Application of an Automated OCR System for Data Processing of Banking Electronic Transfer Slips: A Case Study of a Non-Profit Organization in Thailand

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***Abstract*—This article presents an application of an automated optical character recognition system developed to process transactional data from electronic bank transfer slips. Target users include small businesses, non-profit organizations, and individuals who manually process electronic transfer slips from customers. The objective is to help operators screen transfer slips, enter data, and correct and verify it using a post-OCR algorithm. The Main contribution of this study is the development of the integrated man-machine system, consisting of an OCR tool and rule-based post-OCR scripts that generate data as input for operators' final verification. Challenges include incorrect transfer slips, low-quality slip images, and diverse slip formats from various mobile banking applications. A numerical test of the automated OCR system uses a case study dataset from a non-profit organization. The dataset contains 2,603 submitted transfer-slip images from 10,924 transactions over about one month of operations. The results indicate that the OCR system can achieve 78% accuracy in processing the slips and 90% accuracy in monetary values. With final verification by operators, the system achieves 100% accuracy, saving over 41 hours of operator time.**

***Index Terms*—Optical Character Recognition (OCR), Man-Machine System, Electronic Transfer Slip, Transactional Data, Mobile Banking Application, Operations Efficiency Improvement**

I. Introduction

This article presents the development of an automated Optical Character Recognition (OCR) system specifically to process data from electronic transfer slips in mobile banking applications. The motivation comes from a non-profit organization's need to process and verify many financial transactions daily by hand. In the past decade, businesses, industries, and society have integrated digital technology into daily activities, such as banking, shopping, and donations. The widespread adoption of mobile banking has shifted consumer behavior across diverse demographic groups, including adolescents, working professionals, and older adults. The expansion of online commerce through mobile applications and social media platforms has significantly accelerated the volume of digital financial activities.

In today's mobile banking practices, senders typically provide recipients with proof of payment, most commonly in the form of electronic transfer slips automatically generated by mobile banking applications. These digital documents serve as preliminary evidence of financial transactions and require recipients to manually verify transaction details before executing subsequent operations, such as dispatching goods, confirming delivery schedules, or maintaining financial records. However, the manual verification process poses several operational challenges. It is inherently time-consuming and prone to human error, particularly under high transaction volumes. The task's repetitiveness, combined with cognitive fatigue, increases the likelihood of misprocessing and can result in financial errors and/or significant delays. These issues underscore the need for more efficient, automated verification mechanisms to improve transaction reliability and streamline operational workflows.

To mitigate the inefficiencies associated with manual verification in financial transactions, OCR technology has gained increasing interest as a means of automating the reading and extraction of relevant data from digital financial documents. While OCR can

enhance operational efficiency, its adoption among small-scale enterprises and individual users remains constrained by technical and practical challenges. First, OCR performance depends on image quality. Documents captured at low resolution, with visible folds, shadowing, or glare, often result in inaccurate data extraction. Additionally, diverse transfer slip formats issued by different financial institutions pose a significant barrier to developing universally compatible OCR systems. In addition, conventional OCR algorithms lack contextual awareness and, to some extent, cannot reliably differentiate between similar-looking data elements, such as account numbers and monetary values, or identify essential fields based on functional relevance rather than visual characteristics. These limitations underscore the necessity for more sophisticated, context-specific OCR systems or tools to improve reliability and generalizability across diverse use cases.

Although many free OCR tools are available online, they typically allow users to process only one image at a time. This constraint makes them insufficient for high-volume use cases, such as extracting data from multiple electronic transfer slips. Moreover, these tools often output unstructured text extracted in a linear sequence based on the visual arrangement of text within the image. This format lacks proper organization and does not facilitate efficient data retrieval or further analysis.

For practical applications, particularly in financial workflows, accurate extraction, recording, and storage of information in structured formats such as spreadsheets or databases are often required. Without structured data management, users face inefficiencies when handling large datasets, including duplication risks and difficulty retrieving specific transaction details. Furthermore, most standard OCR tools lack verification mechanisms to cross-reference extracted data with internal records, such as invoices or prior transaction logs. This limitation compromises data integrity and hinders downstream operational accuracy. In addition, reliance on cloud-based or third-party OCR platforms raises serious privacy concerns, as electronic transfer slips frequently contain sensitive personal and financial information, such as account details, sender identities, and transaction amounts. While commercial OCR solutions with enhanced capabilities exist, implementing them often requires substantial financial investment in licensing and customization. Alternatively, developing in-house OCR tools or systems requires specialized technical expertise and significant resources, which may be prohibitive for small-scale businesses, non-profit organizations, and individual users.

In this article, we develop an automated OCR system that integrates OCR technology for image processing and data entry with human judgment for data verification. The system balances efficiency, accuracy, and reliability. By implementing rule-based verification post-OCR scripts, the system facilitates rapid extraction of transaction details, such as sender and recipient information, account numbers, transaction amounts, and timestamps, while allowing human operators to perform targeted verification and review of key information when the OCR system detects anomalies or discrepancies. This verification model reduces cognitive load on users and improves scalability across diverse operational settings. In particular, the OCR system supports customization to specific organizational needs, making it feasible to deploy in resource-constrained environments. Additionally, by storing extracted and validated data in structured formats compatible with spreadsheet applications or database systems, the approach supports traceability, audit readiness, and integration into existing financial workflows. Developing such a system also supports broader efforts to democratize access to intelligent financial tools by providing smaller organizations and general users with affordable, practical solutions for handling critical documentation tasks.

Although OCR technology has advanced considerably and has been successfully applied to financial documents such as invoices, receipts, and bank slips, existing research has primarily focused on improving text detection and recognition accuracy through machine learning and deep learning techniques. Comparatively less attention has been given to developing integrated systems that support the complete operational workflow required for transaction verification, including automated data extraction, structured data management, rule-based validation, and efficient human-assisted verification. This study addresses this gap by developing a customizable OCR-based transaction processing system that integrates these components into a unified workflow for electronic transfer slips generated by mobile banking applications. Beyond improving recognition performance, the proposed system emphasizes practical deployment by supporting efficient processing of large transaction volumes, structured record management, and privacy-preserving operation suitable for resource-constrained organizations and individual users.

