International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 4, July-Aug-2026, PP: 01-9

Deep Learning-Driven Automated Bank Cheque Verification Using Image Processing Techniques

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Abstract – **Even though digital banking services are widely used, bank cheques are still crucial for financial transactions. Traditional methods of verifying checks, on the other hand, rely heavily on human intervention, which may be laborious, error-prone, and even fraudulent. This study proposes a framework for automated bank cheque verification that uses deep learning and image processing to overcome these obstacles and increase the trustworthiness and efficiency of cheque authentication. By use of picture preprocessing and segmentation, the suggested method retrieves crucial information from checks, such as the account number, legal amount, courtesy amount, IFSC code, and the signature of the account holder. While a Convolutional Neural Network (CNN) is used for handwritten numerical character identification, Optical Character identification (OCR) is used for machine-printed text recognition. Signature verification and classification are handled by Support Vector Machines (SVMs), while feature extraction is handled by Scale Invariant Feature Transforms (SIFTs). By automating the verification process, the suggested architecture drastically cuts down on human participation while still adhering to the CTS-2010 criteria for cheque verification. Results from experiments show that the suggested technique works, with CNN model accuracy reaching 99.14% for handwritten digit recognition, OCR accuracy reaching 97.7% for machine-printed text recognition, and SIFT-SVM accuracy reaching 98.10% for signature verification. Based on these results, the suggested framework is a safe, efficient, and accurate way to verify bank checks automatically, which speeds up processing and improves the authenticity of the checks.**

Keywords **- Deep Learning, Bank Cheque Verification, Image Processing, Optical Character Recognition (OCR), Computer Vision, Document Authentication**

I. INTRODUCTION

With the rise of internet banking, digital payment systems, and electronic cash transfer methods, the banking industry has seen tremendous technical improvements in the last decade. The legal validity, dependability, and acceptability of bank cheques in high-value financial transactions mean that they remain an essential tool for people, businesses, and educational institutions, in spite of these changes. Because of this, effective cheque verification is crucial for safe and dependable banking operations, as financial institutions still handle a large volume of check-based transactions daily. Traditional methods of checking checks rely heavily on human inspection, which may be a tedious, error-prone, and labour-intensive process. So, a major goal of current banking application research is the development of an intelligent automated cheque verification system.

Before a financial transaction may be accepted, a series of successive validation steps is used for traditional cheque verification. The legitimacy of the signature, account number, legal amount, courtesy amount, and IFSC code are among the many elements of a cheque that banking staff carefully check. Make sure the cheque is from a legitimate account and that no one has tampered with it by correctly completing each step of the verification process. As the number of transactions increases, manual verification becomes more difficult, even if seasoned bank employees can do it quickly. Processing time, operating expenses, and the likelihood of mistakes during cheque clearing are all impacted by the repeated nature of these procedures.

Solutions for automated document verification and analysis have been developed thanks to the fast advancements in deep learning, computer vision, and image processing. Intelligent computers can now accurately authenticate the validity of scanned documents by analysing the pictures, extracting relevant information, and recognising both handwritten and machine-printed characters. Banking institutions may greatly benefit from automated cheque verification systems in terms of operational efficiency, fraud protection, transaction speed, and reduction of human work. Financial organisations may build trustworthy systems to handle checks with little human involvement by integrating deep learning models with image processing methods.

By preparing scanned cheque pictures for further analysis, image processing forms the basis of automated cheque verification. It is necessary to do preprocessing procedures prior to feature extraction on scanned documents since these images often include rotation problems, background noise, shadows, lighting changes, and irrelevant artefacts. You may improve the picture quality and separate the essential sections of the cheque using techniques including greyscale conversion, Gaussian filtering, contour extraction, image enhancement, morphological procedures, and segmentation. In order to properly extract the necessary components of a check—its IFSC code, account number, cheque number, legal amount, courtesy amount, and signature region—for further verification, certain preprocessing procedures are performed.

