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Development of Chimp Optimization Algorithm and Adaptive Shuffle Attention Net for Automated Bank Cheque and Signature Verification

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Abstract

Processing of cheques has evolved into congestion that can impede the financial system's efficiency as a result of the banking industry's growing digitalization. The verification procedure has historically been done manually, with a bank staff visually inspecting the cheque for fraud or other problems. However, this procedure can be costly, requires more time, and is prone to mistakes. Therefore, the automated check verification system developed, which uses computer vision and deep learning algorithms to extract related data from images of checks and evaluate their legitimacy, is presented as a solution to these problems. Thus, this research work involves acquiring the cheque image from standard databases, and it is followed by the denoising stage to remove any noise or unwanted artifacts. Preprocessing is done by Contrast-Limited Adaptive Histogram Equalization (CLAHE) and median filtering process to remove the unwanted noises from the images. Subsequently, OCR (optical character recognition) is applied to extract the numbers from the cheque. Once the numbers are extracted, they are fed into a handwritten recognition system, which is done by Adaptive Shuffle Attention Net (ASAN). After the handwritten characters are recognized, the deep features of the signature are extracted ASAN. Here, the updated random vector-based chimp optimization algorithm (URV-COA) is used for optimizing the parameters in ASAN. Finally, a similarity check is performed between the extracted signature and the signature on the file stored in the dataset. If the signatures are sufficiently similar, the cheque can be verified as authentic.

Keywords

automated bank cheque and signature verification, optical character recognition, adaptive shuffle attention net, updated random vector-based chimp optimization algorithm

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1 Introduction

1.1 Background of the Study

Today, a variety of biometrics, including the face, iris, voice, fingerprint, palm print, DNA sequence, and odor/scent, are commonly utilized around the globe for personal verification. Additionally, one of the personal features used for authentication is the signature. The cost of using a person's signature for personal verification is low when compared to various biometrics (Dongare & Ghongade, 2016). Millions of signatures are utilized daily in legal documents, agreements, and particularly in banks to verify cheque signatures. The American Banker Association's survey on deposit account scams estimates that cheque scams expense banks roughly $1 billion annually. The signatures on checks are expertly fabricated in

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22% of these forgeries (Swathi et al., 2020). One of the primary processes in a cheque processing system is the verification stage, which is used to identify signature fraud. If the check's signature is recognized as a real signature, the cheque can proceed to the next stage of processing (Rao et al., 2009). Otherwise, the input cheque is rejected from the system as a fraud cheque if the signature is found to be a forgery (Sudharsan et al., 2021). Online and offline methods can be used to verify signatures. Because less useful behavioral data is available about the creator of the signature in terms of pen-point velocity, writing pressure, etc., verification of a signature online is more challenging than verifying a signature offline. Online signature verification is used during the automatic processing of cheques in paper format. Verification of the Latin signature has been the subject of numerous attempts up until this point (Tambade et al., 2018).

1.2 Basic Principles of Existing Techniques

The cheque system, which is presented to the bank as a physical instrument, has superseded conventional cash payment methods with the introduction of information skills (Bramara Neelima & Arulselvi, 2019). The clearance of cheque procedure, on the other hand, entails a physical handshake between the presenter and the clearing bank, with settlement taking place via a third party's payment house (Jagtap et al., 2022). The actual instrument is lost since the relevant banks should physically transfer the cheque. In order to enable the payment settlement of inter-bank using a scanned copy of the manual check delivered to the payment houses, Cheque Truncation System (CTS) was established (Bird et al., 2023). The older CTS utilizes the technology of magnetic ink character recognition (MICR), which mainly focuses the features like ultraviolet rays, watermarks, images of pantographic, and different tiny features on the check's scanned print (Khan et al., 2006). However, the function of the conventional CTS is restricted to checking the check's grayscale image, which makes all of the aforementioned aspects less visible. As a result, errors in the beneficiary name and amount, the copying of features made with an image editing application, the use of invisible ink, and damaged photographs may cause security violations and ultimately result in the creation of a fake cheque (Hanmandlu et al., 2005). This counterfeit cheque avoids the clearing house's image authentication working mechanism (Zheng et al., 2021).

