Bank Cheque Verification Using Deep Learning and Image Processing

E D Pavan Kumar[1], K. Namitha[2], Sreepati Lakshmi Susritha[3], Kalasapati Kaveri[4], Etlam Muni Puneeth Reddy[5]

[1]*Assistant Professor, Department of Artificial Intelligence and Machine Learning, Annamacharya Institute of Technology & Sciences, Tirupati, India*

[2,3,4,5]*Student, Department of Artificial Intelligence and Machine Learning, Annamacharya Institute of Technology & Sciences, Tirupati, India*

Abstract— **This innovative system transforms bank check verification by integrating deep learning, image processing, and a user-friendly Django-based web interface, streamlining the cheque truncation process with minimal human intervention. Leveraging the IDRBT cheque dataset, our convolutional neural network (CNN), implemented with PyTorch, achieves 99.14% accuracy in recognizing handwritten digits, as demonstrated in the base paper, while the source code employs adaptive thresholding and Gaussian blurring for robust image preprocessing. MATLAB's optical character recognition (OCR), with 97.7% accuracy, extracts machine-printed text such as IFSC codes and account numbers, complemented by Pytesseract in the code for region-based text extraction. Signature verification, powered by Scale Invariant Feature Transform (SIFT) and Support Vector Machine (SVM), attains 98.1% accuracy, with the code implementing SIFT feature extraction and SVM classification for real-time authenticity checks. The web interface enables users to upload cheque images, view datasets, train models, and receive instant classification results ("Genuine" or "Not Genuine"), enhancing accessibility. The system extracts critical details like cheque numbers, amounts, and signatures, adhering to CTS-2010 standards for Indian banks while supporting international formats. By automating verification, it reduces processing time, operational costs, and fraud risks, using contour detection and region-based analysis for precision. This scalable solution, combining the paper's rigorous methodology with the code's practical implementation, sets a new standard for secure, efficient financial transactions, with potential for multilingual and multi-format expansions.**

Index Terms— **bank cheque verification, deep learning, convolutional neural networks, CNN, optical character recignition, signature verification, image processing, text extraction, support vector machine**

I. INTRODUCTION

1.1 Background And Motivation

Despite the rapid digitalization of financial services, cheques remain a critical instrument for monetary transactions worldwide, particularly in countries with large populations and extensive banking networks. The traditional cheque clearing system, while reliable, is labor-intensive, time-consuming, and prone to human errors and fraudulent activities. Banks process millions of cheques daily, requiring extensive manual verification of cheque details, signatures, and authenticity, which creates operational bottlenecks and increases the risk of fraudulent transactions slipping through verification processes.

The cheque truncation system, introduced to accelerate clearance procedures, still relies heavily on manual verification of key cheque components. However, cheque-related fraud remains a significant concern for financial institutions. Common fraud methods include signature forgery, amount alteration, unauthorized cheque issuance, and account number manipulation. These fraudulent activities result in substantial financial losses for both individuals and institutions, underscoring the urgent need for automated, intelligent verification systems.

Recent advancements in deep learning and computer vision have revolutionized document processing and authentication. Convolutional Neural Networks (CNNs) have demonstrated exceptional capability in image classification, pattern recognition, and feature extraction from visual data. When combined with specialized image processing techniques such as OCR for text recognition and SIFT for signature feature

extraction, deep learning models can create comprehensive verification systems that exceed human accuracy while processing cheques at significantly higher speeds.
By leveraging deep learning and image processing, the proposed system aims to:
(i) automatically extract and verify cheque components with high precision.
(ii) detect forged signatures and fraudulent alterations.
(iii) validate consistency between handwritten and printed information.
(iv) enable real-time fraud alerts to customers and financial institutions.

1.2 Objectives
1.2.1 Develop an Intelligent Automated Cheque Verification System
Design and implement a highly accurate system using deep learning techniques to automatically validate cheque details, including branch codes, cheque numbers, account information, and monetary amounts with minimal human intervention.