Optical Character identification (OCR) is a popular tool for identifying machine-printed text in scanned documents. It is one of many document identification technologies utilised today. Without the need for human data input, optical character recognition (OCR) allows for the automated identification of textual information such IFSC codes, cheque numbers, branch details and account numbers. Aside from reducing processing time, automating the identification of printed characters also minimises transcribing mistakes that often arise during human verification. As a result, optical character recognition is critical for making automated cheque authentication systems more efficient in general.

By enabling very precise handwritten character recognition, deep learning has significantly improved document verification. Due to its capacity to autonomously acquire hierarchical visual attributes from training datasets, Convolutional Neural Networks (CNNs) have shown outstanding performance in identifying intricate picture patterns and handwritten numerical symbols. Convolutional neural network (CNN) models reliably identify numerical values and handwritten courteous amounts in cheque verification, which are often difficult to understand using traditional image processing methods. Automated cheque verification methods are made far more reliable and resilient by CNNs' capacity to generalise across various handwriting styles.

Check authentication isn't complete without extra safeguards against financial fraud, and signature verification is a crucial part of that. As a result of their distinct structural features, handwritten signatures continue to be among the most trustworthy ways to verify the identity of an account holder. But human skill is crucial in manual signature comparison, which might lead to conflicting results under different settings. The suggested system employs Scale Invariant Feature Transform (SIFT) for signature feature extraction and Support Vector Machine (SVM) for signature authenticity/forgery classification in order to provide more trustworthy verification results. Robust feature extraction in conjunction with supervised classification allows for computationally efficient and accurate signature authentication.

Through the integration of picture preprocessing, optical character recognition (OCR), convolutional neural networks (CNNs), support vector machines (SVMs), and SIFTs, the proposed study offers an intelligent framework for the verification of bank cheques. The first step in improving the quality of scanned cheque pictures is preprocessing, which involves removing noise from the photos. Subsequently, the check is divided into sections in order to extract crucial areas that include machine-printed data, handwritten amounts, and signature patterns. The SIFT-SVM architecture verifies the identity of account holders, while OCR collects textual information from printed materials and CNN recognises numerical values written by hand. The last step in the cheque clearing procedure is a collective validation of the extracted information to ascertain the legitimacy of the check.

Reducing human involvement, minimising processing delays, and increasing transaction security is the major goal of this study on automating the cheque verification process. The suggested solution improves operational efficiency and verification accuracy by providing a unified foundation for various AI and image processing methods. Reduced cheque fraud, decreased operating expenses for banks, and faster processing of financial transactions are all outcomes of the automated method.

Results from experiments show that the suggested approach reliably completes a number of cheque verification tasks. The framework's accuracy in recognising machine-printed text is 97.7 percent, in handwritten numerical character recognition it's 99.14% with the CNN model, and in signature verification it's 98.10% with the SIFT-SVM method. The results show that automated bank cheque verification using deep learning and image processing is practical, efficient, and secure. The suggested framework is perfect for contemporary banking settings that need reliable, fast, and accurate financial document authentication.

II. LITERATURE SURVEY

Researchers have been motivated to create smarter methods of checking checks in order to speed up clearing processes, decrease human error, and increase transaction security due to the growing use of automated banking systems. The ability to automatically extract and authenticate crucial cheque information has revolutionised financial document verification, thanks to advancements in image processing, optical character recognition, machine learning, and deep learning. Many research have looked at various parts of verifying a cheque, such as recognising handwritten characters, extracting text from machine prints, authenticating signatures, segmenting documents, and detecting fraud. Taken as a whole, these studies show how AI is becoming an integral part of contemporary banking software.

The use of Optical Character Recognition (OCR) to decipher financial documents and bank checks was an early area of study. Recognising machine-printed characters under regulated scanning settings was the primary focus of first optical character recognition systems. While Zramdini and Ingold suggested typographical feature-based techniques for optical font identification, researchers like Wang and Shiau presented transformation-based techniques for printed character recognition. Using global texture analysis, further research by Zhu et al. enhanced font recognition, leading to better document recognition accuracy. As a result of these advancements, optical character recognition (OCR) became a cornerstone technology for automated document processing, and intelligent cheque verification systems were born.