Aside from the restrictions described above, bank files are dispersed with servers using fault-tolerance methods such as mirroring, system checkpoint, and the redundant array of inexpensive disks (RAID) levels (Al-Ohali et al., 2003). The conventional cheque-clearing process includes different stages. Once, the cheque has been validated, it is sent to a central bank, where it is then sent on to the issuing bank for further processing (Fallah et al., 2011). After issuing bank checks the transaction's status decides whether to accept it or reject it, the user is then notified that the transaction has been cleared. There is a chance of a security attack at every stage where there are two parties, known as Points of Contact (PoC) (Kierkegaard, 2011). Transactions with inconsistent states may result in security problems, which a bad user could utilize to launch nefarious security attacks (Dhandapani, 2017). The most exposed PoC is the one where the majority of security assaults occur (Gorski, 2007). Therefore, an immutable and consistent distributed ledger scheme can resolve the need for data storage. Additionally, because databases are dispersed, they can be altered by interested parties and even compromised by an enemy (Myint et al., 2019). Therefore, among participating users, a sense of interoperability and trust is necessary. Moreover, the graph matching techniques are implemented according to the multiresolution shape features and also the hidden Markov technique is used to classify the similarity and variability among the patterns. Furthermore, shape analysis models like principle component analysis models are employed to acquire the numerical feature values for better classification. Most of the classical cheque verification mechanisms are prone to different security risks and gained a limited acceptance rate from organizations. Hence, it is important to construct a novel automated bank cheque and signature verification framework regarding deep learning mechanisms to prevent forgeries and also provide an accurate signature verification rate than the classical mechanism.

1.3 Key Formula for Bank Cheque Signature Verification

Key formulas utilized for the bank cheque verification model are listed as follows.

Mathematical equations utilized for the length mapping in the bank cheque leaflet (Agrawal et al., 2021) are given in equation (1).

$$\begin{cases} \dfrac{Qw}{(Qw+z)} = \dfrac{(R_Q - R_w)}{R_2 - R_w} \\ \dfrac{Qw}{(Qw+x)} = \dfrac{(R_Q - R_w)}{R_m - R_1} \\ \dfrac{Qu}{(Qu+v)} = \dfrac{(T_u - T_Q)}{T_u - T_1} \\ \dfrac{Qu}{(Qu+f)} = \dfrac{(T_u - T_Q)}{T_2 - T_Q} \end{cases} \tag{1}$$

Here, the dimensions are presented as Qu and Qw in the above equation which displays the length as well as breadth, the distance attained from the edges of the cheque leaflet is signified as z, f, x, and v. At last, the horizontal and vertical coordination of the data box are indicated by T and R in the equation.

The negative log-likelihood of the original signature of the user trained in the network (Hafemanna et al., 2017) is given in equation (2).

$$A = -\sum_u g_{tu} \log S(g_u/d_t) \tag{2}$$

Here, the true targets are indicated as g_{tu}, probabilities allocated to every class are presented as $S(g_u/d_t)$, and the signature image in the cheque is signified as d_t.

The ranking mechanism utilized to validate the signatures in the bank cheque (Vorugunti et al., 2020) is shown in equation (3).

$$G_j = \frac{1}{Y_j} \sum_{t \in \text{class}} k_t \tag{3}$$

Here, the sizes of the image are given as k_t for the feature vector, the row vector for the size G_j, which represents the mean for entire feature vectors in the jth class, and the counts of the vector classes are signified as Y_j.

1.4 Fundamental Ideas

In recent days, many fraudulent activities have happened via handwritten signatures on the bank cheque. Thus many models are proposed for automated bank cheque and signature verification systems to prevent forgeries. Mudra-chain model is implemented to prevent fraudulent cheques. However, the legacy process of the bank cannot integrate and needs more cost to develop the model. So an effective hidden Markov model (HMM) model is proposed to avoid fraudulent cheques. But, it is sensitive to noise at a moderate stage and cannot operate the process with local features. Then, the k-nearest neighbor (KNN) method is proposed to solve all these challenges. But, the accuracy of the model only depends on the data quality. It is very sensitive to the data's scale and requires high memory. So, an Adaptive Shuffle Attention Net (ASAN) mechanism is introduced in the developed framework to execute handwritten character recognition and also to recognize the individual's signatures. Generally, the Shuffle Attention network combines channel attention and spatial attention to provide better results with minimum computing cost.