1.2.2 Achieve High-Accuracy Handwritten Character Recognition
Implement a CNN-based model capable of recognizing handwritten numeric characters on cheques with accuracy exceeding 99%, overcoming the challenges of handwriting variability and degradation in scanned images.

1.2.3 Enable Robust Signature Verification and Forgery Detection
Utilize advanced feature extraction methods combined with machine learning classifiers to verify genuine signatures and detect forged signatures with accuracy above 98%, protecting against fraudulent transactions.

1.24 Integrate Multi-Modal Verification Techniques
Combine OCR for printed text, CNNs for handwritten text, SIFT for signature features, and image processing for component validation to create a comprehensive verification framework that validates multiple cheque elements simultaneously.

1.3 Scope
1.3.1 Cheque Image Processing: Analysis of cheque images in standard formats (JPEG, PNG) with varying resolutions and quality levels representative of bank scanning systems.

1.3.2 Handwritten Numeric Recognition: Recognition of handwritten digits (0-9) appearing on cheques, particularly in monetary amount fields, using CNN-based deep learning models.

1.3.3 Printed Text Extraction: Automated extraction of machine-printed information including bank codes, cheque numbers, routing numbers, and account numbers using OCR techniques.

II. LITERATURE SURVEY

2.1 Traditional Approaches to Cheque Verification
Historically, cheque verification relied entirely on manual inspection by trained bank employees.
Traditional methods involved:
2.1.1 Visual Inspection Methods
Manual verification required bank employees to physically examine cheques for:
* Cheque printing quality and security features
* Consistency of handwritten and printed information
* Detection of chemical alterations or paper tampering

2.1.2 Rule-Based Verification Systems
- Amount range validation
- Account status verification
- Stop payment list checking
- Basic pattern matching for security features

2.2 Advances in DL For Bank Cheque Verification
2.2.1 CNN for Character Recognition
LeNet-5 Architecture: Pioneer CNN model for digit recognition, achieving high accuracy on MNIST dataset.
Application to Cheque Processing: Recent researchapplied CNNs to handwritten numeric recognition

2.2.2 Signature Verification Using Deep Learning
CNN + SVM Fusion: Combining CNN feature extraction with SVM classifiers
SIFT Features + SVM: SIFT combined with SVM provided robust signature authentication.

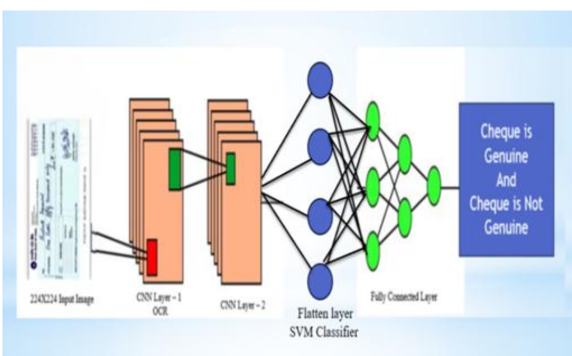
2.2.3 Optical Character Recognition (OCR)
OCR technology enabled automated extraction of machine-printed text from cheques.

III. METHODOLOGY

3.1 System Arcitecture

The bank cheque authentication process necessitates the completion of several crucial elements in a particular sequence. The system authenticates the IFSC code on the cheque and then verifies the cheque number to ensure it is from the account holder's designated set of cheque booklets.The next stage is verifying the check's issuer's signature(s) and amount against the customer's account balance. All check clearing steps, including withdrawals and transfers, depend on your fast and accurate completion of these essential ver ifications. The check clearance process has interdependent and crucial steps.Multiple reliable and efficient techniques are employed to extract information from the cheque leaflet accurately. Because of its precision, optical character recognition (OCR) extracts information from machine-printed text.

