Efficient Bank Cheque Data Extraction through OCR Technology

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Abstract

For financial institutions to function seamlessly, having an accurate and efficient way of processing cheques is pivotal. The manual processing of cheques faces many issues, such as human error and time consumption. This paper looks at how to use Optical Character Recognition's (OCR) ability to convert printed or handwritten text into editable text, which helps automate the processing of cheques. Literature review highlights the importance of OCR and shines light on different approaches and methodologies used. The methodology section details how OCR is used using libraries such as OpenCV and scikit-image, which recognize and extract characters from the cheque. A dataset containing cheque images in different ink colors and textures along with a reference MICR E13B font is used. The code was run on Google Colab, and the resulting image showcases the effectiveness of OCR in cheque processing.

Keywords: *Bank Cheque, MICR, OCR, OpenCV, Streamlit*

I. INTRODUCTION

In the realm of banking and finance, processing bank cheques efficiently and accurately is important for the smooth operations of financial institutions worldwide, as cheques are still a crucial payment method for both consumers and businesses. The rise of Optical Character Recognition (OCR) technology has completely changed the way data is extracted from bank cheques, which has led to an increase in the speed of processing and overall operational efficiency.

However, the traditional methods of manually processing the cheques and entering the data present many challenges, such as human error in entering the data, which is very time consuming and requires lots of resources, leading to potential inconsistencies. As a result, there is a growing demand for a solution to automate and optimize the procedure for processing cheques, which guarantee accuracy and precision. Taking the challenges into consideration, integrating OCR technology is a feasible solution to automate and quicken the processes involved in extracting data from cheques. OCR Technology works by transforming the typed, printed, or handwritten text into a machine readable format, and in conjunction with machine learning algorithms, they improve the accuracy by constantly refining the extraction process, which is based on the variations and patterns found in handwriting styles and cheque layouts. Thus enabling computers to process and interpret the textual information present in scanned documents. Financial organizations can now extract only the important data from cheques more precisely and rapidly by using OCR algorithms. This leads to a boost in overall operational efficiency and a reduction in the possibility of errors.

There is significant potential in this research to improve the dependability and efficiency of cheque processing systems in the banking industry. By automating the cheque processing workflow, lowering fraud, reducing manual error rates, and improving the accuracy and efficiency of OCR-based data extraction procedures, financial institutions can increase client satisfaction.

Problem Statement: The project aims to tackle the errors and inefficiencies that are associated with processing bank cheques manually by using OCR as a solution to automate the process of extracting data precisely and efficiently.

As the banking sector continues to undergo a digital transformation, the need for solutions to extract the details of cheques is expected to grow. By using modern technologies and best practices in the analysis and processing of data, financial institutions can accommodate the requirements of their clients by staying ahead of the curve.

II. LITERATURE REVIEW

Paper [1] presents a hybridization of CNN (Convolutional Neural Network) architecture and ECOC (Error Correcting Output Code) classifier, where CNN is utilized for extracting the features and ECOC addresses the problem of classification. The paper describes ECOC as being used instead of a soft-max layer like in conventional CNNs. The problem posed by multi-class classification is solved by ECOC, which breaks the problem down into several binary problems. The classifier is trained with the features extracted from the CNN. Binary learners in ECOC are fed the extracted features and trained using the traditional linear SVM (support vector machine) model. Probabilities produced by the trained binary learners are joined into a string and used to generate a codeword by using a suitable threshold. The codeword produced is compared with a coding matrix. The predicted output is the class correlating with the closest codeword. Four different CNN-ECOC architecture approaches were tested: LeNet of Type 1, LeNet of Type 2, AlexNet, and ZfNet. The paper proves that classification accuracy can be enhanced by substituting the softmax layer with ECOC and further concludes that the highest testing accuracy is provided when the AlexNet CNN architecture is used to extract the features.