The developed automated bank cheque and signature verification system has some key contributions, and they are listed as follows:

- Designing an efficient automated bank cheque and signature verification model based on deep learning to prevent bank accounts from forged signatures to drop the cash and also to provide great support in the financial industry.
- To verify the numerical characters like MICR code, IFSC code, and account number in the cheque the OCR (optical character recognition) mechanism is utilized, which accurately recognizes the characters and extracts the required numbers from the bank cheque.
- To implement a novel ASAN mechanism for recognizing the handwritten characters and also verify the signature of the individuals in the bank cheque and also its parameters are optimized to verify the genuine signature of the individual.

- To design a novel updated random vector-based chimp optimization algorithm (URV-COA) to attain better signature and handwritten character verification rate in the developed framework and also to enhance the precision and accuracy in the suggested ASAN-based bank check and signature verification mechanism.
- The effectualness rate of the developed model is analyzed with several techniques and performance measures based on the classical bank cheque signature verification framework to provide better results in the validations.

The proposed automated bank cheque and signature verification system's workflow is as follows: section 2 provides the literature survey. Section 3 has the development automated bank cheque and signature verification framework with the support of adaptive deep learning with an attention network. Section 4 provides the bank cheque number extraction with image preprocessing and a description of the developed optimization algorithm. Section 5 offers the handwritten character recognition and signature verification process. The result and discussion are explained in section 6. Finally, section 7 provides the conclusion for the developed automated bank cheque and signature verification model.

2 Literature Survey

2.1 Related Works

In 2014, Coetzer et al. (2014) have developed a model that automatically validated the offline signatures utilizing the HMM and discrete Radon transform (DRT). The global-level features were considered to provide better results. The developed model utilized the database signatures of 924 from 22 numbers of writers and those signatures were taken offline. By utilizing those signatures, the recommended model attained only 18% of error. Moreover, the model utilized another database signature of 4800 from 51 numbers of writers, and those signatures were taken online. By utilizing those signatures, the recommended model attained only 12% of error. Then, the signatures of both two databases were changed into fixed signature images. The result showed the proposed model provided a better outcome and that considered only global-level features.

In 2012, Foroozandeh et al. (2012) have implemented a system to verify the Persian handwritten bank check signatures. The proposed model contained two stages and they were the verification stage and the training stage. In the initial stage, the developed model was trained to utilize some signatures offered by every consumer in the period of training. Then those signatures were taken to the verification stage. The developed multiresolution Box-Counting (MRBC) model was utilized to extract the features. The developed MRBC model was tested by NISDCC databases. The result obtained from the MRBC model was compared with other conventional models to provide promising outcomes.

In 2020, Kabra et al. (2020) have proposed a model named Mudra Chain used for automated check verification. In the developed model, clearance processes were managed with the help of blockchain instead of CTS. The blockchain consisted of (i) a multilevel verification system to secure the model, (ii) a Quick Response (QR) code for digitally signing the cheque, and (iii) two-factor authentications for secure fund transmission. The result from the developed model has indicated the superiority of the developed model. Therefore, the developed Mudra Chain technique allowed a flawless clearance process through the blockchain to the payers and the recipient devoid of any mediators. At last, the developed model addressed the need to build a safe system for the clearance of a cheque.

In 2017, Akbari et al. (2017) have introduced a model for Persian handwritten bank checks (PHBC). The proposed model comprised the courtesy amount, lawful amounts, account number, signatures, and name of the receivers. Moreover, the implemented model also included the handwritten word forms utilized in lawful amount, digits used in courtesy amount, and the contributor's signatures. The data was organized and gathered in two forms. The developed PHBC model was easily applicable to the field of research. The result proved the developed PHBC model was automatically processed to verify the Persian checks and also provided excellent performance compared with various verification and recognition models.

In 2008, Palacios and Gupta (2008) have implemented an integrated model to read the bank check. The developed model comprised three modules, and they were (i) to detect the strings present inside the image, (ii) the recognition and segmentation of the string, and (iii) to detect the problems after processing that helped to provide more accuracy. The main advantage of the developed integrated model was the capacity to identify difficult issues while reading the handwritten bank checks. All three modules were executed and tested to read the check's value using the image databases. The designed model played an excellent role in creating a balance between the level of rejection and the imprecise readings based on the preferences of the users. The investigated result showed the developed model attained the best result by integrating the three modules.