II. Literature Review

This section contains recent developments in OCR technology and its implementation across various fields. This section reviews research studies on OCR for handwritten text to identify ongoing research directions and trends [1]. Because OCR systems digitize handwritten and printed text, the outputs often contain inaccuracies, necessitating post-processing or post-OCR techniques to correct errors. [2] This

survey reviews cutting-edge post-OCR methods, evaluation metrics, and available datasets and tools. These methods are categorized as manual, (semi-) automatic, and automatic techniques, further divided into isolated-word and context-specific approaches. To address language-specific challenges, a mask Region-Based Convolutional Neural Network (R-CNN)-based model was proposed to detect text bounding boxes in Thai-language documents such as ID cards, passports, and bank slips [3]. This approach outperforms the Character-Region Awareness for Text Detection (CRAFT) model in both accuracy and efficiency, contributing to improving OCR preprocessing for non-Latin scripts. [4] proposed an OCR framework for Vietnamese identity cards. The authors use a pretrained multi-language Connectionist Text Proposal Network (CTPN) to crop all text regions in both training and testing images. To capture Vietnamese tone marks, they expand the cropped regions by 20%. A customized Convolutional Recurrent Neural Network (CRNN) is then employed for recognition and model training. The framework achieves over 96.7% character-level accuracy and 89.7% word-level accuracy.

In finance and banking, a hybrid of OCR and artificial intelligence/machine learning has gained prominence to streamline labor-intensive accounting processes. For example, OCR has been applied to recognize digits and capital letters in cheque processing, achieving high accuracy using a model trained on the extended Modified National Institute of Standards and Technology (EMNIST) dataset [5]. [6] Extended the application of OCR to financial reimbursement. The study presents a smartphone-based intelligent reimbursement system that uses deep learning to automate invoice processing. The system achieves an average OCR accuracy of 99.1% and employs a regular matching and Recursive Segmentation (RMRS) algorithm.

Beyond identity verification and reimbursement, a growing body of research explores OCR for financial ticket recognition, including receipts and invoices; see [7]-[9]. In addition, the challenge of diverse financial ticket layouts and mixed Chinese-English text was addressed by proposing an all-content recognition method that combines a Pixel Aggregation Network (PAN) for text detection with a Financial Ticket Character Recognition Framework (FTCRF) based on faster R-CNN [10]. Their system achieves 91.75% accuracy at the string level and 87% at the whole-ticket level, demonstrating how OCR overcomes ticket variability to enhance automation and compliance in financial documentation. Nacsoft OCR, a deep learning-based engine optimized for Turkish receipts, was later developed [11]. The system combines ResNet34-Unet for receipt area detection, YOLOv4 for text localization, and a C-RNN for word recognition. Nacsoft OCR achieves the highest accuracy on Turkish receipts (93.89% Character Error Rate CER) and competitive results on English datasets, while also offering faster processing speeds. In retail applications, OCR supports tasks such as reading receipts, interpreting price tags, and capturing inventory labels, reducing manual input and improving operational speed. A transformer-based OCR model, SRRNet, is introduced in [12] to recognize text from shopping receipts while preserving the two-dimensional spatial layout. SRRNet achieves high accuracy on large-scale receipt datasets and public scene-text benchmarks, effectively handling distorted and irregular text. Similarly, [13] integrates OCR into a multimodal product recognition system for real-time inventory tracking, automated checkout, and stock monitoring, achieving 94.6% accuracy and demonstrating OCR's utility in retail automation for standardizing extracted data.

Advanced post-OCR techniques are essential for extracting structured data from documents with complex layouts. In [14], OCRMiner, a rule-based system, is proposed to identify key invoice fields by leveraging both textual and layout features. [15] explores language-specific customization, addressing limitations of standard OCR engines like Tesseract for Turkish-language invoices. The proposed system integrates template-matching techniques and significantly outperforms baseline models, validating the importance of language adaptation. However, challenges remain in generalizing across diverse invoice templates and image qualities, highlighting broader issues such as sensitivity to layout variations, visual inconsistencies, and low-resolution scans. Data quality remains a critical constraint in OCR-based systems.

[16] presents a web-based invoice processing platform featuring an annotation tool and an extraction module. The system utilizes OpenCV for image preprocessing and a fine-tuned Tesseract engine for text extraction, achieving 85-95% accuracy across more than 25 invoice formats. In [17], multimodal models are evaluated by fine-tuning LayoutXLM on OCR-extracted tokens from 1,503 scanned German Company records. The model outperforms unimodal and large language model baselines in document classification tasks.

In the retail domain, [18] addresses OCR-induced errors in product names from receipts by introducing a graph-based agglomerative clustering method using Levenshtein distance to group similar name variants. Tested on synthetic data, the method effectively identifies coarse-grained relationships such as product categories and families. Additionally, [19] combines OCR output with text classification and Mondrian conformal prediction to detect anomalies like barcode switching and mis-scans in grocery store

data. The system demonstrates OCR's value not only in text extraction but also as a reliable foundation for anomaly detection and classification, helping reduce shrinkage loss.

Overall, the reviewed studies demonstrate that recent OCR research has achieved substantial improvements in text detection and recognition accuracy through deep learning, transformer-based models, language-specific adaptations, and advanced post-processing techniques. However, most existing studies evaluate OCR performance primarily at the character, word, or document level, emphasizing recognition accuracy for specific document types and benchmark datasets. Comparatively less attention has been given to developing integrated transaction-processing systems that combine OCR with rule-based validation, structured data management, and human-assisted verification to support real-world financial workflows. Furthermore, many reported systems are designed for specific document templates or languages, which may limit their adaptability to diverse electronic transfer slips generated by different banking applications. These observations indicate the need for a practical OCR-based system that extends beyond text recognition to support reliable transaction verification and structured financial data management in real-world applications.

III. Problem Statement

The design, development, and implementation of the automated data processing system utilize OCR technology to extract and manage information from electronic fund transfer slips. The system's primary functions include extraction, preliminary validation, and structured data writing from transfer slips. The test data are from a non-profit organization in Thailand, referred to as "the user." The organization receives financial contributions, referred to as "donations," from a wide range of individual and institutional donors across Thailand.

Donations are typically made through two channels: a direct deposit over the counter at a bank or through a mobile banking application. With the mobile banking application, a donor can choose a direct transfer to the user's savings account (select the user's bank, enter the account number, and specify the transfer amount), or an electronic donation, so-called "e-donation," by scanning a QR code that the bank issues to the user. The Revenue Department, Ministry of Finance, facilitates e-donations through an official platform that enables donors to claim tax exemptions for donations to registered non-profit entities. After completing a transaction on the mobile banking application, the system automatically generates an electronic transfer slip and stores it on the donor's mobile device.