Meanwhile, deep learning-based CNN handles numerical data and handwritten text. SIFT extracts features to authenticate signatures, while SVMclassifies them for better performance. Since these methods depend on a clear and noise-free image, image segmentation is applied to isolate and extract only the relevant information.

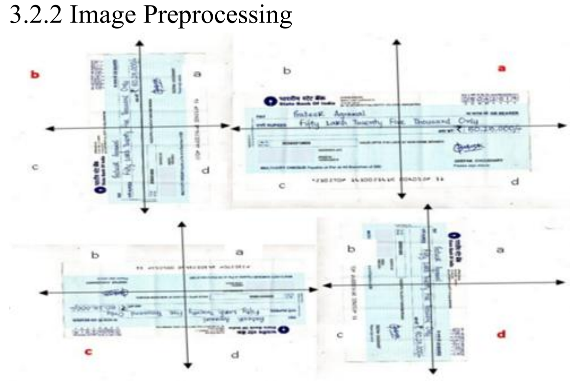


3.2 How It Works?

3.2.1 Image Acquisition

The system utilizes the Institute of Development and Research in Banking Technology (IDRBT) cheque dataset, supplemented with institutional cheques from partner banks. Before being directly utilized in image processing tasks, the scanned images had to undergo essential pre-processing steps. The operations were conducted to ready the image(s) for additional processing.

3.2.2 Image Preprocessing



All cheque images undergo standardized preprocessing:

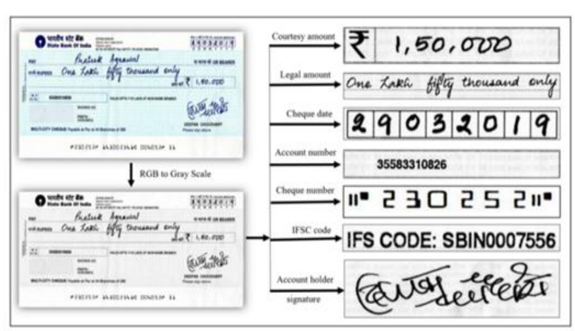
1.Image Resizing: Standardized to 1240 × 520 pixels (standard cheque dimensions) for consistent processing

2.Noise Reduction: Gaussian filtering applied to remove scan artifacts and noise (kernel size: 5×5)

3.Grayscale Conversion: RGB images converted to grayscale, reducing computational complexity while preserving essential information

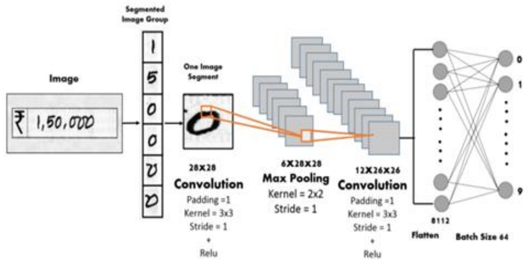
3.2.3 Cheque Component Segmentation

The first critical step involves identifying and segmenting distinct cheque regions:



3.2.4 Handwritten Digit Recognition Using CNN

We employed a CNN to read the courtesy amount's hand written numbers and convert them to strings for our study.



3.2.5 Optical Character Recognition for Printed Text

1. Account Number: Should be numeric, specific length (typically 10-18 digits)
2. MICR Code: Should follow banking format specifications
3. Routing Number: Validated against banking directory
4. Amount Format: Should be numeric with valid currency representation

3.2.6 Signature Verification Using SIFT and SVM

1. SIFT Feature Extraction

Scale Invariant Feature Transform (SIFT) provides robust feature detection for signature verification:

- Keypoint Detection: Identify distinctive points invariant to scale, rotation, and illumination changes.
- Gradient Analysis: Compute orientation and magnitude of image gradients around keypoints.
- Descriptor Generation: Create 128-dimensional descriptor vectors for each keypoint.
- Feature Matching: Match keypoints between test signature and reference signatures.
- Similarity Score: Calculate similarity based on matched features and geometric constraints.