In 2021, Agrawal *et al*. (2021) have designed a method named as Institute of Development and Research in Banking Technology (IDRBT) for the clearance of cheques based on the Convolutional Neural Networks (CNN) technique. The developed CNN-based IDRBT model provided 99% accuracy in recognizing the numeric characters of handwritten bank cheques. The recommended system enhanced the handwritten elements of the bank cheque's precise and accurate assessments. The developed model used Scale Invariant Feature Transform to verify the signatures and extraction. The outcome attained by the developed model was compared with other techniques to provide accurate verification.

In 2014, Narkhede and Patil (2014) have implemented the offline signature verification method to verify the credentials of persons to continue the transaction process properly. The signature verification method was accurate and powerful to validate the signature. Context shape was utilized to validate whether the shapes were dissimilar or similar. The developed framework was utilized in different fields like classification of three-dimensional objects, trademark recovery, digits classification, etc. The developed model used an advanced version of the context shape process to verify the signature with the help of the KNN technique.

In 2014, Sadri et al. (2014) have implemented a structure for Persian handwritten bank cheques. Supremacy and the importance of the developed model were revealed by performing various analyses. The database was developed to conduct the analysis. The generated database contained 500 numbers of handwritten bank cheques regarding the implemented model. Overall analysis showed the importance and usefulness of the newly implemented technique to verify the Persian handwritten bank cheques that provided the normal guidelines to implement the process.

In 2023, Upadhyay et al. (2023) have implemented a novel multidilation CNN framework for handwritten signature verification. The suggested framework didn't require a preprocessing procedure and also it used the hardware resources like Graphics Processing Unit (GPU). Moreover, the implemented mechanism was validated with the standard dataset. Further, state-of-the-art validations were performed in the suggested framework and attained a better accuracy rate than the classical mechanism.

In 2023, Abdulhussien et al. (2023) have suggested a novel Quantum Inspired Genetic Algorithm (QIGA) based on the integration of discriminant feature selection and multifeature fusion. Here, the QIGA model was designed by the quantum computing concepts and also offered the linear superposition with rising gene diversity. Moreover, the Quantum Rotation Computing (QRC) procedure was utilized to improve the population diversity rate of the system to resolve the computation complexity issues.

In 2024, El Melhaoui et al. (2024) have implemented a statistical mechanism with three different phases preprocessing the data, extracting the essential features, and classifying the signatures. Initially, different image preprocessing mechanisms were utilized to extract the signature pixels and noise pixels from the environment. Next, the statistics were extracted based on the discriminate characteristics and provided as the input to the developed Fuzzy Min-Max Classifier to classify the signatures whether it is real or not.

2.2 Problem Statement

Automated bank checks and signature verification are important in this modern world. Many fraudulent activities are happening via fake signatures. Proper signature verification is needed to secure the money of the customers and transfer the money. Several banks are processing the checks automatically by accepting fake checks. Many models have been developed to control these mistakes. Multiple challenges attained in the conventional bank cheque verification model are detailed as follows.

- The classical bank signature verification model gained more errors due to noisy input data. So, in the developed model essential datasets are collected from the benchmark dataset to provide accurate signature recognition outcomes.
- In the classical bank check signature verification model it takes more time to train the significant data. So, to eliminate the redundant information in the input data preprocessing procedure is introduced in the developed to resolve the validation time issues.
- In the conventional signature verification model unnecessary data presented in the system degrade the efficacy rate of the system. Hence, to resolve these issues feature extraction procedures are implemented in the suggested bank cheque verification model to cut down the unnecessary data and noise presented in the preprocessed data.
- The existing bank cheque signature verification model utilized more parameters in the network which slowed down the verification rate of the system. So, shuffle attention networks are used to minimize the parameter count in the network and also accurately verify the signatures in the bank cheque.

The features and challenges of existing bank cheque signature verification models are described in Table 1.

2.2.1 Motivation. Due to globalization and the development of information technology systems, electronic banking gained more attention from experts. These electronic banking models work as the self-service delivery channel and permit

Table 1. Features and Challenges of Conventional Automated Bank Cheque and Signature Verification.