A non-profit organization can manage multiple good cause projects and initiatives, prompting donors to specify the intended purpose of their donations. A donor can choose to submit their transfer slip to the user and state the donation's intended purpose. In other words, the user must accurately verify and categorize a submitted transfer slip according to its designated donation purpose. In contrast, a transaction made without submitting the slip is counted as a general donation, which the user can use for any purpose.

This article's case study uses one specific donation purpose as a representative example to illustrate the operational challenges. To count as a donation for the purpose, the donor must state their intention and submit an image of the electronic transfer slip through the user's social media channels, Facebook or Line Applications. On any given day, fewer slips are usually submitted than the total number of donations made. To use the donation funds for the intended purpose, the user must accurately total the donation amounts from the submitted slips. Currently, this process is performed manually by human operators, who have other full-time job and only help out as volunteers The OCR system is, therefore, developed to perform preliminary tasks of screening, verifying, and recording critical transaction details, including the date and time of transfer, the accuracy of the user's bank and account number, and the donation amount to assist human operators, to improve efficiency of the process.

IV. Data Collection and Operational Challenges

The OCR system inputs image files of transfer slips generated by mobile banking applications. Figs. 1 to 4 show examples of electronic transfer slips from various mobile banking applications that the OCR system and post-OCR scripts can process easily. Key information identifying the user and the donor is blurred for confidentiality reasons. Transfer slips vary in format because each bank uses its own slip design. Additionally, most mobile banking applications permit users to personalize the background of their transfer slips, further contributing to format variability. The size and quality of these images also vary considerably, largely depending on the donors' technical proficiency.

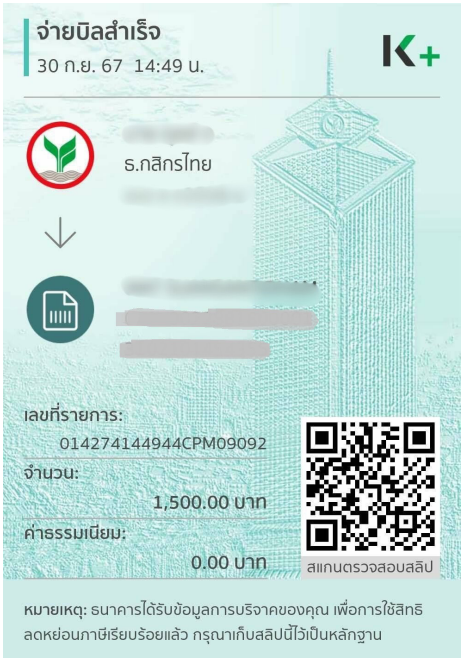

Fig 1. Examples of electronic transfer slips from the K-Bank mobile application

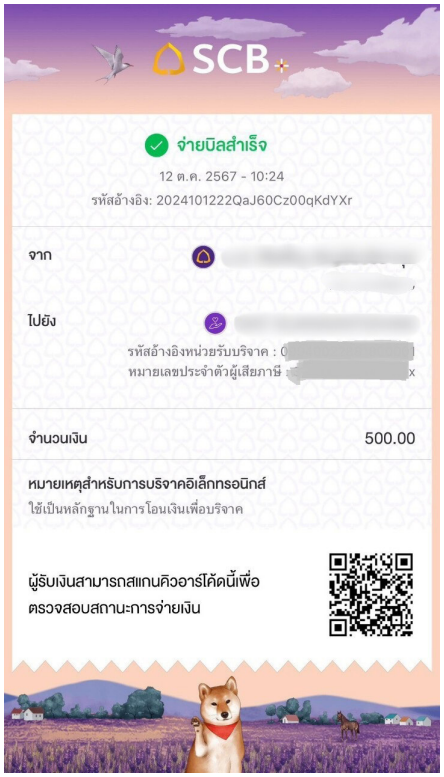

Fig 2. Examples of electronic transfer slips from the SCB mobile application



Fig 3. Examples of electronic transfer slips from the KTB mobile application



Fig 4. Examples of electronic transfer slips from the K-Bank mobile application with a personalized background

In addition, donors with limited experience using mobile devices often submit low-resolution images with small file sizes, resulting in unclear or partially legible text and numbers. Moreover, some submitted slips are not generated by the mobile banking application. Instead, some donors manually take pictures using their devices' camera function and submit the images as proof of transactions. Representative examples of such transfer slips are shown in Figs. 5 to 8.

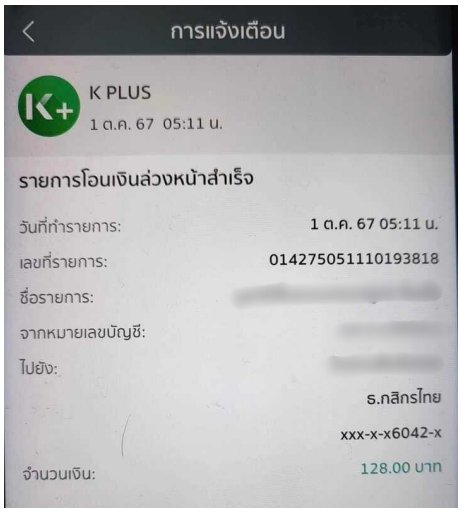

Fig 5. Picture of a complete transaction taken from the screen of a mobile banking application



Fig 6. Picture of a printed transfer slip from an ATM

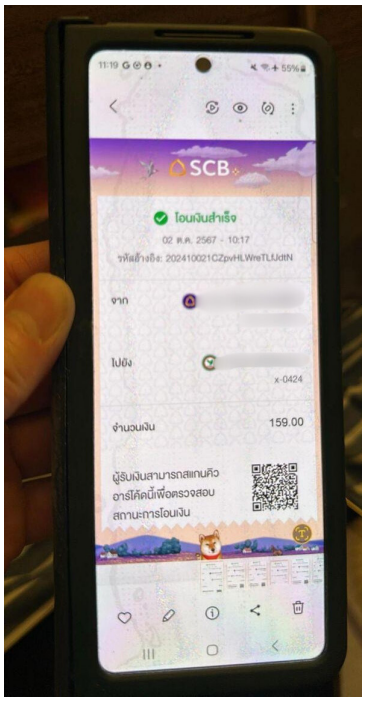

Fig 7. A picture showing the whole mobile device

As shown in the figures, some submitted transfer slips not generated by mobile banking applications are highly inconsistent and have poor image quality, which directly impacts the OCR system's performance.