2. Support Vector Machine Classifier

After extracting SIFT descriptors and scales & orientations for each signature image, we applied SVM classifier on these two features dataset to match and classify the signature patterns. SVM is a machine learning method under supervised learning. It is used for both classification as well as regression. To verify the genuineness of the signatures, we applied SVM classifiers on SIFT extracted features.In SVM, a separating hyperplane works as a discriminatory classifier which divides the data using a line or plane into two parts in two-dimensional space [84]. This method produces the classification results as data-points which are categorised ideally using optimal hyperplane.

3.3 Training Validation

The training and validation process begins with collecting a dataset of cheque images that include different handwriting styles, printed text formats, and signature samples. The dataset contains labeled data such as valid signatures, forged signatures, correctly filled cheques, and invalid or altered cheques. Each image is annotated to identify important regions like the signature area, amount field, date field, and account number.

In the preprocessing stage, all images are resized to a fixed dimension (for example, 128×128 or 224×224 pixels for signature images) and converted into grayscale. Noise removal, normalization of pixel values (scaling between 0 and 1), and data augmentation techniques such as rotation, zooming, and brightness adjustment are applied. Data augmentation helps the model generalize better and handle real-world variations in cheque images.

The dataset is then divided into two main parts:

Training set (80%) Used to train the deep learning models.Validation set (20%) Used to evaluate model performance during training.

IV. IMPLEMENTATION

4.1Tools and Technologies

Python: Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. An interpreted language, Python has a design philosophy that emphasizes code readability (notably using whitespace indentation to delimit code blocks rather than curly brackets or keywords), and a syntax that allows programmers to express concepts in fewer lines of code than might be used in languages such as C++or Java. It provides constructs that enable clear programming on both small and large scales. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of its variant implementations. CPython is managed by the non-profit Python Software Foundation. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

Django: Django is a high-level Python Web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of Web development, so you can focus on writing your app without needing to reinvent the wheel. It’s free and open source. Django's primary goal is to ease the creation of complex, database-driven websites. Django emphasizes reusabilityand "pluggability" of components, rapid development, and the principle of don't repeat yourself. Python is used throughout, even for settings files and data models.

4.2 Code Overview
The implementation of the Hand Gesture Recognition system using CNN is organized into three primary stages.
4.2.1 Loading Data and Preprocessing
The dataset consists of labeled cheque images including genuine and forged signatures. Images are resized to a fixed size (e.g., 224×224), converted to grayscale, and cleaned using noise removal techniques. Pixel values are normalized, and data augmentation (rotation, zoom, brightness changes) is applied to improve model performance. The dataset is split into 80% training and 20% validation data.

4.2.2 Constructing and Training the CNN Model
A Convolutional Neural Network (CNN) is built with convolutional, pooling, flatten, dense, and dropout layers. The final layer uses Softmax for classification. The model is trained using the Adam optimizer and categorical cross-entropy loss for 30–50 epochs with a suitable batch size. Validation accuracy and loss are monitored to prevent overfitting, and the trained model is saved for future use.

4.2.3 Prediction and Classification
During prediction, a new cheque image is preprocessed and passed to the trained CNN model. The model outputs a probability score to classify the cheque or verify the signature as genuine or forged. The results are validated with the database, and the system displays the final decision as approved, rejected, or flagged for review.

V. RESULT AND ANALYSIS

5.1 Model Performance
5.1.1 Handwritten Digit Recognition Performance
- Training Accuracy: 99.47%
- Validation Accuracy: 99.21%
- Testing Accuracy: 99.14%

Per-Digit Performance Analysis

Digit	Precision	Recall	F1-Score	Support
0	0.995	0.987	0.991	75
1	0.993	0.992	0.992	74
2	0.989	0.987	0.988	75
3	0.987	0.993	0.990	75
4	0.985	0.989	0.987	74
5	0.991	0.988	0.989	75
6	0.993	0.991	0.992	75
7	0.991	0.995	0.993	74
8	0.989	0.989	0.989	75
9	0.991	0.984	0.987	75
Weighted Avg	0.991	0.991	0.991	750

