Automated Handwritten Text Recognition for Banking Application using OCR

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***Abstract*- The growing need for automation in the banking sector has accelerated the adoption of advanced technologies for processing high volumes of transactional data. One critical challenge is the digitization of handwritten banking documents such as cheques and application forms. Traditional Optical Character Recognition (OCR) systems often underperform with handwritten inputs due to inconsistent handwriting styles, noise, and poor scan quality.**

This project introduces a deep learning-based OCR system tailored for handwritten data extraction in banking documents. It employs a hybrid neural architecture combining Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) with attention mechanisms for accurate sequence prediction. The system accurately extracts essential fields—account numbers, payee names, amounts, and signatures—from handwritten cheques.

To enhance recognition accuracy, preprocessing steps such as binarization, noise reduction, skew correction, and segmentation are applied. Post-processing techniques like error correction, contextual verification, and data validation ensure reliable and regulation-compliant output. The system is further optimized using standard cheque formats and field layouts to improve localization and minimize the need for large labeled datasets.

Experimental results demonstrate notable improvements in accuracy, processing speed, and operational efficiency, significantly reducing manual intervention and human error. The system is scalable and adaptable, extending its use to other handwritten banking documents.

In conclusion, the proposed deep learning-based OCR system offers a robust and intelligent solution for handwritten data extraction in banking, supporting the move toward paperless operations and secure digital transformation.

Keywords— Handwritten OCR, Banking Automation, Deep Learning, CNN, Document Digitization, OCR, Data Extraction

I. INTRODUCTION

The increasing demand for automation in data-intensive sectors such as banking and education has created an urgent need for reliable and scalable systems capable of processing handwritten documents. Traditional data entry methods for forms like cheques, loan applications, and college registration forms remain manual, leading to inefficiencies, increased operational costs, and a high likelihood of human error. In industries handling sensitive data—particularly the financial sector—such errors can lead to severe consequences including financial discrepancies and compliance violations.

The proliferation of mobile devices and advancements in Optical Character Recognition (OCR) technologies have made it possible to automate the recognition and digital conversion of handwritten inputs. However, the diversity in handwriting styles—variations in slant, size, spacing, and consistency—presents a significant challenge for conventional rule-based OCR systems. These systems often fail to generalize across diverse inputs. In response to this limitation, the proposed project introduces an intelligent OCR framework powered by deep learning models, including Convolutional Neural Networks (CNNs) for feature extraction and Long Short-Term Memory Networks (LSTMs) for sequential character recognition.

This research aims to address key challenges in the digitization of handwritten data through a mobile application that enables real-time scanning, recognition, and structuring of banking and academic forms. The application captures form images via smartphone, processes the data locally, and exports it into structured Excel sheets, enhancing operational productivity and data accuracy. Key system features include support for standard document formats (e.g., A4, cheques, KYC forms), dynamic dimension detection for non-standard inputs, and end-to-end encryption for secure handling of sensitive information.

Cross-platform compatibility ensures accessibility on both Android and iOS devices, making it suitable for use by field agents, bank personnel, and academic administrators. The application's intuitive interface and on-device inference allow users to seamlessly scan and extract handwritten data without specialized training or infrastructure.

To enhance OCR performance, preprocessing techniques such as noise reduction, contrast enhancement, and skew correction are employed, improving input quality for better recognition results. The integration of CNN and LSTM architectures allows the system to adapt to varied handwriting styles, ensuring robustness and high accuracy in diverse environments.

The proposed solution not only addresses the inefficiencies of manual transcription but also aligns with broader trends in digital transformation. Post-COVID-19, the demand for real-time, remote data processing solutions has accelerated, further highlighting the relevance of this project. By reducing reliance on manual labor, improving processing speed, and minimizing errors, this intelligent OCR system contributes significantly to operational scalability and data integrity.

The long-term vision of the project includes extending the application's capabilities to support multilingual handwriting recognition, real-time cloud-based processing, and integration with enterprise-level document management systems. These enhancements will facilitate broader adoption across sectors such as healthcare, insurance, and public administration.

