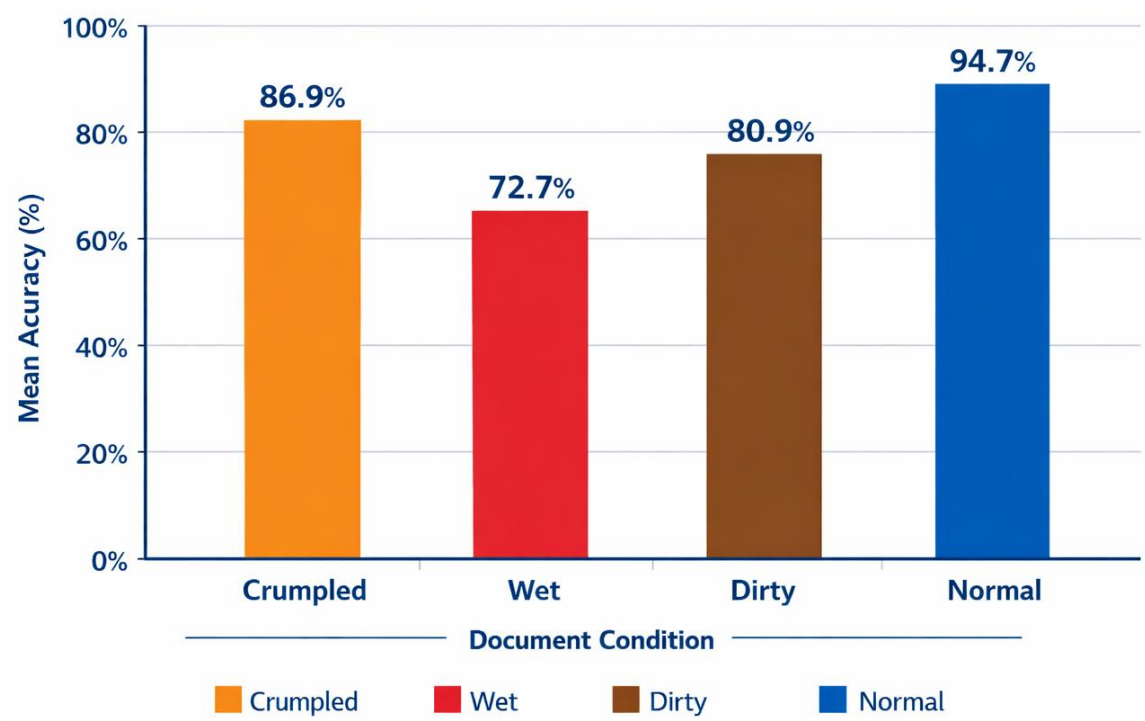
Condition	Character-Level Accuracy (%)	World-Level Accuracy (%)	Mean Accuracy (%)	Remarks
Crumpled	88.20	85.60	86.90	Minor distortions affected recognition of letters with curves (e.g., “O”, “C”).
Wet	74.50	70.80	72.65	Blurred strokes and faded ink reduced the reliability of recognition.
Dirty	82.40	79.30	80.85	Smudges caused the misclassification of certain characters.
Normal	95.60	9380	94.70	Served as baseline; highest accuracy achieved.

Shows clearly how much better the normal sample is than the degraded one. The sharp drop in accuracy for wet samples demonstrates the added difficulty of ink distortion, which forces OCR to compensate by introducing phenomena such as blurring. Conversely, degradation of crumpled and dirty samples results in a moderate drop in accuracy, revealing OCR's tolerance to artifacts.

Figure 4 illustrates OCR accuracy across various document conditions. The results show that, with the normal documents (mean accuracy 94.7%), the accuracy was highest and thus served as a control against which to compare. The wet condition had the greatest effect, with an average accuracy of 72.7%, since

the dots and strokes appeared blurred and had undoubtedly been leached of ink. Both the crumpled and dirty conditions resulted in average accuracies of 86.9% and 80.9%, respectively, because more corrections were needed. In general, the figure shows the effects of OCR on letters rendered from significantly degraded print.