[2] discusses the development of an artificial intelligence-based offline Handwritten Character Recognition (HCR) system for the Gujarati language. The dataset was created from scratch. The image is obtained, and a region of interest is found using canny edge detection. The region is further grayscaled, binarized, and undergoes skewness correction. This image is then segmented into words, lines, and characters and fed to the CNN model. The post-processing stage included grouping, error identification and correction, text file generation, Unicode encoding, and a graphical user interface that combines all the processes to show the output.

The system proposed by paper [3] describes an effective bank cheque bounce detection model. The detection can be made by automating the entire process of scanning the bank details and contacting the bank to request customer details. The bank cheque image is inputted through a scanner or camera and converted into grayscale. This is done through binarization, which is the primary process in many cheque processing models. The bank name is identified through the bank logo on the cheque, and the branch is identified through the IFSC code. Logo is checked using the pattern matching algorithm, and IFSC code is detected through OCR. Support Vector Machines are used to classify the cheques, and forward the image to the specified bank for processing. The signatures are verified through pattern matching, and the date and amounts are verified through OCR. The amount is withdrawn from the bank account once all processes are completed and the customer is informed about the transaction. If the verification of either of the above three fails, the cheque is considered to have bounced. Through this process the entire cheque bounce detection system is automated, resulting in time and work efficiency.

An automated system that can be procured by financial firms to gather information directly from cheques and verify the information present is the system presented on paper [4]. The paper discusses a method to reduce human effort and increase efficiency through image processing of bank cheques. The image of the cheque is acquired through a camera and scanner, which is further manually cropped to extract essential information. The data is then preprocessed in order to eliminate noise. Pre-processing includes normalization, which eliminates singular pixels in contrasting backgrounds. The image is then binarized to remove color and background. Morphological operations are performed, and finally, the hough transform of the image is taken. The text extracted from the cropped image is read and stored in a CSV file. The data is separated and organized in a precise and clear manner that is easy to comprehend. The process of information extraction can be followed by signature verification using neural networks, which further increases the effectiveness of the system.

[5] discusses the development of an Optical Character Recognition (OCR) system for printed Bangla characters using neural network technology. Firstly, the dataset for the Bangla characters was created from scratch in different fonts, one hot encoding was applied to the dataset, and it was then split into training and testing datasets. Next, an artificial neural network with a back propagation algorithm with two hidden layers is used on the dataset. Neurons in each layer are specified, and random weights are assigned. It then does forward propagation, and the sigmoid activation function is applied, followed by back propagation. A graphical user interface (GUI) application for character recognition was built, in which the image is converted to grayscale and then to binary. Feature extraction is performed and a predicted character image is generated.

The paper [6] discusses a project on Handwritten Text Recognition (HTR) using OpenCV and a Convolutional Neural Network (CNN). The main goal is to transcribe images of handwritten text into digital text with high accuracy. The project involves two datasets: A_Z Handwritten Data for English alphabets and the MNIST dataset for digits. The architecture of the project is divided into segmentation and training modules, where the segmentation module processes the input images and the training module predicts the text. The experimental results demonstrate the process of segmenting images and training the model using CNN, achieving a training accuracy of 0.9184 and a test accuracy of 0.9626. The document also outlines future enhancements for increasing accuracy, including using larger datasets, more suitable algorithms, and deeper architectures, as well as extending the application's scope to different writing styles.

The paper [7] describes another system to read cheques as input images, and detect if the cheque has bounced or not. The system design aims for better performance, by reducing the chances of falsification. The system verifies mechanized signatures and performs meticulous cheque handling to guarantee the desired execution. The system is divided into the Signature Analysis Module, and the Account Number Analysis Module. The signature module aims to extract the features of the signature and prevent unauthorized access, using binarization, dilation, and thinning. The Account Number Analysis Module uses OCR to interpret the amount to be withdrawn as an ASCII character, and checks if the amount is less than the amount in the account. The analysis modules are further divided into an online analysis system and an offline analysis system. The Online Analysis System records data through sensors, and usually stores information that is unchanged for an individual. The offline analysis system acquires static information. The paper suggests that further research is needed to increase the accuracy of the falsification , so as to perfect the system.