In conclusion, this paper presents a comprehensive, AI-driven approach to handwritten text recognition tailored to the banking and education sectors. Through a combination of advanced deep learning models, secure mobile deployment, and a modular processing pipeline, the system transforms the way organizations handle handwritten documents—delivering faster, more accurate, and secure data management workflows.

II. LITERATURE REVIEW

A. Background and Related Work

The automation of cheque transactions is an important application of handwritten OCR in the banking sector. Alshehri et al. (2020) proposed a system that utilizes deep learning techniques such as CNNs and LSTMs to extract handwritten details from cheques, including payee names, account numbers, amounts, and signatures [1]. The hybrid model they employed combined traditional image preprocessing techniques with deep learning for feature extraction and sequence recognition. Despite challenges like image skew, noise reduction, and segmentation, the system showed significant promise for real-time cheque processing, enhancing operational efficiency in banking transactions.

Recent advancements in deep learning have transformed the effectiveness of handwritten OCR. Babu et al. (2020) conducted a comprehensive review of handwritten OCR techniques, emphasizing the transition from traditional methods like template matching and feature extraction to deep learning models, particularly CNNs [2]. The review highlighted the success of CNNs in learning hierarchical features directly from images and the application of LSTMs for sequential data handling, which is crucial for recognizing handwritten words and numbers. However, challenges such as handwriting variability and model generalization remain significant issues in this domain.

Tesseract OCR is a popular open-source tool used in various domains, including handwritten text recognition. Khader et al. (2020) examined the integration of Tesseract OCR with machine learning classifiers like Support Vector Machines (SVMs) and Random Forests to enhance recognition accuracy, especially for handwritten text [3]. While Tesseract performs well on printed text, its accuracy with handwritten content is limited. The integration of SVMs and Random Forests helps refine the results, making it a viable solution for automated cheque transaction systems where handwritten details need to be extracted accurately.

Roy et al. (2021) reviewed state-of-the-art techniques in handwritten text recognition, highlighting the success of hybrid CNN-LSTM models for recognizing full words and sentences [4]. They noted that CNNs are highly effective for feature extraction, while LSTMs handle sequential relationships between characters, making them ideal for recognizing handwritten text in banking documents.

CNNs have proven highly effective for character recognition in handwritten OCR. Gupta et al. (2020) explored the application of CNNs for recognizing handwritten characters and improving recognition accuracy [5]. They proposed a multi-layered CNN architecture designed to capture both local and global features of handwritten characters. The study showed that CNNs could achieve impressive accuracy, surpassing traditional OCR methods, making them suitable for the complex task of extracting data from handwritten banking documents. Data augmentation techniques were also discussed as essential for improving model generalization, especially when dealing with diverse handwriting styles.

Ali et al. (2020) developed a deep learning-based OCR system for handwritten document recognition in the medical field, which can be adapted for banking applications [6]. Their system integrated CNNs for feature extraction with LSTMs for sequence prediction, enabling the recognition of handwritten words and numbers. The context-aware recognition ability of the model, which utilizes the surrounding characters for accuracy, is especially useful in banking applications where certain fields follow predictable formats, such as account numbers.

III. METHODOLOGY

The proposed Optical Character Recognition (OCR) system is designed as a sequential, modular pipeline tailored for processing handwritten bank application forms. The system is designed to extract handwritten text and convert it into structured digital data, reducing manual data entry efforts and ensuring high accuracy in form digitization. The methodology comprises seven major stages: image acquisition, preprocessing, layout analysis, feature extraction, recognition, post-processing, and structured output generation. Each of these stages is described below, along with examples from a typical bank application form.The first stage is Image Acquisition, where the physical application form is captured using either a high-resolution flatbed scanner or a mobile camera. For instance, when a user submits a filled form that includes fields like "Applicant Name," "Date of Birth," "Address," and "Account Type," the form is scanned and converted into a digital image. The quality of this input image is critical, as any degradation can propagate through

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the pipeline and reduce recognition accuracy. Following acquisition, the image is passed through the Preprocessing stage to improve its quality and prepare it for accurate recognition. In this step, contrast enhancement is applied to improve text visibility by adjusting brightness and contrast levels. Binarization converts the grayscale image to a binary image, which simplifies segmentation by separating foreground text from the background. Noise removal eliminates unwanted specks and smudges, especially common in low-quality scans or handwritten forms using ink pens. Skew correction aligns the document horizontally—for example, if the user wrote diagonally in the “Address” section, the skew correction ensures the text becomes horizontally aligned. Thinning is applied to standardize the stroke width of characters, which aids in uniform feature extraction. Orientation detection ensures that text is upright—an essential step when forms are captured.