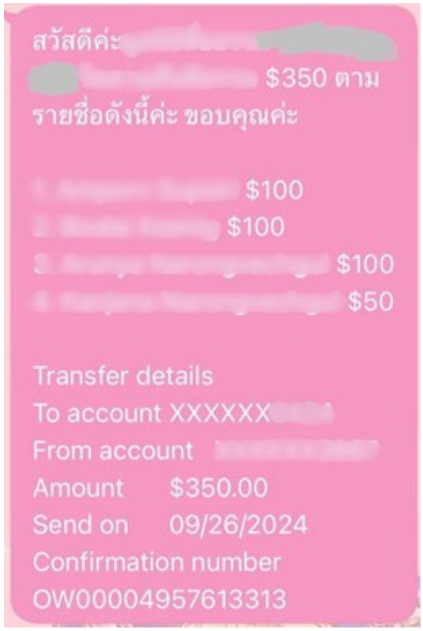

Fig 8. Picture of an SMS notification via chat message with a USD amount instead of a THB amount

In Fig. 5, instead of downloading or sending the transfer slip directly from their mobile device, the donor took a picture of the mobile banking application screen showing a completed transaction, which results in poor image quality. Fig. 6 shows a printed transfer slip from an ATM. Fig. 7 is another example of the donor using a different mobile device to take a picture of their own mobile device, showing the mobile banking application screen with a completed transaction. Fig. 8 shows a text message stating that four donors are making four donations in USD.

In manual verification scenarios, poor image quality or incorrect slips can prolong inspection times, complicate the review process, and contribute to operator fatigue. With an automated OCR system, low-quality images may lead to recognition errors or incomplete data extraction. Preliminary analysis reveals that low-resolution and partially legible images typically have file sizes below 100 kilobytes (kB).

The user collects transfer slip images submitted by donors through social media platforms daily. The user reviews, records, and stores these images in a folder categorized by the slip submission date. However, the transaction date indicated on the slip may differ from the submission date, as donors do not always submit their slips on the same day after completing a transaction. This discrepancy often results in mismatches between the actual transaction date and the date of the folder used for image storage. Following the collection and review process, several operational challenges have been identified:

- High number of image submissions: Each day, there are over 300 transactions. Approximately 90 transfer slips are received, with over ten formats varying across different banks.
- Low image quality: Many slips are difficult to read due to poor resolution. Some submissions are screenshots with blurred text and figures rather than the original digital files.
- Incorrect account number: Some slips contain transactions directed to incorrect bank accounts.
- Duplicate submissions: Repeated uploads of the same transfer slip can lead to double-counting and errors in data entry and verification.

In the case study dataset, 2,603 slips were submitted out of 10,924 total transactions (24%). Each channel has approximately the same number of transactions. The table shows that the number of submitted slips on each day can vary significantly, from a minimum of 13 slips on 26 September 2024 to a maximum of 726 slips on 19 October 2024, which is the day before a particular event organized by the user (i.e., the reason the number of submitted slips surges). The user and its operators face the challenge that all slips must be processed manually, and many arrive the day before an important event. Table I shows the number of transactions from each donation channel and the number of submitted slips.

TABLE I
NUMBER OF TRANSACTIONS IN EACH CHANNEL AND NUMBER OF SUBMITTED SLIPS IN THE CASE STUDY DATASET

Date	e-Donation (Transactions)	Direct Transfer (Transactions)	Total Number of Transactions	Number of Submitted Slips	Percentage
21 September 24	622	256	878	271	31%
22 September 24	248	196	444	117	26%
23 September 24	170	186	356	110	31%
24 September 24	117	147	264	54	20%
25 September 24	192	217	409	68	17%
26 September 24	95	138	233	13	6%
27 September 24	85	137	222	66	30%
28 September 24	105	145	250	32	13%
29 September 24	132	142	274	19	7%
30 September 24	102	160	262	17	6%
1 October 24	100	212	312	90	29%
2 October 24	106	204	310	42	14%
3 October 24	74	147	221	30	14%
4 October 24	91	136	227	35	15%
5 October 24	130	153	283	34	12%
6 October 24	106	148	254	40	16%

TABLE I
NUMBER OF TRANSACTIONS IN EACH CHANNEL AND NUMBER OF SUBMITTED SLIPS IN THE CASE STUDY DATASET (CON.)

Date	e-Donation (Transactions)	Direct Transfer (Transactions)	Total Number of Transactions	Number of Submitted Slips	Percentage
7 October 24	87	133	220	42	19%
8 October 24	73	148	221	26	12%
9 October 24	65	144	209	44	21%
10 October 24	105	161	266	38	14%
11 October 24	75	126	201	39	19%
12 October 24	121	132	253	41	16%
13 October 24	169	180	349	46	13%
14 October 24	169	155	324	112	35%
15 October 24	122	171	293	92	31%
16 October 24	144	189	333	95	29%
17 October 24	208	239	447	100	22%
18 October 24	279	189	468	164	35%
19 October 24	1451	690	2,141	726	34%
Total	**5543**	**5381**	**10,924**	**2,603**	**24%**

V. DESCRIPTION OF THE OCR SYSTEM

The automated OCR system is developed using Python. EasyOCR was selected as the OCR engine because it is an open-source framework that supports multilingual text recognition, including Thai and English, without requiring language-specific model development. EasyOCR framework provides pretrained deep learning models that can be readily integrated into Python applications, making it suitable for rapid system development and deployment. Furthermore, EasyOCR performs robustly on digital images captured from mobile devices and offers sufficient recognition accuracy for electronic transfer slips while allowing local execution without relying on cloud-based services. This local processing capability is important for preserving the privacy of sensitive financial information contained in transfer slips. Fig. 9 presents the system logic diagram. The system description uses the notation below.

Notation

l: Index of image files

m: The total number of images for a given day, $l = 1, 2, \ldots, m$

Notation (Continued)

i: Index of extracted text elements in a list called *test*, where an element is a set of strings read by the OCR

n: The total number of elements, $i = 1, 2, \ldots, n$

count: Counter for image files

file: A list containing the image file names

test: Raw data of elements read from slips by the OCR

info: A list containing important elements to be written to a spreadsheet, *info* = [Name, ID, Amount, Time]

main: A master list containing all elements in *info* read from all slips on a given day

suc_read: A list containing file names that the OCR can successfully read

failed_read: A list containing file names that the OCR cannot accurately read

The system description in Fig. 3 is written as pseudo-code as follows:

The system begins by importing six required open-source libraries of OCR tools (i.e., *easyOCR*), data management, and file management.

The system loads a function (i.e., a post-OCR script) called Tester, created specifically for this system. It post-processes the output by removing unwanted text and correcting text read by *the easyOCR* package.