Author [citation]	Methodology	Features	Challenges
Herbst *et al.* (Coetzer et al., 2014)	DRT and HMM	• It is a stable method • High global-level features are used to verify the process of the model	• This model is sensitive to noise at a moderate stage • This model cannot operate the process with local features
Foroozandeh *et al.* (Foroozandeh et al., 2012)	MRBC	• City block distance is used in this model for measuring the distance accurately • The generated database is easily available to the investigative field	• A few numbers of features are used here to verify the signature • Distance measures are not trained
Kabra *et al.* (Kabra et al., 2020)	Mudra-chain	• This model can send the check transaction to the client account within seconds • It gives more protection against the parameters	• The legacy process of the bank is not integrated into this model • Developing cost is more
Akbari *et al.* (Akbari et al., 2017)	PHBC	• This method helps to compare the verification methods and various recognitions	• It is not an end-to-end computerized processed system
Palacios and Gupta (Palacios & Gupta, 2008)	Automation of banking systems	• It can sufficiently manage the various check styles that exist in the region of the world • It helps to produce a suitable balance between the rejection stage and inaccurate reading • It can identify the difficult problem of handwritten checks	• Sometimes this model provides incorrect readings due to some difficulties • It requires more time to operate the model
Agrawal *et al.* (Agrawal et al., 2021)	CNN	• It effectively converts the numbers into the word format • It requires less time for processing	• It is applicable only for checks written in English languages • It gives the best result by using the particular database
Girish and Patil (Narkhede & Patil, 2014)	KNN	• Computational time is low • It does not require any alignment work to process the model • It helps to prevent the fraudulent check	• The accuracy of the model only depends on the data quality • It is very sensitive to the data's scale • It requires high memory
Sadri *et al.* (Sadri et al., 2014)	A novel structure for Persian handwritten bank cheques	• It can resolve technical issues such as segmentation, classification, and preprocessing • It aids in easily exchanging cheques between various banks • It can remove irreparable errors	• This method is applicable only in the Persian language

CNN= Convolutional Neural Networks; DRT=discrete Radon transform; HMM= hidden Markov model; KNN=k-nearest neighbor; MRBC= multiresolution Box-Counting; PHBC= Persian handwritten bank checks.