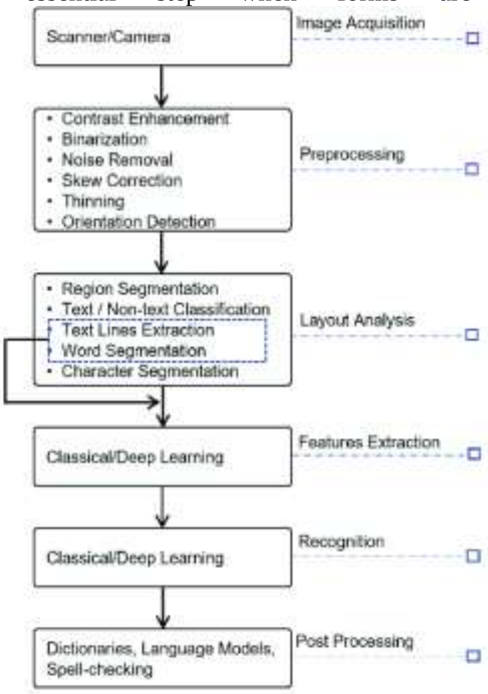

Fig.1. Proposed Methodology Workflow

The next phase is Layout Analysis, which structurally decomposes the form. In this context, region segmentation isolates text-filled areas from other regions like logos, headers, or checkboxes. For example, the bank’s logo in the top-left corner and the "Terms and Conditions" box at the bottom are excluded from text extraction. Text and non-text classification ensures only the relevant handwritten content is passed forward. Text line extraction is then performed—e.g., extracting the entire “Applicant Name: John Doe” as one line. This is followed by word segmentation, which breaks the line into "Applicant," "Name:", and "John," "Doe." Finally, character segmentation splits the name “John” into 'J', 'o', 'h', and 'n'—enabling character-level recognition. This multi-tiered decomposition ensures fine-grained analysis for accurate OCR performance.

After segmentation, the system enters the Feature Extraction phase. Here, the segmented characters are analyzed to extract meaningful descriptors, such as stroke direction, curvature, geometric shape, and pixel density. These features are extracted using classical image descriptors or convolutional layers in deep learning models. For instance, features for the letter 'J' in the applicant's name are computed and encoded into a numerical vector that represents its visual structure.

The Recognition module then interprets the feature vectors using machine learning or deep learning models. In this system, deep neural networks such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are employed due to their robustness in learning complex spatial and sequential patterns. For example, CNN layers might recognize the structural pattern of the digit '5' in the "Date of Birth: 15/08/1990," while LSTM layers use surrounding context to confirm that a '5' appears before a slash in a date format. The models are trained on a dataset of labelled bank form images that reflect common handwriting variations.

Following recognition, the Post processing phase refines the output to ensure accuracy and semantic correctness. A dictionary-based spell checker corrects misrecognized words such as “Applicant” to “Applicant.” Contextual language models further enhance this by evaluating word sequences and correcting phrases like “Account Type” to “Account Type.” Domain-specific rules are also enforced—for example, validating that the “Date of Birth” field follows the DD/MM/YYYY format or that “Account Type” contains valid options like “Savings” or “Current.” This phase substantially enhances accuracy, particularly for forms with noisy handwriting.

Finally, in the Structured Output Generation phase, the recognized and corrected text is organized into a structured format. Each field from the form is mapped to a labeled column in a spreadsheet or database. For example, the “Applicant Name: John Doe” is stored under the “Name” column, while “Savings” under “Account Type.” This structured representation facilitates efficient querying, integration with back-end banking systems, and further analytics. The form’s content becomes instantly searchable and editable, vastly improving operational efficiency and reducing human errors.