- To record the computational time required to process a set of images, the *timer* is triggered to start.

- Next, the folder containing all images to be processed for a given day is loaded.

- Six lists, including *file*, *test*, *info*, *main*, *suc_read*, and *failed_read*, are initialized

- Index of image files, *l*, is set to zero.

- The system checks whether all images have been processed, i.e., $l > m$. If not, the system proceeds to (A); otherwise, it goes to (B).

(A) There are images remaining to be processed:

- The current image file, indexed by number *l*, is processed by the easyOCR tool, and the extracted elements are stored in the list called *test*. The index *i*

for the extracted text elements in *test* and the image-file counter are set to zero.

- The name of the current file being processed is recorded in the first entry of the list *info*, and the *count* is increased by one.

- [Checkpo[Checkpoint 1] The system checks whether all the elements are recorded, i.e., $i > n$. If $i > n$, then proceed to [Checkpoint 2]. Otherwise, it proceeds to the *post-OCR* scripts.

- [Checkpoint 2] The system checks whether the information in the list *info* is complete.

• Complete information in the *info* is recorded as a successful reading by the OCR tool, where the file name of the current image is recorded in the *suc_read* list.

• Incomplete information in the *info* is recorded as a failed reading by the easyOCR tool, where the file name of the current image is recorded in the *failed_read* list.

• Information (complete or incomplete) read by easyOCR is appended to the *main* list. The *test* list and *info* list are reset to be empty lists, ready for the next image to be processed.

• Index *l* is increased by one, and the OCR tool proceeds to the next image.

- Post-OCR scripts: If i<n, i.e., not all the elements are already recorded, then the post-OCR script proceeds to perform the following checkpoints sequentially:

• [Checkpoint 3] whether the currently read element's data type is a date type. If it is a date type, the system records the date data in the 4th entry of the info list and increases the count by one. Increment i, and return to [Checkpoint 1]. Otherwise, go to [Checkpoint 4].

• [Checkpoint 4] The system checks whether the current element is the last, i.e., *count* = 4. If so, the system proceeds to [Checkpoint 2]. If not, it proceeds to [Checkpoint 5].

[Checkpoint 5] checks whether the currently read element contains the correct account number, i.e., the read element contains a 13-digit string that represents an e-donation (i.e., 099x00xxxxxxx, note that X marks are used to mask the non-profit organization ID), or contains a 10-digit string that represents a direct transfer to a savings account (i.e., xxx-x-x6042-x). If it is the correct account information, the system records the account number data in the 2nd entry of the info list and increases the count by one. The system increments i and returns to [Checkpoint 1]. Otherwise, go to [Checkpoint 6].

• [Checkpoint 6] The system checks whether the current element is the last, i.e., *count* = 4. If so, the system proceeds to [Checkpoint 2]. If not, it proceeds to [Checkpoint 7].

• [Checkpoint 7] The system checks whether the currently read element is a valid donation amount. The Tester function performs this check. If it is a valid amount, then the *amount* data is recorded in the 3rd entry of the *info* list, and the *count* is increased by one. Then, increment i, and return to [Checkpoint 1]. Otherwise, go to [Checkpoint 8].

• [Checkpoint 8] The system checks whether the current element is the last, i.e., *count* = 4. If so, the system proceeds to [Checkpoint 2]. If not, the system increases index i by one and returns to [Checkpoint 1].

(A) All images are already processed:

- Two sub-folders, [Successful Reading] and [Failed Reading], are created to essentially separate the image files, which are successfully read and unsuccessfully read, to facilitate the operators during verification of the transfer slips accordingly.

- All the image files that the OCR tool and post-OCR scripts can process completely, whose file names are recorded in the list *suc_read*, are copied to the [Successful Reading] folder.

- In addition, all the image files that cannot be read completely, whose file names are kept in the list *failed_read*, are copied to the [Failed Reading] folder.

- All the texts processed by the system are recorded into a spreadsheet file, ready to be verified by the operators.

- Finally, the *timer* is stopped, and the computational time is recorded.

In addition, the *Tester* function corrects the donation amount based on common errors read by *easyOCR,* as listed below.

-Replace the English alphabet "l" with a numeric "1" (one)

- Replace the English alphabet "n" with the Thai alphabet "ท"

- Replace the English alphabet "o" with a numeric "0" (zero)

- Replace the English alphabet "s" with a numeric "5" (five)

- Replace the punctuation mark comma "," with a punctuation mark period "."

- Replace the English alphabet "s" with a numeric "5" (five)