The paper [8] introduces a system for recognizing both handwritten and printed text using Optical Character Recognition (OCR) and a k-nearest neighbor algorithm and classifier. The image is scanned and converted to grayscale to increase the speed of processing. Segmentation is done, and each character is bound in a rectangular box. Next, feature extraction is done to capture the important details of the character. These characters are classified using k-nearest classifier. The output is generated based on the text and it shows which style the text was in.

The paper [9] describes the development of an Android application for handwritten character recognition using Optical Character Recognition (OCR). The goal is to convert handwritten text into an editable electronic format. The process involves capturing the image through the phone camera, and is preprocessed using grayscale conversion, binarization, thinning, skewing, and normalization. Next, it is segmented into lines, then words, and finally characters. Feature extraction is performed after classifying the character. This character is converted into an editable text form, which can be opened and edited later.

The paper [10] introduces a style-conditioned generative adversarial network (SC-GAN) for augmenting handwritten optical character recognition (OCR) training with online handwriting samples. The goal is to synthetically create realistic text line images from a skeleton image paired with the style. First, the skeleton image is processed by the content encoder and its output is processed by a decoder to get the synthetic image. For the style, a style encoder is used, followed by a pooling operation. This style code is used in the AdaIN operation and is normalized to generate the synthetic image with the style. A GAN discriminator is used to make the image appear more realistic. Loss functions are used to make the output more realistic and similar to the input images.

The system proposed in paper [11] is a technique that is used to validate the signature of bank cheques through an artificial network. Image processing techniques can be used to verify these signatures based on the features extracted from them. Data is acquired through a camera or scanner and converted to a grayscale image for efficient processing. The unimportant pixels of the image are cropped out, and a Gaussian filter is applied along with an opaque filter. This is done to eliminate the noise from the image acquired while scanning. The filtered image is thresholded using an edge sensor, in binary. Feature extraction is performed by designing a function that can be used as a relative measure. Since the process is very delicate, more than one function can be produced. The images are further analyzed and classified into different categories, after which an artificial neural network with a Radial Basis Function as an activation function is used to verify the signature.

This paper [12] uses deep learning to recognise banknotes and detect fake banknotes. The methodology includes identifying the best freezing points in models by using transfer learning and proposes a custom model using a sequential Convolution Neural Network (CNN). Dataset of 7280 images of banknotes was collected and augmented. The results of the comparison of the models show that the custom model has better inference time for both CPU and GPU and accuracy. The paper also provides insights on selecting the most appropriate model for the task. It also discusses architecture recommendations and the pros and cons of using a custom model.

The presented Optical Handwritten Character Recognition (OHCR) software utilizes Convolutional

Neural Network (CNN) and Residual Network (ResNet) to convert handwritten or printed text into digital form. The focus of paper [13] includes recognition of alphabetic characters, cheques, postal addresses, and menu cards. The image is first scanned using a scanner and then converted to grayscale. It is then normalized, which helps in character classification, and then denoised by applying a blur to the image. Further, it is binarized, which focuses more on the writing, de-skewed, does not mix up numbers and letters that look similar, and cropped, which saves the important part of the image. The CNN and ResNet architectures are employed for feature extraction and classification,after which the system demonstrates successful character recognition and prediction with applications in identifying bank cheques, including bank name, amount, cheque number, and date.

The paper [14] focuses on extracting data from daily-use printed bills and invoices using Optical Character Recognition (OCR) technology. The extracted data, such as final bill amounts, itineraries, and dates, can be used for machine learning or statistical analysis. Using OpenCV, canny edge detection is used to get the contours, and the largest rectangular object in the image can be identified and assumed to be the bill. Next, the image is grayscaled and cropped to get a top-down view of the image. The image is passed on to Tesseract OCR, which analyzes connected components. Further, text segmentation is performed, and the words are passed to the adaptive classifier, which helps give a better result. The extracted data, such as final bill amounts, itineraries, and dates, can be used for machine learning or statistical analysis.