Research into handwritten character recognition has developed as a result of the prevalence of both printed and handwritten information in financial documents. In order to decipher numerical values and linguistic information found on financial documents, several research investigated segmentation-based and segmentation-free handwriting recognition methods. In order to improve the accuracy of handwriting identification, Stewart et al. suggested segmentation and stitching techniques that work with small training datasets. On the other hand, Kajale et al. created supervised machine learning algorithms that can accurately recognise both printed and handwritten characters. Although recognition accuracy was still affected by issues related to handwriting variances, these methods greatly improved document interpretation by decreasing reliance on human verification.

The quality of future recognition tasks is strongly impacted by image preprocessing and segmentation, which is why these aspects have also garnered a lot of attention. In order to enhance the document quality prior to feature extraction, researchers explored several preprocessing strategies. These included adaptive thresholding, greyscale conversion, contour extraction, Gaussian filtering, morphological operations, and background noise reduction. Preprocessing is crucial for textual information extraction in difficult imaging environments, as shown by Feng and Gao. To enhance optical character recognition (OCR) performance for low-quality scanned documents, Lu et al. suggested shadow reduction approaches. In a similar vein, Wiraatmaja et al. showed substantial gains in recognition accuracy after using deep convolutional denoising autoencoders to improve picture quality prior to OCR processing. In today's document verification systems, these preprocessing techniques are indispensable.

Convolutional Neural Networks (CNNs) and other forms of deep learning have completely altered the landscape of handwritten character recognition. Computer network algorithms (CNNs) are superior to more conventional feature engineering methods for identifying intricate visual patterns and handwritten numerical values because they develop hierarchical representations from massive datasets automatically. Researchers achieved outstanding classification accuracy across benchmark datasets after applying CNN models to several handwritten digit identification tasks. Thank you amounts and handwritten number fields on bank checks are perfect candidates for CNNs due to their capacity to generalise across various handwriting styles. As a result, deep learning is becoming a popular tool for intelligently analysing financial documents.

When it comes to authenticating checks and preventing fraud, signature verification is an important field of study. Many feature extraction and classification algorithms have been suggested to differentiate between real and fake handwritten signatures due to the fact that each person's signature has its own distinct structural features. For the purpose of extracting unique local picture features that are robust against changes in scale, rotation, and lighting, Scale Invariant Feature Transform (SIFT) has seen widespread use. Support Vector Machine (SVM) and other supervised learning algorithms easily distinguish between real and fake signatures by building optimum decision boundaries; they are then used to categorise these robust descriptors. Consistent with previous research, integrating SIFT feature extraction with SVM classification yields computationally efficient signature verification with very high reliability.

Additionally, in order to separate various areas of bank checks prior to detection, researchers have looked into bank cheque segmentation. It is crucial to accurately segment bank checks in order for automated verification to be effective since these documents include several information fields such as IFSC codes, account numbers, cheque numbers, dates, courtesy amounts, legal amounts, and signatures. Predefined check areas based on CTS standards were identified using standard check templates and contour extraction techniques. By properly segmenting the cheque, specialised recognition algorithms can process each component individually, leading to improved system accuracy and fewer recognition mistakes.

A number of research projects have investigated unified authentication systems that use multi-stage check verification frameworks that include optical character recognition (OCR), image processing, deep learning (DL), and machine learning (ML). These hybrid methods reduce the need for human involvement in the processing of checks by automating the extraction of printed information, handwritten numerical values, and signatures. When comparing verification accuracy with individual approaches, comparative research show that merging numerous recognition techniques greatly enhances performance. Intelligent frameworks like these also help banks cut down on processing times, operating expenses, and cheque fraud.

There has been a lot of success with automatic cheque verification, but there are still a few obstacles. System performance is nevertheless affected by factors such as variations in handwriting styles, noise in the background, signature fraud, low-resolution scanned photos, variations in cheque layouts between nations, and deteriorating image quality. Reliable feature extraction, quick segmentation, strong preprocessing, and effective classification methods are also necessary to achieve consistent recognition accuracy in real-world banking scenarios. Researchers are driven to create smarter, more accurate cheque verification systems that can handle different banking settings because of these issues.