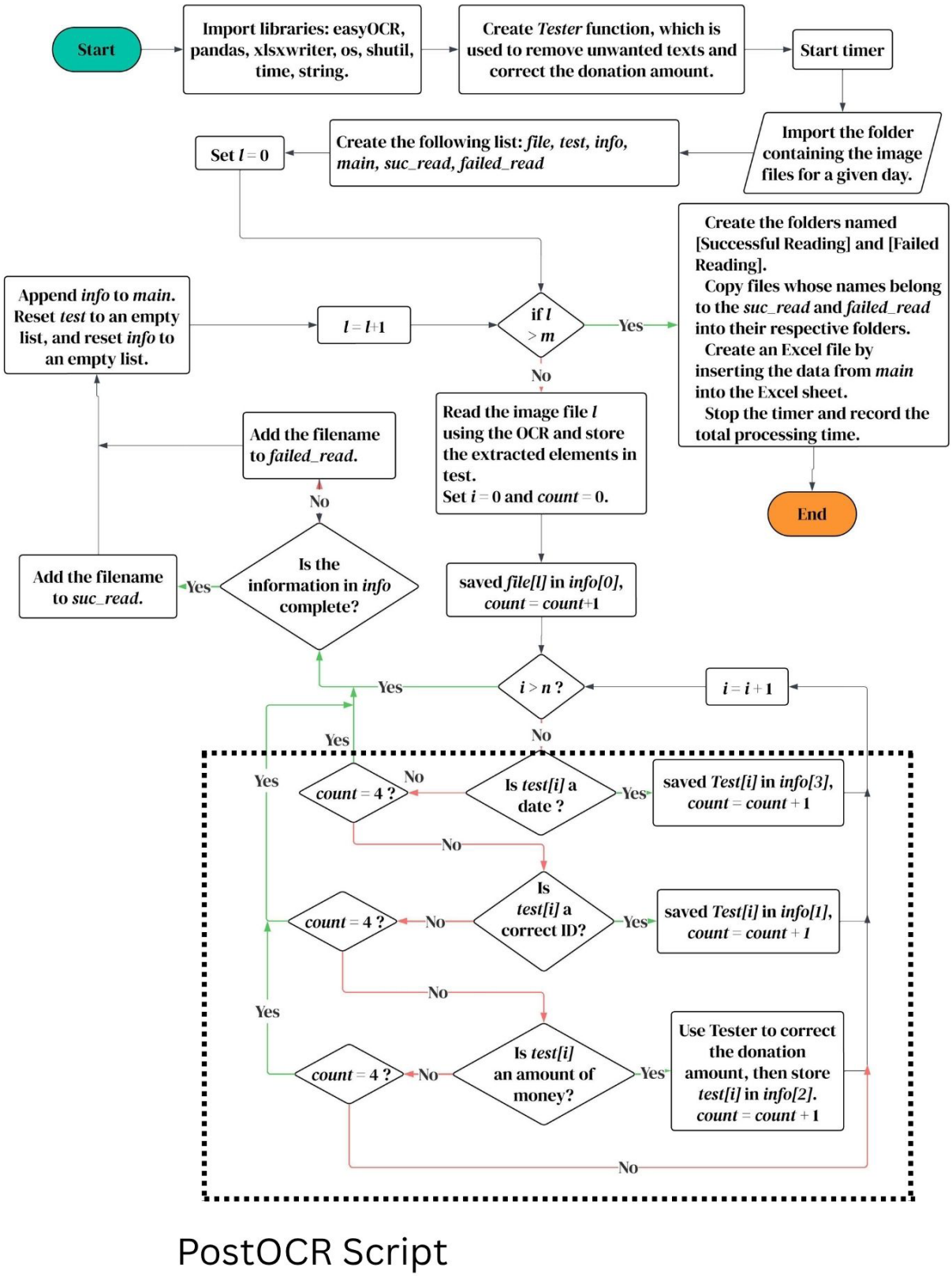

Fig. 9. Logic diagram of the automated OCR system

VI. Computational Test Results and Discussion

A. Overall Performance of the Automated OCR System

After processing all the image files, examples of results are shown in Table II. The 1st example indicates that the ID (i.e., account number) cannot be read. In the 2nd example, the system incorrectly reads the donation amount as zero, and it cannot read the date.

TABLE II
Examples of Incorrect Reading and Correct Reading by The System

Filename	ID	Amount	Date	Remark
LINE_ALBUM_xxxxxx_11.jpg	ID Pass	500	7 October 24	Cannot read ID
LINE_ALBUM_xxxxxx_40.jpg	xxx-x-x6042-x	0	Time Or Day	Amount is 0, and cannot read the date
LINE_ALBUM_xxxxxx_161.jpg	099x00xxxxxxx	200.008	10 October 24	Incorrect amount (Read B as 8)
LINE_ALBUM_xxxxxx_30.jpg	099x00xxxxxxx	2000	13 October 24	Correct reading

The third example shows that the donation amount, which is 200.00B (B is for Thai Baht), is read incorrectly as 200.008. The last example is a correct reading and the most typical result. The performance of the developed automated OCR system, which features post-OCR scripts, is evaluated in terms of the accuracy and efficiency of slip screening and reading using the test dataset.

B. Accuracy Analysis of the Automated OCR System

Table III presents the system's accuracy in terms of the number and percentage of slips read correctly, total donation amount, and daily computational time. In total, 2,603 images (slips) are processed, of which 2,031 slips are processed correctly, i.e., the four key pieces of information are read and recorded in a spreadsheet. This gives an overall accuracy of 78.03%, where percent accuracy is the ratio of accurately read slips to the total number of slips. Similarly, donation amount accuracy is the ratio of the read amount to the actual transaction amount. Although slip-level accuracy is moderate at 78.03%, donation-amount accuracy reached 90.04%, indicating that the system extracts the most critical financial information in most cases. This difference suggests that many OCR failures involve secondary fields (e.g., account numbers or dates) rather than monetary values, making the system suitable as a preprocessing tool before human verification.

TABLE III
Percent Accuracy of The OCR Tool and Computational Time

Date	OCR Reading Accuracy (Slips)			OCR Reading Accuracy (%)		Run-Time (s)
	Incorrect	Correct	Total	Slips	Donation Amount	
21 September 24	68	203	271	74.91%	86.24%	1,941.6
22 September 24	24	93	117	79.49%	86.87%	1,052.7
23 September 24	32	78	110	70.91%	75.48%	871.0
24 September 24	18	36	54	66.67%	78.19%	425.9
25 September 24	13	55	68	80.88%	97.38%	568.6
26 September 24	2	11	13	84.62%	41.40%	119.2
27 September 24	15	51	66	77.27%	95.45%	471.8
28 September 24	6	26	32	81.25%	88.82%	319.3
29 September 24	3	16	19	84.21%	79.73%	160.4
30 September 24	3	14	17	82.35%	88.92%	153.3
1 October 24	24	66	90	73.33%	60.26%	647.6
2 October 24	14	28	42	66.67%	85.87%	336.0
3 October 24	7	23	30	76.67%	89.24%	251.3
4 October 24	6	29	35	82.86%	86.19%	274.0

TABLE III
PERCENT ACCURACY OF THE OCR TOOL AND COMPUTATIONAL TIME (CON.)

Date	OCR Reading Accuracy (Slips)			OCR Reading Accuracy (%)		Run-Time (s)
	Incorrect	Correct	Total	Slips	Donation Amount	
5 October 24	6	28	34	82.35%	92.95%	237.9
6 October 24	11	29	40	72.50%	91.52%	322.8
7 October 24	8	34	42	80.95%	87.39%	320.6
8 October 24	9	17	26	65.38%	88.03%	198.8
9 October 24	14	30	44	68.18%	46.69%	340.9
10 October 24	12	26	38	68.42%	71.92%	324.8
11 October 24	4	35	39	89.74%	97.71%	345.7
12 October 24	8	33	41	80.49%	99.19%	291.7
13 October 24	1	45	46	97.83%	99.69%	347.2
14 October 24	28	84	112	75.00%	82.31%	845.3
15 October 24	16	16	92	82.61%	98.33%	722.9
16 October 24	20	75	95	78.95%	95.44%	694.5
17 October 24	13	87	100	87.00%	48.27%	715.4
18 October 24	21	143	164	87.20%	98.30%	1,318.3
19 October 24	166	560	726	77.13%	94.31%	10,833.6
Total	**572**	**2,031**	**2,603**	**78.03%**	**90.04%**	**25,453.1**

Unlike many OCR-based document processing systems that rely on OCR confidence scores to decide whether to accept recognition results, the proposed framework instead performs deterministic, rule-based validation followed by mandatory human verification. This design suits financial transactions, where even a single undetected recognition error may lead to monetary loss.