The paper [15] describes the automation of processing cheques using Optical Character Recognition (OCR), Convolution Neural Network (CNN), and deep learning. The cheque is preprocessed, and essential details such as name, amount, date, and bank name are isolated and their text extracted using CNN. Signatures are extracted and verified with an existing signature in the database using PCA (Principal Component Analysis). Results show a high accuracy of 99.94% for the recognition of characters and digits using CNN, and signature verification had an accuracy of 98.1% using SIFT and SVM.

This paper [16] proposes an Optical Character Recognition (OCR) method using deep learning to read Arabic Arabic characters using You Only Look Once (YOLO). The YOLO4 model was customized by training it on deep Convolutional Neural Networks (CNN) to recognise the Arabic characters. It also retains the most accurate bounding box for each character and is compared with the Hunspell library for any misspelled words. Using these techniques, the model achieved a Word Recognition Rate (WRR) of 82.4%, which is higher when compared to other OCR systems like Tesseract. It also discusses the complexity of Arabic OCR due to its cursive nature and high similarity between the letters.

This paper [17] discusses the importance of Optical Character Recognition (OCR) technology in transforming the text in the image into editable text. It talks about the demands of OCR in different fields and its historical development up to the present. It also delves into challenges faced by OCR, like lighting conditions, blur, and aspect ratio. The architecture includes phases such as preprocessing, segmentation, normalization, feature extraction, classification, and postprocessing. The paper also highlights the limitations of the current OCR technology and acknowledges the ongoing efforts to improve OCR extraction.

The paper [18] focuses on an application-based approach for verifying bank cheques, without any machine learning or deep learning algorithms. It solely uses the libraries available in Python to verify an image of a cheque. Once the image of the cheque is acquired, it is preprocessed using the Gaussian blur effect to eliminate noise. Images are both cropped and processed individually using the OpenCV module, and information is extracted using the EasyOCR module. EasyOCR is used for handwriting recognition as the module gives more accurate results when compared to Keras-OCR and Pytessarect. The system compares the features of the extracted signature with those stored to determine validity. The SIFT algorithm is used for feature extraction, and knnMatcher is used to map similarity between the images. Signatures with a ratio of closest to second-closest distance of 0.8 or less are considered to be matches; otherwise, they are not validated. Since the dataset used is specific to a bank and a machine learning model has not been trained, it makes it difficult for another new bank cheque to be validated. However, the application serves its purpose by automating the process of authenticating signatures.

A combination of two neural networks was used to extract information from both printed and handwritten cheques on paper [19]. The dataset used was the IDRBT image dataset, consisting of diverse bank cheques. The system incorporates a mobile application, a DL system, a web service, and an information matching system. One Neural network was used for object detection through contrasting learning, which uses the positive and negative pairs generated from the ROI (region of interest). The other neural network was trained for handwriting recognition using CTC loss function, which did not require annotations of image in each step. The model prediction depends on the curvature score and image embedding 82.4%, which are provided as inputs to alternative branches of the neural network. The output is concatenated and finally fed into a connected layer for classification. This system is implemented on a mobile application for easy access for users, as well as a web application for easy commercial access. This automates the cheque collection and verification process and provides a more user-friendly experience for customers.