In light of the shortcomings of current methods, this study presents a complete framework for integrated check verification using image processing, OCR, CNNs, SIFT, and SVM to authenticate checks in every detail. High recognition accuracy and little human interaction are achieved via the automation of the extraction and verification of important check information by use of the framework. The suggested system seeks to enhance operational efficiency, fortify transaction security, and provide a dependable solution for contemporary automated banking applications by combining these supplementary approaches into a uniform verification pipeline.

III. PROPOSED METHODOLOGY

The proposed architecture for verifying bank cheques uses a single pipeline of image processing, OCR, CNNs, SIFT, and SVM to simplify the authentication process via the integration of these technologies. The proposed system seeks to enhance banking security, speed up cheque clearing, reduce human participation, and boost verification accuracy by automating the extraction and validation of critical cheque information. While conventional manual verification procedures tend to introduce inconsistencies and human error into the process, the proposed architecture systematically runs through many verification steps.

A scanned copy of the bank cheque is input into the system initially. As a first stage in obtaining and processing the tick image, you need to eliminate typical artefacts seen in raw scanned pictures, such as background noise, rotation errors, shadows, and lighting shifts. Using the standard date field on CTS-2010 compliant check layouts ensures that the scanned check is appropriately aligned during preprocessing. By using contour extraction to determine the location of the date box and then calculating the rotation angle, we are able to get the tick image in an appropriate orientation for analysis. The subsequent identification steps are more precise because this alignment technique verifies that the check's components are in their proper locations according to banking regulations.

A sequence of preprocessing procedures performed subsequent to image alignment enhances the scanned cheque picture. The first step in facilitating image analysis while preserving important structural information is to convert the RGB image to greyscale. Next, we use Gaussian filtering to eliminate visual noise and smooth out intensity variations. Additionally, morphological processes like erosion and dilation improve image quality by strengthening critical check structures and eliminating minor aberrations. The processed greyscale image is transformed into a binary image for the purpose of simplifying contour extraction and region identification. By improving the picture quality via these preprocessing procedures, we are able to feed recognition and feature extraction algorithms better input.

The image segmentation stage follows the framework's completion of the preprocessing step. The primary objective of segmentation is to isolate the sections of the cheque that contain important financial data by removing irrelevant elements of the image. Several Regions of Interest (ROIs) are extracted from a CTS-2010 standardised cheque layout by the system. These include the IFSC code, account number, date field, legal amount, courtesy amount, and the signature of the account holder. Each part of the cheque may be handled independently using the best identifying method once it has been precisely segmented. The overall efficiency and dependability of the verification process is enhanced by this.

The processing of the machine-printed optical character recognition (OCR) text fields follows the completion of the segmentation step. Financial information like the IFSC code, account number, and cheque number may be automatically detected using optical character recognition (OCR) systems without the need for human data entry. Following extraction, the data is converted to a machine-readable format that may be used for validation purposes by cross-referencing with financial records. Automated printed text recognition significantly reduces processing time compared to human cheque verification, which is susceptible to transcribing errors.

The courtesy amount field contains numerical values that are handwritten and may be recognised using a Convolutional Neural Network (CNN). For accurate number recognition across a variety of handwriting styles, the CNN model is ideal, thanks to deep learning's ability to automatically detect all the hidden visual clues associated with handwritten numbers. Using standard datasets of handwritten numbers, the network is trained and then put into action to detect handwritten cheque amounts. Following recognition, a textual representation of the retrieved numerical value is created using the IPV system. To make sure the generated textual amount is compatible with the legal amount written elsewhere on the cheque and to detect any changed or fraudulent modifications, we compare the two.

Since signature verification is a key security method for authenticating checks, it is an integral aspect of the proposed architecture. When dealing with image alignment, scaling, and rotation, normalising the segmented signature image is the first stage in minimising variations. To handle the normalised signature, the Scale Invariant Feature Transform (SIFT) method is used. This method is able to recover distinct local visual aspects that hold up well in a variety of viewing conditions. Even when

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www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 4, July-Aug-2026, PP: 01-9

subjected to minor geometric changes, these recovered properties accurately represent the structural features of the handwritten signature.