Detailed inspection of failed cases revealed that most errors stemmed from poor image quality, including low resolution, compression artifacts, partial cropping, glare, and non-transfer-slip images. These conditions reduce OCR recognition accuracy, and the rule-based post-OCR algorithm cannot fully correct them.

C. Efficiency Improvement of the Operators with the Assistance of the Automated OCR System

For operational efficiency, the OCR system demonstrates clear time savings over manual processing. Based on operator experience, manual handling of transfer slips, including reading, verifying, and all data entry, typically takes an average of one minute per slip. With the OCR system, the same task requires 25,453.10 seconds (i.e., 7 hours, 4 minutes, and 13.1 seconds), or 9.78 seconds of computer time per slip. This is followed by a brief manual verification requiring, on average, three seconds of operator time per correctly processed slip, or 15 seconds for incorrectly processed slips (including non-transfer slips that are submitted), and these estimated average times per slip come from operators' actual time to do their jobs, with and without the automated OCR system. Table IV estimates operator time savings with the system.

TABLE IV
ESTIMATED OPERATOR'S TIME SAVINGS

Method	No. of Slips	Operator Time (min)
Manual work	2,603	2,603
Automated OCR system		
Correctly processed	2,031	101.55
Incorrectly processed	572	143
Total	**2,603**	**244.55**
Savings	**-**	**2,358.45**

From the table, estimated operator-time savings are 2,358.45 minutes (39 hours and 18 minutes), representing over 90% savings for the case study dataset of 2,603 submitted slips. The results demonstrate an important operational tradeoff. Rather than eliminating human involvement, the proposed framework substantially reduces repetitive manual work while preserving human oversight for critical financial verification. Consequently, operator effort

is reduced without compromising the reliability required in financial applications.

D. Factors Affecting OCR System Performance

Further analysis of image file sizes helps clarify the impact of input image quality on OCR system performance. Table V provides details on the OCR system accuracy with respect to image file size. The results show that average accuracy increases with larger image files. Very small-sized images (<100 kB) exhibited a high error rate of about 51.25%, indicating that low-resolution images significantly affect reading accuracy. Only slightly larger images (at least 100 kB) generally perform better. Overall, medium-to-high resolution images (i.e., at least 200 kB) are recommended for more accurate results. Distributions of the number of incorrect readings, the total number of slips, and the correct reading percentages are shown in Figs. 10 to 12, respectively.

TABLE V
PERCENT ACCURACY OF THE OCR TOOL BY FILE SIZE

Date	Number of Incorrect Readings (Slips) of Each Size (kB)						Number of Images (Slips) of Each Size (kB)						Correct Reading Percentage					
	< 100 kB	100 kB	200 kB	300 kB	400 kB	500 kB	< 100 kB	100 kB	200 kB	300 kB	400 kB	500 kB	< 100 kB	100 kB	200 kB	300 kB	400 kB	500 kB
21 Sep 24	2	24	30	12	0	0	5	89	107	57	12	1	60.0%	73.0%	72.0%	79.0%	100.0%	100.0%
22 Sep 24	2	7	12	3	0	0	2	29	57	25	3	1	0.0%	75.9%	79.0%	88.0%	100.0%	100.0%
23 Sep 24	1	10	14	6	1	0	1	30	43	29	7	0	0.0%	66.7%	67.4%	79.3%	85.7%	-
24 Sep 24	0	5	9	3	0	1	1	12	22	14	3	2	100.0%	58.3%	59.1%	78.6%	100.0%	50.0%
25 Sep 24	0	4	5	4	0	0	1	19	29	16	3	0	100.0%	79.0%	82.8%	75.0%	100.0%	-
26 Sep 24	0	2	0	0	0	0	0	10	3	0	0	0	-	80.0%	100.0%	-	-	-
27 Sep 24	0	6	7	2	0	0	0	22	24	16	4	0	-	72.7%	70.8%	87.5%	100.0%	-
28 Sep 24	1	1	2	2	0	0	1	4	14	9	4	0	0.0%	75.0%	85.7%	77.8%	100.0%	-
29 Sep 24	0	2	0	0	1	0	0	3	6	6	4	0	-	33.3%	100.0%	100.0%	75.0%	-
30 Sep 24	0	2	1	0	0	0	0	5	8	4	0	0	-	60.0%	87.5%	100.0%	-	-
1 Oct 24	0	11	9	3	1	0	0	27	42	17	2	2	-	59.3%	78.6%	82.4%	50.0%	100.0%
2 Oct 24	3	1	7	3	0	0	4	10	15	11	2	0	25.0%	90.0%	53.3%	72.7%	100.0%	-
3 Oct 24	0	2	3	1	1	0	0	9	13	5	2	1	-	77.8%	76.9%	80.0%	50.0%	100.0%
4 Oct 24	1	1	3	1	0	0	1	5	16	11	2	0	0.0%	80.0%	81.3%	90.9%	100.0%	-
5 Oct 24	0	2	3	1	0	0	0	10	19	4	1	0	-	80.0%	84.2%	75.0%	100.0%	-
6 Oct 24	0	5	5	1	0	0	0	8	19	12	1	0	-	37.5%	73.7%	91.7%	100.0%	-
7 Oct 24	1	4	2	1	0	0	2	13	21	6	0	0	50.0%	69.2%	90.5%	83.3%	-	-
8 Oct 24	0	4	2	3	0	0	0	9	7	9	1	0	-	55.6%	71.4%	66.7%	100.0%	-
9 Oct 24	0	2	10	0	2	0	2	11	21	6	3	1	100.0%	81.8%	52.4%	100.0%	33.3%	100.0%
10 Oct 24	0	5	4	3	0	0	0	10	18	8	1	1	-	50.0%	77.8%	62.5%	100.0%	100.0%
11 Oct 24	0	1	2	0	0	1	0	8	12	14	3	1	-	87.5%	83.3%	100.0%	100.0%	100.0%
12 Oct 24	2	3	3	0	0	0	2	19	14	6	0	0	0.0%	84.2%	78.6%	100.0%	-	-
14 Oct 24	0	9	14	3	2	0	2	34	53	19	4	0	100.0%	73.5%	73.6%	84.2%	50.0%	-
15 Oct 24	1	7	7	1	0	0	4	30	40	14	4	0	75.0%	76.7%	82.5%	92.9%	100.0%	-
16 Oct 24	2	0	14	4	0	0	2	25	49	14	5	0	0.0%	100.0%	71.4%	71.4%	100.0%	-
17 Oct 24	3	5	5	0	0	0	4	26	47	18	5	0	25.0%	80.8%	89.4%	100.0%	100.0%	-
18 Oct 24	4	3	10	4	0	0	7	39	80	34	4	0	42.9%	92.3%	87.5%	88.2%	100.0%	-
19 Oct 24	17	59	65	22	3	0	38	246	314	110	17	1	55.3%	76.0%	79.3%	80.0%	82.4%	100.0%
Total	**41**	**187**	**248**	**83**	**11**	**2**	**80**	**776**	**1131**	**502**	**101**	**12**	**48.8%**	**75.9%**	**78.1%**	**83.5%**	**89.1%**	**91.7%**