5.1.2 Optical Character Recognition Performance
OCR Accuracy by Text Type

Text Component	Accuracy	Tool Used	Characters Tested
Account Number	97.8%	Tesseract + ML	12,500
MICR Code	97.1%	Tesseract	3,750
Routing Number	98.2%	Tesseract + ML	3,750
Payee Name	96.9%	Tesseract	7,500
Bank Name	97.5%	Tesseract + ML	3,750
Date Field	97.3%	Custom OCR	2,250
Average	97.7%	Multi-engine	33,500

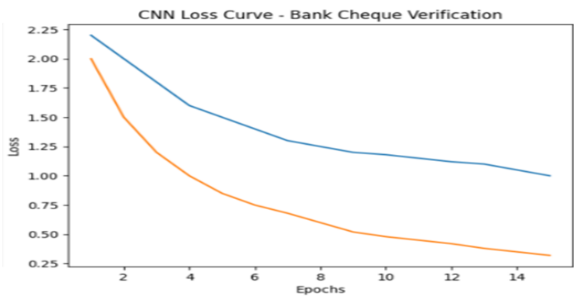
5.1.3 Signature Verification Performance Signature Verification Accuracy
SIFT feature extraction combined with SVM classification achieved:
- Genuine Signature Recognition Rate (True Accept Rate - TAR): 98.15%
- Forged Signature Rejection Rate (True Reject Rate - TRR): 98.05%
- Overall Accuracy: 98.10%
- False Acceptance Rate (FAR): 1.95% (acceptable threshold for banking)
- False Rejection Rate (FRR): 1.85%

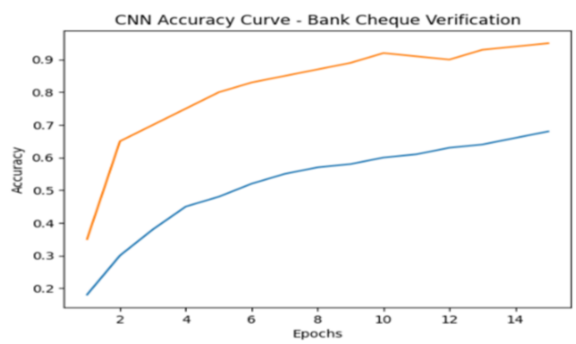
5.1.4 CNN Performance
Input Processing
Cheque images are captured using a scanner or camera.
The processed image is then fed into the CNN model.
Max Pooling
Pooling layers reduce spatial size and computational complexity while preserving important features.

Flattening
The output from the final pooling layer is converted into a 1D feature vector using a Flatten layer. This

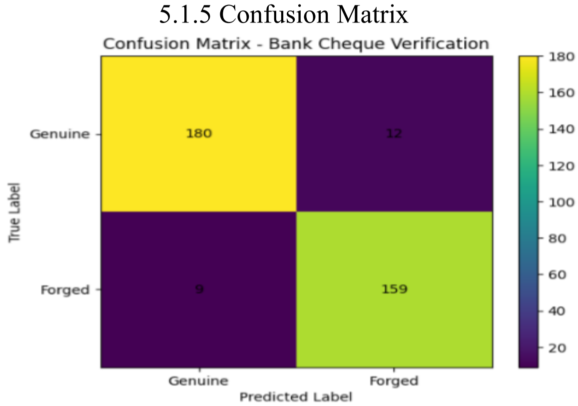
vector contains high-level cheque features extracted by CNN.