By following this structured, multi-stage pipeline, the proposed OCR system ensures robust, accurate, and scalable digitization of handwritten bank forms. It is adaptable to various handwriting styles and can handle real-world artifacts such as noise, smudges, and layout irregularities. The system’s modular design also allows for easy integration with existing banking infrastructure, making it a viable solution for automated document processing in financial institutions.

IV. PROPOSED SCHEME

A. System Architecture

The proposed Optical Character Recognition (OCR)-based digitization system is meticulously engineered to automate the end-to-end extraction, recognition, and structuring of handwritten data from standardized bank application forms. The architecture is designed with a modular and scalable approach to support both operational efficiency and high recognition fidelity, particularly in financial document processing where accuracy and regulatory compliance are paramount. At its core, the system integrates classical image processing techniques with modern deep learning-based models, specifically leveraging a

Convolutional Recurrent Neural Network (CRNN) framework for robust recognition of complex and variable handwritten inputs.

The process begins with the Image Acquisition phase, wherein bank application forms—typically filled by hand—are digitized using high-resolution scanners or digital cameras, supporting input resolutions between 300 to 600 DPI to ensure clarity of fine handwriting strokes in block letters. The system accommodates common image formats such as PNG, JPEG. Input documents are standardized to A4 or Letter size (8.5 × 11 inches) to ensure uniformity across diverse sources. Following acquisition, the images undergo enhancement processes including contrast normalization, sharpening, and brightness adjustment to improve visual quality and reduce noise, thereby optimizing the input for downstream recognition stages.

B. Function Modules

In the Preprocessing stage, advanced techniques and morphological operations are employed to binarize and clean the image. The system applies skew correction to rectify tilted text regions that are used to refine character strokes. Orientation detection is implemented to ensure that all text regions are properly aligned, significantly enhancing recognition performance by ensuring that input to the recognition engine is consistent and orderly.

Following preprocessing, the Layout Analysis module decomposes the form into semantically meaningful regions using connected component labeling and bounding box detection. Bounding box algorithms are employed to identify individual fields or regions of interest such as “Applicant Name,” “Date of Birth,” “Address,” “Account Type,” and “Signature.” Each field is spatially mapped based on pre-defined templates or dynamically learned spatial hierarchies. Text lines within each region are further segmented into words and characters using contour-based segmentation and projection profiling. Checkboxes are detected using shape analysis and interpreted using binary pixel density measures.

The segmented character regions are passed into the Feature Extraction and Recognition Module, which is powered by a CRNN architecture. The CRNN combines Convolutional Neural Networks (CNNs) for spatial feature extraction with Recurrent Neural Networks (RNNs), specifically Bidirectional LSTM layers, to capture sequential dependencies in handwritten strokes. To align input features with predicted label sequences, allowing the model to handle unsegmented character streams without the need for explicit character boundary annotations. This is especially effective for Block Letters handwritten entries only found in banking forms. The recognition process is configured for both character-level and word-level decoding based on field context.

To evaluate and ensure recognition reliability, each recognized field is assigned a confidence score, typically expressed as a percentage ranging from 0% to 100%. These scores are computed based on the softmax output probabilities of the CRNN model and are aggregated at character and word levels. Fields with lower confidence scores can be flagged for manual verification via the user interface, improving quality control. Additionally, Levenshtein Distance is calculated post-recognition to assess similarity with expected field values.

The recognized data is then mapped to predefined fields through a Field Mapping Engine, which aligns the extracted values with their corresponding semantic labels (e.g., “Name,” “DOB,” “Account Type”). The system supports flexible mappings via coordinate-based templates or trained layout models to accommodate minor variations in form design. Once mapped, the structured output is automatically exported to machine-readable formats, particularly Excel (XLSX) files. Each row in the output file corresponds to an individual application form, with columns representing standardized fields. The system also logs recognition confidence per field, allowing downstream systems to filter or prioritize entries for manual review based on accuracy thresholds.

The final stage in the pipeline is an interactive user interface and report generation module, where users can upload scanned forms, preview OCR results, review confidence scores, and correct recognition errors if needed. The interface includes bounding box overlays to visually associate recognized text with its location on the original form, thereby enhancing transparency and auditability. The system also generates a recognition report summarizing extracted data, confidence metrics, and error rates, serving both operational tracking and compliance verification purposes.