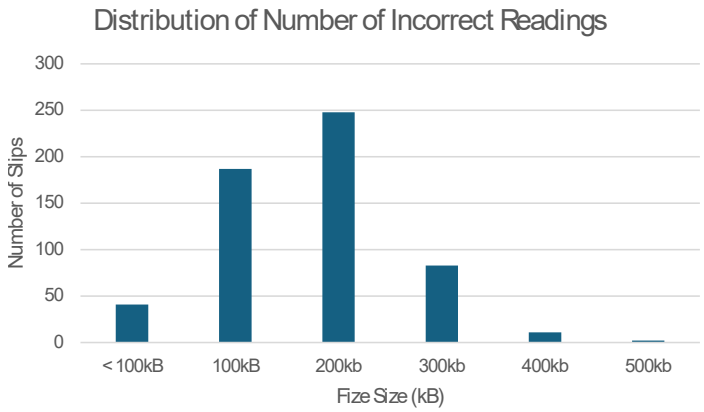

Fig 10. Distribution of the incorrect readings

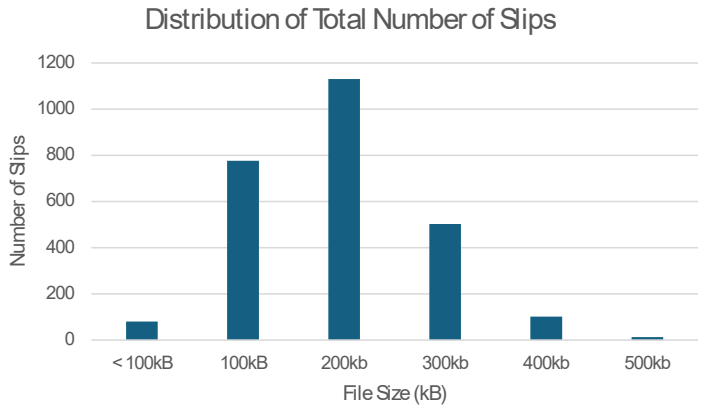

Fig 11. Distribution of the total number of slips

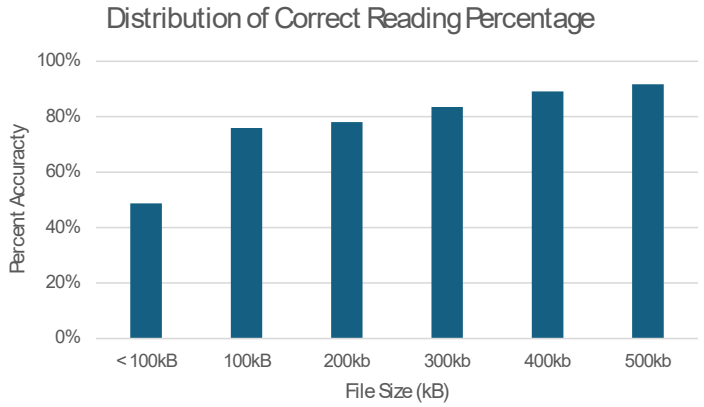

Fig 12. Distribution of the correct reading percentage

From Figs. 10 and 11, the distributions look similar, with more slips at lower file sizes than at the average file size. Fig. 12 clearly shows that a higher accuracy percentage can be achieved for larger file sizes

The observed trend suggests that image resolution is a dominant factor affecting OCR performance. Larger image files generally contain more visual detail, allowing character boundaries to be recognized more reliably. Consequently, image acquisition guidelines specifying a minimum image quality may substantially improve OCR performance without modifying the recognition algorithm. From an operational perspective, encouraging users to upload higher-quality images may represent a more cost-effective strategy than developing increasingly sophisticated OCR algorithms. Similar to previous studies, OCR accuracy is strongly influenced by image quality. However, unlike studies focusing solely on OCR recognition performance, the proposed framework demonstrates that combining OCR with rule-based post-processing and reliability required for financial document processing human verification can substantially improve operational efficiency while maintaining the VII.

VII. Conclusion

This article demonstrates the development and application of an automated OCR tool with a post-OCR algorithm to improve accuracy performance. Computational test results indicate that OCR technology, as a pre-processing tool for human operators, has acceptable accuracy in both the number of slips and the monetary amount. While manual review by operators, when executed meticulously, may yield near-perfect accuracy, it remains highly time- and labor-intensive. Although the OCR tool exhibits slightly reduced accuracy, it offers substantial gains in slip-processing efficiency. This work introduces a practical framework that integrates an OCR tool, a post-OCR correction algorithm, and human verification into a unified operational workflow for real-world financial document processing. Within this workflow, the OCR tool and post-OCR algorithm perform the initial data extraction and correction. At the same time, human operators conduct the final verification, leveraging the complementary strengths of automation and human oversight. This integrated workflow enables near-zero verification errors while reducing manual workload by approximately 95%, making it especially effective for this problem, which requires both scalability and reliability. Experimental results confirm the OCR tool's robust, consistent performance. Based on the evaluated dataset, which is 29 days of operations, the man-machine approach produces reliable outputs, indicating its potential for full deployment.

Overall, this study demonstrates that the proposed human-in-the-loop OCR framework offers a practical solution for improving document-processing efficiency while preserving data accuracy. By combining automated OCR with targeted human verification, the framework remains effective despite variations in document quality, making it particularly suitable for resource-constrained organizations that require scalable and reliable document processing. Future research should evaluate the proposed framework across similar applications to establish its generalizability further and identify context-specific errors. Sources that can guide the development of improved post-OCR algorithms.

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