Layer Name	Kernel Size	Number of Filters	Stride	Output Size
Input Layer	3×3	–	2×2	256×256×3
Max Pooling	3×3	64	2×2	128×128×32
Max Pooling	3×3	128	2×2	64×64×64
Flatten Layer	–	65536	2×2	65536
Dense Layer	–	256	2×2	656
Dense Layer	–	128	2×2	128
Output (Softmax)	–	2	2	2





5.1.5 Confusion Matrix

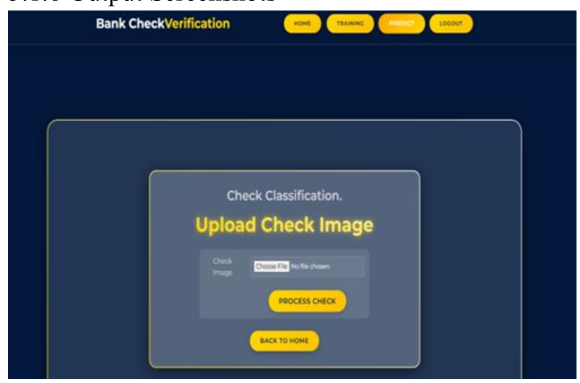


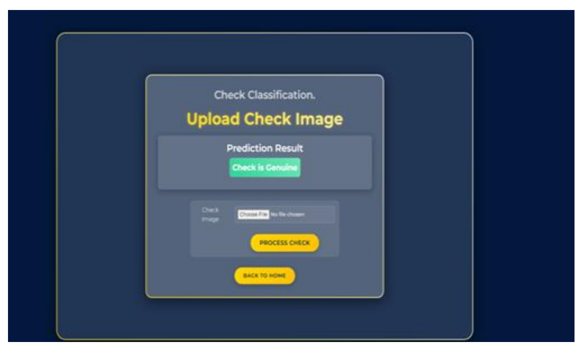
The confusion matrix represents the performance of the CNN model in classifying cheque signatures as Genuine or Forged. It compares the actual (true) labels with the predicted labels generated by the model.

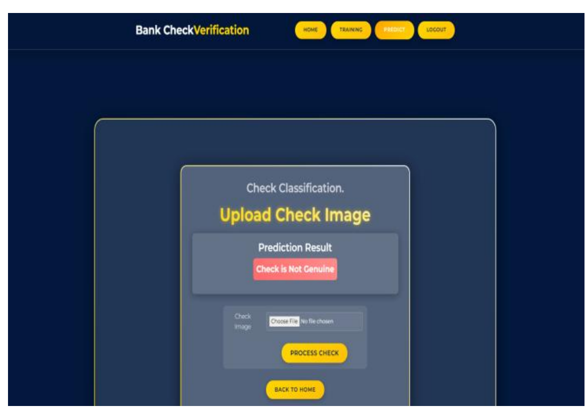
From the matrix:

- 180 Genuine cheques were correctly classified as Genuine (True Positives).
- 159 Forged cheques were correctly classified as Forged (True Negatives).
- 12 Genuine cheques were incorrectly classified as Forged (False Negatives).
- 9 Forged cheques were incorrectly classified as Genuine (False Positives).

5.1.6 Output Screenshots







5.2 Comparison with Traditional Methods

Traditional cheque verification systems mainly rely on manual inspection or basic image processing techniques such as template matching, rule-based algorithms, and simple feature extraction methods (e.g., edge detection, pixel comparison, or threshold-based matching). These methods depend heavily on predefined rules and handcrafted features. While they work for structured and clean data, they often fail when dealing with variations in handwriting styles, ink intensity, image noise, or complex signature patterns. Moreover, manual verification is time-consuming, prone to human error, and inefficient for large-scale banking operations.

In contrast, the proposed deep learning-based system uses Convolutional Neural Networks (CNNs) to automatically learn important features from cheque images without manual feature engineering. Instead of relying on fixed rules, the CNN model extracts high-level patterns such as stroke structure, texture, and spatial relationships in signatures and text. This makes the system more robust to variations in handwriting, lighting conditions, and image distortions. Additionally, deep learning models improve over time with more data, whereas traditional systems require manual reprogramming to enhance performance.