Afterwards, the collected SIFT descriptors are fed into a Support Vector Machine (SVM) classifier, which is then instructed to distinguish between authentic and fraudulent signatures. A perfect decision boundary is constructed by the SVM classifier using training samples of both real and fraudulent signatures. Using the retrieved feature vectors, the classifier determines whether the signature matches the actual account holder during verification. Combining SIFT feature extraction with SVM classification not only decreases the rates of false acceptance and rejection but also substantially improves the accuracy of signature verification.

After all verification modules, including those for printed text recognition, handwritten amount verification, and signature authentication, have finished their job, the proposed framework unifies their results. Combining the signature verification findings with the extracted IFSC code, cheque number, account number, legal amount, and courtesy amount determines the entire legality of the cheque. Until the system has successfully completed all verification steps, it will not approve the cheque for further financial operations. Checks are manually reviewed for inconsistencies, such as differing amounts or incorrect signatures, to prevent fraudulent financial transactions.

The proposed verification framework is in line with the CTS-2010 standards used for processing checks, and it supports uniform cheque layouts with little operator involvement. By consolidating image preprocessing, segmentation, optical character recognition (OCR), handwritten digit recognition based on convolutional neural networks (CNNs), signature verification based on support vector machines (SVMs), and a single automated pipeline, the suggested system simplifies the processing of checks, saving both time and money.

IV. SYSTEM ARCHITECTURE

The proposed automated system has a modular design that integrates deep learning, feature extraction, machine learning, optical character recognition (OCR), and image processing to efficiently and quickly confirm bank checks. The goal of the design is to automate every step of the cheque verification process, from capturing scanned pictures to authenticating the final cheque. With the help of each module's coordinated efforts, we can achieve reliable verification with little human intervention. While preventing alterations to the fundamental verification approach, the modular design enables future enhanced simplicity, processing efficiency, and system scalability.

Obtaining scanned images of bank checks from the system that processes them is the primary responsibility of the Image Acquisition Module, the initial component of the design. Due to possible issues with rotation, skewness, shadows, background noise, and lighting differences, scanned images of cheques cannot be processed instantly. In the preprocessing step, a variety of improvement processes are applied to the acquired image in order to improve its quality prior to information extraction.

The scan of the cheque must be prepared for further processing by the image preprocessing module. To get the alignment right on a CTS-2010 check, you have to rotate the image so it lines up with the standard location of the date box. We use morphological methods and Gaussian filtering to remove noise and unnecessary background data after everything is in its correct location. The RGB image is grayscaled and then converted to binary to make region identification and contour extraction easier. These preprocessing steps not only increase the overall reliability of the recognition algorithms, but they also highlight textual information and handwriting components.

The Segmentation Module takes the preprocessed check image and uses the check's traditional layout to identify critical ROIs. Checks are segmented in a variety of ways; some of them include the following: account number, IFSC code, date field, legal amount, courtesy amount, and account holder's signature. Contour extraction algorithms and predefined check templates may properly localise these locations. Segmenting the cheque into its component parts may increase identification accuracy and reduce computation complexity. This allows for the analysis of each field independently by specialist recognition algorithms.

To process them, the OCR Module is used once the machine-printed regions have been removed. With the use of optical character recognition software, some text fields may be automatically detected, such as IFSC codes, cheque numbers, account numbers, and others. By making it machine-readable, we get the collected text ready for further verification. By decreasing the need for human data entry, improving operational efficiency, and eliminating transcribing errors, automated text recognition simplifies the check-clearing process.

The Handwritten Character Recognition Module employs a Convolutional Neural Network (CNN) to identify handwritten numerical values that appear in the courteous amount section of the check. The CNN model is able to automatically categorise numerical characters and extract hierarchical visual aspects from handwritten numbers, regardless of variations in handwriting style. After the politeness amount is identified, the numerical value is converted to its textual representation using the Indian Place Value (IPV) system. This translated value is cross-referenced with the legitimate amount mentioned on the cheque to guarantee accuracy and uncover any alterations or fraudulent modifications.