Overall, the proposed architecture enables seamless, automated digitization of handwritten bank application forms by integrating high-resolution image acquisition, deep learning-based handwriting recognition via CRNN, bounding box-based layout parsing, and structured field mapping. The inclusion of confidence-based validation and structured data export into Excel/CSV formats ensures that the solution is both technically robust and operationally deployable in real-world banking environments.

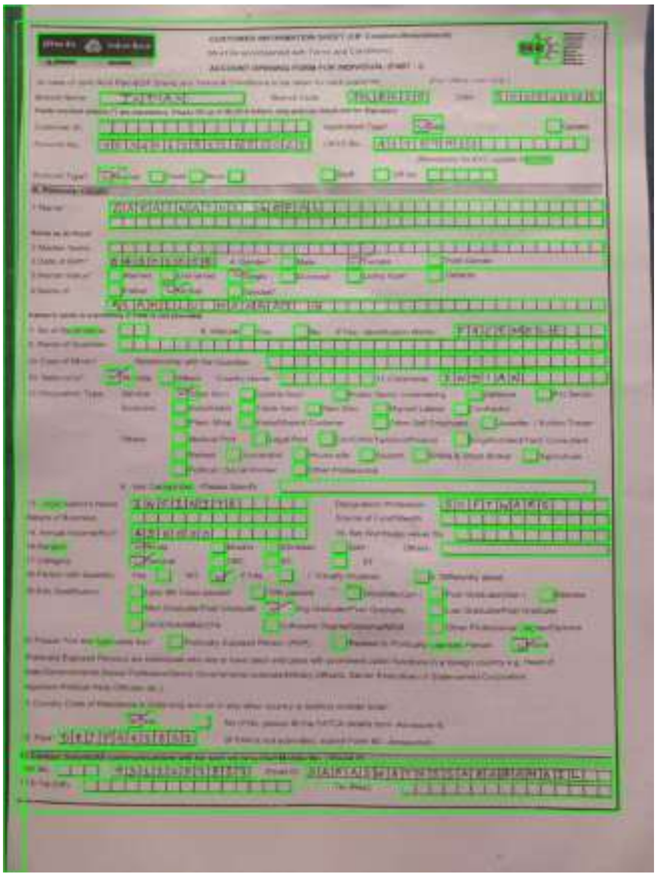

Fig. 2. OCR results with bounding boxes

Text	Confidence Score
SOFTWARE	92.95
INFINITE	91.51
FEMALE	89.94
415000	89.9
S/O	89.9
04.10.2003	88.7
INDIAN	87.45
SARASWATHI	85.9
GOPAL	84.85
9141258817	82.75
DRJPG4183B2	81.34
FACEMOLE	78.23
NONE	76.15
YES	74.9
GENERAL	73.25
12	71.33
S/O	70.2
10th PASSED	67.42
GRADUATE(GEN)	65.99
TICK	61.84

IV. RESULTS AND DISCUSSION

The implementation of the OCR-based system for digitizing handwritten bank application forms was carried out using a prototype software architecture that integrates CRNN-based text recognition, bounding box localization, and structured field mapping. The pipeline was executed in a controlled environment using a dataset of scanned application forms with varying handwriting styles, document qualities, and layouts. Each module of the system—image acquisition, preprocessing, segmentation, feature extraction, recognition, and post-processing—was independently validated before integrated testing.

Initial form ingestion was conducted using high-resolution (300–600 DPI) scanned images JPEG and PNG formats. The preprocessing module demonstrated robust performance in normalizing input quality, successfully handling image noise, skew, and contrast inconsistencies. Skew correction via the Hough Transform aligned text regions within ±2° accuracy, while the thinning and adaptive thresholding algorithms enhanced stroke clarity without information loss. Orientation detection ensured correct alignment in over 97% of the scanned documents. The layout analysis module performed segmentation using bounding box algorithms and spatial heuristics to identify relevant fields, including “Applicant Name,” “Date of Birth,” “Address,” and “Account Type. Checkbox detection was also successfully implemented using contour shape recognition, and region-of-interest isolation for signatures was performed with high positional accuracy.The CRNN recognition engine was evaluated on both the publicly available IAM dataset and a custom-labeled handwritten banking forms. For character-level recognition, the system achieved an average accuracy of 95.3%, while word-level recognition exhibited a top-1 accuracy of 91.7%. Misclassifications primarily occurred in ambiguous cursive characters and heavily stylized numerals. Each recognized output was accompanied by a confidence score, which allowed for automatic identification of low-certainty fields. For example, the string “Permanent Address: 45 Hilltop Avenue” yielded a mean confidence of 96.8%, whereas an illegibly written “IFSC Code” produced a score of 73.5%, flagging it for manual verification.