The paper [20] proposes an automated system for extracting and verifying bank cheque details using optical Character Recognition (OCR) and Deep Learning. The system utilizes OCR to identify machine typographic characters with high accuracy and efficiency and Convolutional Neural Networks (CNN) to precisely recognize handwritten digits on cheque leaflets. Additionally, the system implements an algorithm to convert numbers into words, addressing a major cause of cheque bounces and transaction halts. The OCR technique achieves 95% accurate matching for machine-printed digits, and the CNN model attains an accuracy of 99.14% for digit recognition and 99.94% for character recognition. Furthermore, the system uses Support Vector Machine (SVM) and Scale-Invariant Feature Transform (SIFT) for signature feature extraction and verification, achieving an accuracy of 98.1%. The proposed system aims to streamline cheque processing, reduce time and costs, and enhance efficiency and performance.

2.1. Dataset

At IDRBT, a dataset [21] of bank checks with a variety of textures and ink colors has been assembled. The source document comprises 112 cheque leaves from four distinct banks in India. Seven blue and seven black pens are used in order to replicate the pen-ink difference seen in cheque leaves. Nine distinct volunteers actively participated in gathering the dataset, that is, in writing the checks, in order to prevent bias arising from writing. Pen-ink data generation uses 126 pen-volunteer combinations in total. Two volunteers write each check with two different pens (either black or blue). As a result, 42 different combinations of blue and black pens were used to create the data set. Every check leaf is scanned using a standard scanner at 300 dpi.

A reference image of the MICR E13B font, which is used for the printing of cheques is used. It contains characters that are usually found in cheques like digits from 0 to 9, and some special symbols.

III. METHODOLOGY

3.1. Architecture

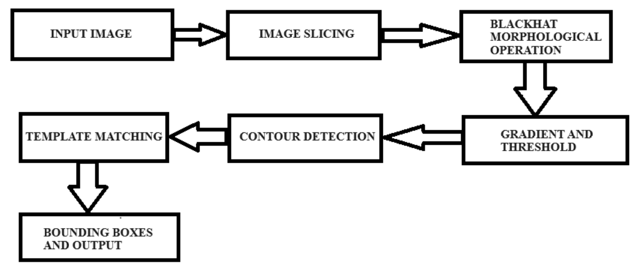

Fig 1. Architecture Diagram

3.2. Data Preprocessing

In the preprocessing step, the input images undergo transformation to enhance the MICR code which is the relevant feature to improve the performance of detecting the MICR code. Here, the images are converted to grayscale to make the processing simpler and then thresholding to segment the MICR from foreground. After that erosion is applied to smooth the segmentation boundaries. The resulting image will give a more focused input for the analysis of the task of detection facilitating more accurate feature extraction. This plays a crucial role in robustness of image processing and computer vision applications.

Fig 2. Before Preprocessing

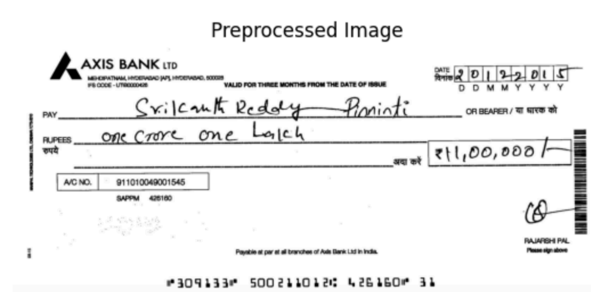

Fig 3. After Preprocessing

3.3. Implementation

Libraries such as OpenCV, Numpy, and scikit-image were used for the processing and analysis of the image. Functions to display images, extract each digit and symbol from the cheque were created. A reference to the MICR E13B font is loaded, converted to grayscale, and further thresholded to create a binary image. Here, the digits will appear white on a black background. Contours are found, and characters are extracted. A dictionary is made that maps each character to its corresponding ROI.

Next, the input is loaded, and only the bottom 20% of the image is retained as the MICR is present there. A blackhat morphological operation is used to find any dark regions against a light background. The gradient is calculated and thresholding is done such that the digits are segmented from the background. Contours in the thresholded image are found to identify groups of characters. The contours are only considered if they have sufficient width and height.