International Journal for Novel Research in Economics , Finance and Management
www.ijnrefm.com
ISSN:3048-7722
Volume 4, Issue 4, July-Aug-2026, PP: 01-9

Verifying the account holder's signature is essential for a cheque to be deemed valid. Normalising the segmented signature begins with erasing scale, rotation, and alignment inconsistencies. Applying the Scale Invariant Feature Transform (SIFT) method to the normalised signature image allows for the extraction of robust local descriptors that represent distinct signature attributes. After that, these feature vectors are sent into the Support Vector Machine (SVM) classifier, which uses a comparison of the extracted characteristics with learned signature patterns to determine the authenticity of the signature. When SIFT feature extraction and SVM classification are combined, signature verification becomes very efficient and trustworthy.

The Decision-Making Module integrates OCR, CNN, and SVM outcomes after each verification phase is complete. Combining the signature verification findings with the extracted IFSC code, cheque number, account number, legal amount, and courtesy amount determines the entire legality of the cheque. Before reaching a conclusion on verification, the system ensures that all extracted fields are consistent. Upon completion of all necessary verification processes, the check is released for further financial dealings. To prevent unauthorised financial activities, the cheque is marked for human inspection if such information is not available.

After all checks have been extracted and the authentication status has been shown, the verification process is closed by the Output Module. Banking experts may easily see the highlighted sections of the validated cheque, allowing for immediate confirmation of successful verification. Any differences discovered during the verification process may be quickly investigated by bank officials since they are revealed.

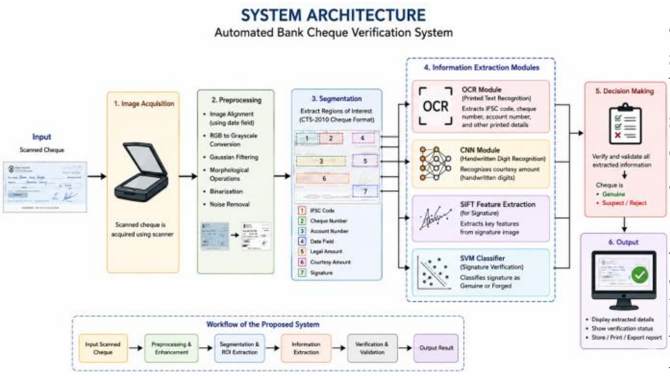

Fig.1 System Architecture

By including image preprocessing, segmentation, OCR, SIFT feature extraction, signature verification using support vector machines (SVMs), and CNNs for handwritten digit identification, the proposed system architecture achieves a unified automated verification framework. When these modules work together, it's easier to extract, authenticate, and validate cheque information; there's less need for human intervention; cheque clearing is quicker; operational costs are reduced; and security against cheque fraud is better. Consequently, modern banks and other financial organisations have a reliable and scalable solution for intelligent bank cheque verification owing to the modular architecture.

V. RESULTS AND DISCUSSION

To determine how well the proposed bank cheque verification system might automatically validate cheque components using deep learning and image processing, we ran tests. Convolutional Neural Networks (CNNs), Scale Invariant Feature Transform (SIFT) with Support Vector Machine (SVM) for signature verification, and Optical Character detection (OCR) for handwritten digit detection were all examined. The goal was to identify machine-printed text. Check authentication has shown to be very accurate and reliable with little human intervention using a unified verification architecture that integrates many intelligent recognition methods.

Scanned images of checks were preprocessed to improve their quality before data extraction. By using picture enhancement methods such greyscale conversion, contour extraction, morphological processing, and image alignment, the background noise was effectively removed and rotational fluctuations were corrected. These preprocessing steps produced uniform cheque images, which improved the accuracy of the subsequent segmentation and recognition operations. The comprehensive preprocessing allowed for the reliable retrieval of important check sections in various scanning scenarios.

After preprocessing, the segmentation program accurately identified the predefined ROIs according to the CTS-2010 cheque format. Information such as the IFSC code, account number, legal amount, courtesy amount, date field, signature area and cheque number were correctly isolated before identification. Structured segmentation enables specialist recognition algorithms to handle each tick component independently, improving identification accuracy while reducing computer complexity.