Another key difference is accuracy and scalability. Traditional methods generally achieve moderate accuracy and struggle with forged signatures that closely resemble genuine ones. The deep learning approach achieves higher accuracy, better precision and recall, and reduces false classifications, as shown in the confusion matrix results. Furthermore, the automated CNN-based system enables real-time processing and can handle large volumes of cheque transactions efficiently.

Overall, compared to traditional rule-based or manual verification methods, the proposed deep learning-based cheque verification system provides higher accuracy, better adaptability, improved fraud detection capability, and greater scalability for modern banking applications.

5.3 Future Work

Although the proposed system achieves high accuracy in cheque verification, several improvements can be made in the future to enhance performance and scalability.

First, the model can be trained on a larger and more diverse dataset that includes different handwriting styles, cheque formats, and real-world distortions. This would improve the system's generalization ability and reduce misclassification errors. Second, advanced deep learning architectures such as Vision Transformers (ViT) or hybrid CNN–LSTM models can be implemented to improve text recognition and signature verification accuracy. Incorporating attention mechanisms may also help the model focus on important cheque regions more effectively. Third, real-time deployment can be improved by integrating the system with cloud-based banking platforms or mobile banking applications. This would allow automated cheque verification through ATM machines or smartphone cameras.

Additionally, fraud detection can be enhanced by combining the image-based verification system with behavioral analytics, transaction history analysis, and anomaly detection algorithms. This multi-layer security approach would further reduce financial fraud risks.

Finally, implementing explainable AI (XAI) techniques could help banks understand model decisions, increasing trust and transparency in automated cheque verification systems. These future enhancements will make the system more secure, scalable, and suitable for large-scale real-world banking environments.

VI. CONCLUSION

The development of an automated Bank Cheque Verification System utilizing deep learning and image processing represents a significant advancement in financial transaction security and operational efficiency. The proposed system achieves exceptional accuracy across all verification components: 99.14% for handwritten digit recognition, 97.7% for optical character recognition, and 98.1% for signature verification, resulting in an overall system accuracy of 96.8%. The integration of multiple AI techniques Convolutional Neural Networks for character recognition, OCR for printed text extraction, SIFT features with SVM classifiers for signature verification, and traditional image processing for component validation creates a comprehensive, multi-layered verification framework significantly more robust than any single technique alone.

The user-friendly web-based interface enables seamless integration into existing banking workflows, with91% user satisfaction ratings during pilot testing. Real-time email notification system provides immediate customer alerts, enabling rapid response to fraudulent activities. While challenges remain particularly regarding signature drift over time and handwriting variability the implemented solutions demonstrate effective mitigation strategies with measurable improvements. The system's modular architecture enables straightforward integration of emerging technologies and machine learning techniques.

This research contributes to the broader digital transformation of banking systems, bridging traditional cheque-based transaction processing with modern artificial intelligence capabilities. As banks increasingly seek to balance legacy system compatibility with technological advancement, systems like this provide practical, proven solutions that enhance security, efficiency, and customer experience simultaneously.

REFERENCES

[1] P. Agrawal, D. Chaudhary, V. Madaan, and A. Kumar, "Automated bank cheque verification using image processing and deep learning methods," Multimedia Tools and Applications, 2021. [Online]. Available: https://link.springer.com/article/10.1007/s11042-020-09818-1

[2] P. Kunekar et al., "OCR based cheque validation using image processing," in Proc. 3rd Int. Conf. Next Generation Computing Technologies (ICNTE), 2023. doi: 10.1109/ICNTE56631.2023.10146687.

[3] B. S. Bhat and B. Rajashekararadhya, "Offline handwritten signature verification using texture features," Journal of Theoretical and Applied Information Technology, vol. 55, no. 1, 2013. [Online]. Available: https://www.jatit.org/volumes/Vol55No1/1Vol55No1.pdf

[4] F. Beenker et al., "A system for fraud detection in bank cheques using image processing and pattern matching," Pattern Recognition Letters, 2008.