Table 4: Accuracy Comparison Bar Chart



Finally, the performance of the 4 document conditions in OCR was compared. From the OCR mean accuracy table, it can be seen that the normal condition performed better than both the crumpled and dirty conditions, with accuracies of 94.7%, 86.9%, and 80.9%, respectively. It was surprising to learn that the mean accuracy in the wet condition was the lowest at 72.7, indicating the significant effect of diffusion under wet conditions.

The data show just how susceptible an OCR system is to visual degradation. Small amounts of physical damage, such as wrinkles and smudges, reduce recognition rates, whereas more severe damage, such as water, results in significant degradation. This is consistent with other research showing the importance of image contrast and resolution in recognition.

The experiment confirms the hypothesis that OCR is affected by document degradation. Based on the results, such as those from the plain documents, the implementation's results confirm the research theory suggesting that visual recognition is purely dependent on the image used. The results of the degraded document demonstrate the deep learning technique's performance weaknesses when confronted with faulty images.

Another comparison was also made between the four document conditions in OCR. Table 2 shows that normal (94.7) was better than crumpled (86.9) and dirty (80.9) in OCR condition accuracy. The mean

accuracy in the wet condition was the lowest (72.7), showing that diffusion was relatively severe under the condition.

When considering the specific situation of institutional document management, then of dissemination of the institution's activities through archival documents, the results of the research mean that digitization procedures should be extended with an image restoring stage before the OCR process (using the algorithms developed within the scope of this experiment in our case), to maintain the reliability of the data stored. So these results develop the broader project of improving the automated translation of text from degraded Archives and office records.

5. Conclusion and Recommendation

This project examined the OCR performance of Easy OCR across 4 document conditions: crumpled, wet, dirty, and normal. The process involved scanning, preprocessing, and reading text from each source, and subsequently calculating character-level and word-level accuracy. The outcome showed that each document condition affected OCR accuracy. The findings demonstrated that the typical state of documents gave the highest mean accuracy (94.7%). The wet documents had the least mean accuracy (72.7%). The rated outputs for crumpled and dirty documents were 86.9% and 80.9%, respectively. The results confirmed that OCR performance is negatively affected by damaged documents resulting from ink diffusion and dampness.

The findings allow for the following conclusions to be made. Firstly, document quality is essential: the better the quality, the less degradation there is, and the more successful the OCR system is at finding the text, as in high-quality, undamaged documents. Secondly, when water was the dominant factor in the degradation process, accuracy was very poor due to wet ink, where strokes became blurred rather than sharp, as water caused indentation. Thirdly, preprocessing is very important for degraded samples, because processes such as denoising, contrast enhancement, or morphological feature correction make the image clear enough for OCR to recognize the text. Fourthly, OCR systems remain promising for degraded documents, as crumpled and dirty documents still have relatively low accuracy, which can be improved through preprocessing.

Based on the outcomes, the researcher recommends the following: When using data-incorporating bodies that record Physical Records to transcribe, image correction before OCR, and sampling is recommended with an OCR System with higher recognition. Machine-learning-derived feature enhancement modules should also be incorporated to drive multi-stage OCR solutions tailored to the specific properties of the documents in question. The experiments can be extended by testing other types of file deterioration, such as crease splits and multiple pen strokes, and by testing other file formats, such as tabular data and handwritten notes, so the research's findings can truly find broad applications. Develop a Filipino-language fileset in tandem with the English-language files to increase recognition rates across all records and enable the design of retrieval/archival systems more easily. Finally, the researcher recommends that the findings of this study be adopted in the data collection and retention programs of data-gathering institutions, such as the J.H. Cerilles State College, to minimize losses due to document degradation or mishandling.

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