Automated financial document identification was accomplished using a module known as Optical Character Recognition (OCR). Automated data extraction and translation into machine-readable format was performed on the printed fields of the cheque, including the IFSC code, account number, cheque number, and other required data. Optical character recognition (OCR) achieved a total identification accuracy of 97.7 percent in experiments that scanned images of cheques, accurately identifying printed characters. Automation of printed text extraction considerably reduced the need for human data entry, enhanced processing efficiency, and reduced transcribing errors when it came time to validate a cheque.

The numerical values writing in the courtesy amount section were identified by means of a Convolutional

Neural Network (CNN) model. The deep learning architecture was able to properly identify numerical values despite variations in handwriting style by acquiring hierarchical visual signals associated with handwritten digits. The results demonstrate that the CNN model achieved a recognition accuracy of 99.14% when tasked with identifying handwritten digits, surpassing all conventional image processing approaches. We used the Indian Place Value (IPV) approach to convert the acknowledged numerical amount to text so we could be sure it was consistent and find any modifications to the cheque. After that, it was contrasted with the official cheque amount.

Feature extraction using Scale Invariant Feature Transform (SIFT) and classification using Support Vector Machines (SVM) were used to evaluate the signature verification module. Initially, SIFT was able to identify handwritten signatures by gleaning distinct local characteristics that mirrored their underlying structure. The next step was to feed these feature vectors to the SVM classifier. By applying the learned decision boundaries, it could distinguish between authentic and false signatures. The integrated SIFT-SVM system achieved a total signature verification accuracy of 98.10 percent, demonstrating its ability to reliably provide authenticity despite variations in image and handwriting quality.

VI. FUTURE ENHANCEMENT

The proposed automated bank cheque verification framework incorporates many enhancements to enhance the accuracy, reliability, and efficiency of cheque authenticity. The system validates and extracts critical check information properly while reducing the need for human interaction. It does this with the use of a unified verification architecture that integrates image processing, OCR, CNNs, SIFT, and SVM. All things considered, these updates make modern banking systems more secure, expedite the clearance of checks, and streamline processes. The suggested system has many enhancements, one of which is an intelligent image preparation approach. In preparation for further analysis, the preprocessing module executes morphological operations, aligns the pictures, grayscales them, applies Gaussian filtering, and extracts contours. This is essential because to the prevalence of rotation problems, background noise, shadows, lighting fluctuations, and unwanted artefacts in scanned cheque pictures. The picture quality is much improved by these preprocessing procedures, which enables the recognition algorithms to function more reliably and precisely. The verification procedure is made more robust and identification errors caused by incorrect scanning settings are reduced with improved image quality.

Another noteworthy development is the incorporation of automatic cheque segmentation using the CTS-2010 standard cheque design. The framework identifies and isolates certain ROIs, including the IFSC code, account number, legal amount, courtesy amount, date field, and account holder's signature, instead of processing the whole cheque image all at once. This structured segmentation methodology allows for the optimal recognition method to be applied independently to each portion of the check. More precise extractions, less computer overhead, and improved processing efficiency result from this.

In order to further enhance printed text recognition, the proposed system makes use of Optical Character Recognition (OCR). Optical character recognition (OCR) eliminates the need for human data entry by automatically retrieving machine-printed financial information, reducing the risk of human error and labour. Accurately identifying IFSC codes, cheque numbers, and account numbers enables faster verification and more uniform banking operations. Automating printed text extraction for financial transactions has further advantages, such as streamlined procedures and speedier cheque processing.

An important enhancement of the proposed system is the use of a Convolutional Neural Network (CNN) for the purpose of numerical character detection in handwriting. Traditional methods for image processing have a hard time recognising handwritten numbers due to differences in handwriting style, stroke thickness, and writing direction. Deep learning based on convolutional neural networks (CNNs) can automatically learn complex visual representations of handwritten numbers, which might lead to the correct recognition of politeness amounts on bank checks. The discovered numerical values are converted to textual representations and checked with the actual amount written on the cheque as an additional security measure against cheque fraud and forgeries.