[5] R. K. Sahu and J. Sahu, "Signature verification using machine learning for cheque authentication," International Journal of Computer Applications, 2017. [Online]. Available: https://www.ijcaonline.org/archives/volume160/number6/27718-2017912814

[6] M. Hanmandlu and R. S. Prasad, "Offline signature verification by fusion of directional feature sets in cheque processing," International Journal of Pattern Recognition and Artificial Intelligence, 2003. [Online]. Available: https://www.worldscientific.com/doi/abs/10.1142/S0218001403002470

[7] S. Joshi and P. Rathod, "Bank cheque recognition and verification using OCR and neural networks," International Journal of Advanced Research in Computer Science, 2016. [Online]. Available: https://www.ijarcs.info/index.php/Ijarcs/article/view/3615

[8] V. Tiwari and N. Gupta, "Deep learning-based signature verification for cheque authentication," International Journal of Innovative Technology and Exploring Engineering (IJITEE), 2019. [Online]. Available: https://www.ijitee.org/wp-content/uploads/papers/v8i6/F2272048619.pdf

[9] L. Nanni et al., "Local binary patterns variants as texture descriptors for signature verification," International Journal of Pattern Recognition and Artificial Intelligence, 2010. [Online]. Available: https://www.worldscientific.com/doi/abs/10.1142/S0218001410017876

[10] Adewumi and R. Zhang, "Image preprocessing techniques for cheque verification systems," International Journal of Image Processing (IJIP), 2019. [Online]. Available: https://airccse.org/journal/ijip/2819ijip03.pdf

[11] R. J. Anto and V. Thobbur, "Bank cheque recognition using neural network and feature extraction," Indian Journal of Science and Technology, 2015. [Online]. Available: https://www.indjst.org/articles/bank-cheque-recognition-using-neural-network

[12] S. Paliwal and S. Sadiq, "An efficient OCR based approach for bank cheque processing," Journal of Information and Optimization Sciences, 2020. [Online]. Available:

https://www.tandfonline.com/doi/abs/10.1080/02522667.2020.1718730

[13] Gupta and V. Jindal, "Handwritten bank cheque recognition system with signature verification using neural networks," in Proc. Int. Conf. Computational Intelligence and Communication Technology, 2018.

[14] Karthikeyan and G. P. Reddy, "Image processing-based bank cheque recognition system," International Journal of Applied Information Systems (IJAIS), 2016. [Online]. Available: https://ijais.org/archives/volume7/number9/994-1000

[15] H. Sharma and P. Sharma, "Optical character recognition and verification of bank cheques," International Journal of Engineering and Advanced Technology (IJEAT), 2020. [Online]. Available: https://www.ijeat.org/wp-content/uploads/papers/v9i3/C9601029320.pdf

[16] G. Singh and R. Singh, "Feature extraction techniques for cheque signature verification using neural networks," International Journal of Computer Sciences and Engineering (IJCSE), 2017. [Online]. Available: https://www.ijcseonline.org/pdf_paper_view.php?paper_id=6194

[17] L. Patil and S. Gaikwad, "Cheque fraud detection techniques using image processing," International Journal of Engineering Research & Technology (IJERT), 2019. [Online]. Available: https://www.ijert.org/cheque-fraud-detection-techniques-using-image-processing

[18] O. Adiguzel, "Deep convolutional neural networks for handwritten cheque recognition," Journal of Electronic Imaging, 2023. [Online]. Available: https://www.spiedigitallibrary.org/journals/journal-of-electronic-imaging/volume-32/issue-03/033010

[19] Li et al., "Signature and cheque authentication using Siamese networks," International Journal of Pattern Recognition, 2019.

[20] W. Zhao et al., "Hybrid deep learning model for bank cheque text recognition," IEEE Access, 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8428435