For each group of characters, the characters are extracted and compared with the reference characters using template matching. The character with the highest matching score is assigned as the recognized character. Next, bounding boxes are drawn for each group of characters, and the recognized characters are overlaid on the image. The final output of OCR is displayed on the image.

The code was executed using Google Colab, which is a cloud-based Jupyter notebook environment. For compatibility, Python 3 was selected as the runtime type, and a T4 GPU hardware accelerator was used to speed up the processing tasks of the image.

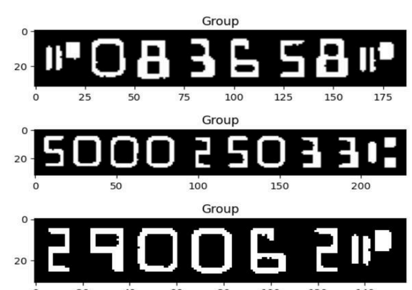

Fig 4. Grouping of Characters

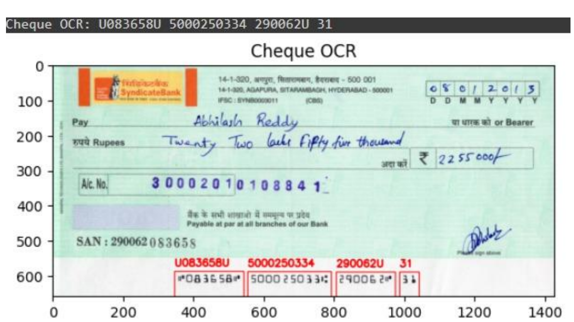

Fig 5. Output Image

3.4. GUI

After displaying the OCR on the cheque image, the next phase involved creating a user-friendly app for detecting the MICR code and displaying the OCR. We leveraged streamlit, which is free open source software used to visually represent the analysis of the project. The platform provides users with an intuitive platform to input relevant parameters, images, or videos and display the required results.

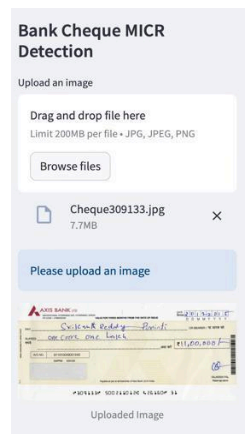

Fig 6. Uploading an Image

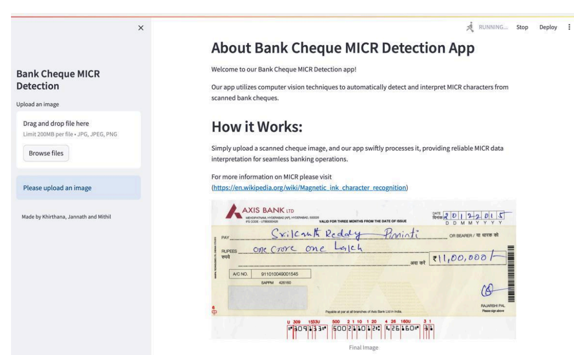

Fig 7. Displaying the MICR Code

IV. RESULTS

The groups of characters present in the MICR are displayed separately. The cheque image is displayed along with bounding boxes on the group of characters present in the MICR. Furthermore, the characters recognized are overlaid on the image. The MICR code is also shown in text form in the terminal. A Graphical User Interface (GUI) is created, prompting the user to upload an image of the cheque. On uploading, the image created using OCR is displayed as the output, containing the MICR in a bounding box. This shows how OCR can be used to automate and quicken the procedure for processing cheques.

V. CONCLUSION

This paper explores the concept of automating the process of extracting details from cheques, making it faster for banks to perform transactions. We have focused on extracting the MICR details, which verify the legitimacy of the cheque. To make the model more user-friendly, we have implemented a GUI using streamlit, allowing the user to directly upload a cheque to detect MICR values. This model can be further expanded to extract the handwritten text, as well as digits to completely automate bank cheque transactions. A system to verify signatures and details can also be implemented to introduce an aspect of security to the process.

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