In addition to a high-level signature authentication method, the proposed system makes use of Scale Invariant Feature Transform (SIFT) and Support Vector Machine (SVM). To begin with, SIFT is able to extract distinct local attributes from the account holder's signature even when the signature is distorted, rotated, or illuminated. The next step in determining whether the signature is genuine or fake is to use the SVM approach for feature vector classification. The accuracy of signature verification is significantly improved and the rates of wrong acceptance and rejection are concurrently decreased when these two elements are combined. The automatic signature verification process greatly improves monetary safety by doing away with subjective human comparison and providing reliable authenticity.

The use of many levels of verification is an additional enormous benefit. Instead of checking each component separately, the proposed method checks the cheque number, legal amount, courtesy amount, IFSC code, account number, and signature simultaneously. Verifying each of these parameters separately increases the reliability of cheque authentication and decreases the probability of fraudulent transactions passing verification. If there is a mismatch among these fields, extra verification is prompted before a check may be cleared.

Further improvement in processing efficiency is achieved by the proposed architecture via automation of the whole workflow for validating checks. Manually verifying the legitimacy of each cheque by bank employees increases processing time and operational costs. Automated verification pipeline steps carry out preprocessing, segmentation, text recognition, handwriting digit recognition, and signature authentication in a sequential fashion, all without continual human involvement. This implies that the proposed framework may facilitate the easy handling of many financial documents by banks, which in turn speeds up the clearance of checks.

The framework has also made significant progress in enabling standardised banking operations in accordance with the CTS-2010 cheque criteria. By sticking to common cheque layouts, the system provides continuous verification performance and can adapt to forms from varied financial institutions. Because of its adaptability, the proposed approach might be extended to additional standardised financial documents in the future, making it more useful to existing banking systems.

With the new features added to the proposed bank cheque verification framework, accuracy in verification, operational efficiency, transaction security, and fraud detection capabilities are all significantly improved. By integrating state-of-the-art image processing techniques including optical character recognition (OCR), support vector machines (SVM), and convolutional neural networks (CNN), a comprehensive intelligent verification system is created. Using this approach, bank checks may be successfully authenticated with little effort, processing delays, and human interaction. These enhancements demonstrate the efficacy of combining deep learning with image processing for automated cheque verification.

VII. CONCLUSION

Using Machine Learning, this study presented a novel Smartphone Addiction Prediction Framework that can identify individuals exhibiting behaviours characteristic of heavy phone users. Using a structured dataset that includes 21 predictive variables extracted from around 500 survey responses, the proposed method delves into demographic information, smartphone use patterns, and psychological factors. A plethora of machine learning techniques were investigated with the purpose of identifying patterns of smartphone addiction. Adam, Decision Tree, Random Forest, Logistic Regression, Multi-Layer Perceptron (MLP), and so on were all part of the set. The objective was to build reliable prediction models.

Prior to model building, the collected data was preprocessed to improve learning efficiency and prediction performance. Normalising features, encoding labels, and handling missing data were all part of this. Factors that contribute to the likelihood of addiction include the frequency with which you check your notifications, the duration of your phone usage, the level of stress you're experiencing, your gender, and your age, according to research. Research shows that machine learning algorithms can identify complex patterns of behaviour associated with smartphone addiction with high reliability and efficiency.

The proposed prediction system could have some useful applications for healthcare professionals, educational institutions, guidance counsellors, and app developers. An early risk assessment may pave the way for more targeted counselling, more timely behavioural interventions, and more public awareness campaigns to encourage safer smartphone usage. Furthermore, by illuminating the association between character attributes and smartphone reliance, the developed prediction engine contributes to data-driven healthcare preventive decision-making.

Lastly, the proposed machine learning framework employs behavioural research and advanced classification techniques to demonstrate that smart prediction models may enhance smartphone addiction assessment. By integrating machine learning, mobile technology, and behavioural analytics, this study paves the way for future smart healthcare applications that will encourage digital wellness and mitigate the negative consequences of smartphone addiction.

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