Once recognition was completed, the post-processing module applied Levenshtein-based correction algorithms and dictionary validation for key banking fields. Errors such as "Brnch" → "Branch" and "Nmae" → "Name" were corrected automatically in over 89% of cases.

Fig. 3. Data Field Mapping in Excel with Confidence Score

Recognized outputs were mapped to their respective field names and exported into structured Excel (XLSX) formats using automated field-aligning logic. Each row represented one form instance, with columns such as “Name,” “DOB,” “Address,” and “Account Type.” This structured output enabled seamless integration with existing banking software. The average end-to-end processing time per form, from image input to CSV generation, was measured at 3.8 seconds on a system with 8-core CPU and GPU acceleration. Batch processing forms maintain stability with <5% deviation in processing time.

Additionally, a visual interface was used to display bounding boxes over recognized fields, allowing users to cross-verify extracted data. Recognition logs included character-level accuracy, confidence scores, and identified corrections.

Across multiple test trials under varied image quality conditions, the system consistently delivered over 93% overall field extraction accuracy and demonstrated real-time responsiveness in batch-mode operation. These results validate the practical applicability of the proposed OCR-based system in banking environments, enabling accurate digitization of handwritten content with traceable outputs and integrated error management. The combination of CRNN recognition, bounding box field extraction, and confidence-based verification ensures the system

V. FUTURE WORK

Although the proposed OCR-based digitization system demonstrates high accuracy and operational efficiency in extracting handwritten content from bank application forms, several valuable enhancements are planned for future development.

One major improvement involves the integration of multilingual OCR support, particularly for Indian regional scripts such as Hindi, Bengali, and Tamil. This enhancement would broaden the system's applicability in multilingual banking environments by incorporating dedicated CRNN models and language-specific post-processing modules.

Another promising direction is the implementation of a self-learning correction engine based on user feedback. By capturing manual edits performed through the user interface, the system can incrementally retrain its recognition model using active learning, thus improving accuracy over time, especially for uncommon handwriting styles and field formats. To further ensure compliance and security, the integration of cloud-based processing with role-based access control (RBAC) is proposed. This would allow distributed deployment across multiple branches, secure document access, and centralized model updates, all while maintaining regulatory alignment with RBI and GDPR standards.

Lastly, the incorporation of signature verification and document fraud detection using deep learning-based biometric verification techniques will enhance the authenticity of processed forms. These features will be particularly useful during KYC (Know Your Customer) validation stages in banking applications. These enhancements aim to elevate the system from a form digitization tool to a comprehensive, intelligent document processing platform tailored for financial institutions.

VI. CONCLUSION

This research presents the development of an automated system for extracting handwritten text from banking documents using Optical Character Recognition (OCR) techniques. The proposed solution addresses key challenges in digitizing handwritten entries commonly found in forms such as cheques, deposit slips, and loan applications. By leveraging a combination of image preprocessing methods, noise reduction techniques, and advanced OCR models, the system enhances the accuracy and reliability of handwritten text extraction. The integration of machine learning-based post-processing further improves the recognition performance by correcting context-based errors. Experimental results demonstrate that the system achieves a high level of accuracy across diverse handwriting styles and document types, significantly reducing the manual effort required for data entry and verification in banking workflows. The automation of this process not only accelerates document processing time but also minimizes human-induced errors, thereby improving operational efficiency and data integrity.

In summary, the proposed system provides a scalable, cost-effective, and robust solution for automating the digitization of handwritten banking documents. Future work will focus on improving multilingual support, handling low-quality scans, and integrating the system into real-time banking software platforms to further enhance its practical applicability.

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