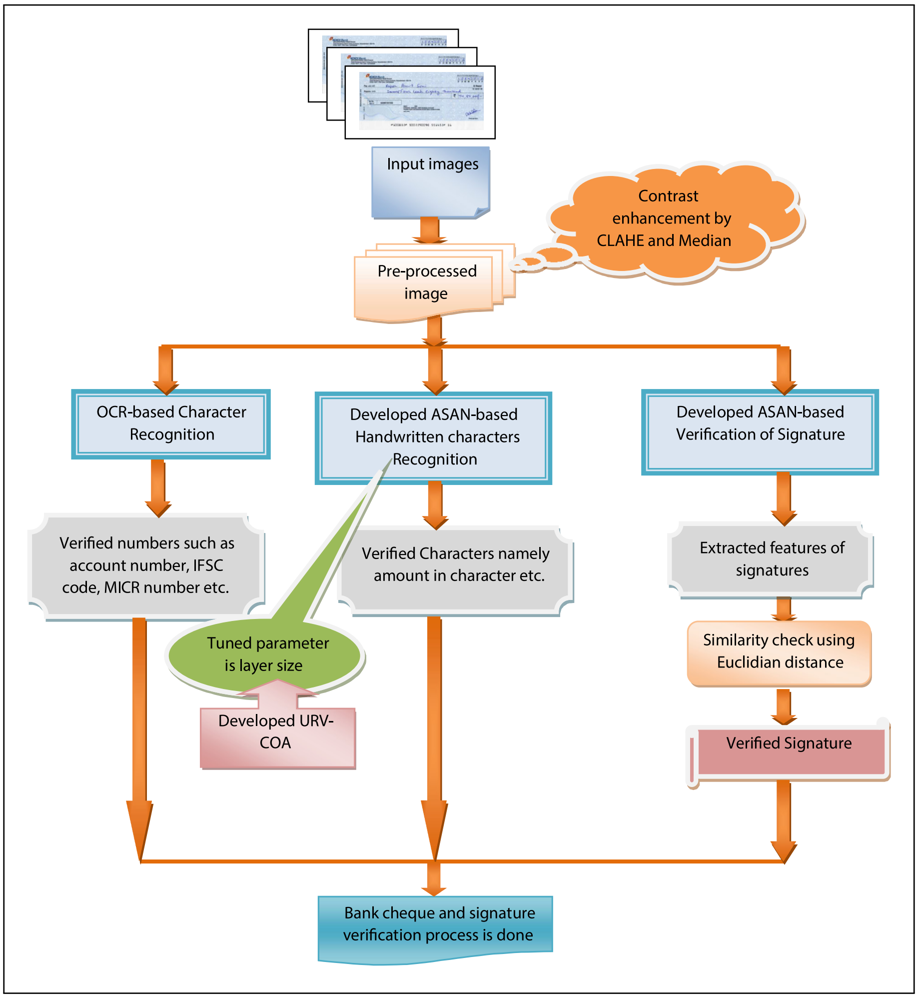


Figure 1. Pictorial depiction of the developed automated bank cheque and signature verification system.

the bank to offer accurate data and services to the user through mobile phones. In digital banking, the automatic bank cheque and signature verification are to resolve the fraudulent activities attained in the money transaction. These bank cheque and signature verification mechanisms are highly useful in the banking sector and multilevel organizations for improving service quality. Thus, we implemented the automated bank cheque and signature verification model regarding deep learning to prevent forgeries.

3 Developing Automated Bank Cheque and Signature Verification Framework With the Support of Adaptive Deep Learning With Attention Network

3.1 Developed Automated Bank Cheque and Signature Verification Framework

In this developed world, biometrics is used to verify the person. The verification processes are taken via the fingerprint, voice, iris, etc. On the other hand, handwritten signatures become the most common verification tool in many fields (Sharma et al., 2022a). Consequently, we developed a new automated bank cheque and signature verification model based on deep learning to provide the best output (Sharma et al., 2022b). Deep learning-based verification models are effective in identifying the challenging handwritten cheque problem (Sharma et al., 2023a). They can easily convert the numbers into the form of words and require less time to process (Sharma et al., 2023b). From the exact location in the bank cheque, the corresponding details like numbers, characters, and signatures are fetched and detected using deep learning (Sharma & Tripathi, 2022). The pictorial depiction of the developed automated bank cheque and signature verification system is shown in Figure 1.

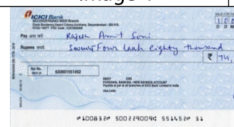
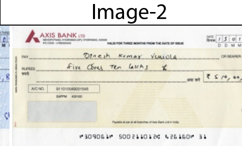
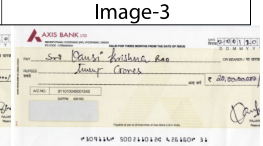
Description	Image-1	Image-2	Image-3
Sample Bank Cheque Images			

Figure 2. Collected bank cheque images.

The developed deep learning-based automated bank cheque and signature verification model is used to prevent the bank account from fraud cheques and also it helps to give protection in different financial fields like insurance, banking, etc. Input images are collected from standard resources and given to the image preprocessing stage. In this preprocessing stage, the image's contrast is increased using contrast-limited adaptive histogram equalization (CLAHE). Once contrast levels are applied to the images, a median filtering process is applied to remove the unwanted noises in the images. Then, the preprocessed images are used to extract and verify the number in the cheque using the OCR model and provide the verified number as the output. Next, the preprocessed bank cheque images are used to recognize the handwritten characters and the developed ASAN model is employed to recognize and verify the characters with the support of the developed URV-COA algorithm. Here, the layer size in the recommended ASAN model is optimized using the proposed URV-COA model to provide the verified character as the output. Later, preprocessed bank cheque images are given to the verification process and essential features are extracted by the proposed ASAN model. After this process, the extracted features are taken to check the similarity using Euclidean distance. It helps to identify whether the signatures are real or fake. Then it is compared with the selected database. The most similar feature is taken as the real signature. Finally, the developed ASAN model provides the verified cheque images as the final output. Further, several experimental validations are executed in the developed framework over the conventional mechanism to display its effectualness rate. Hence, the developed model automatically fetches and detects the exact location of the bank cheque, and the corresponding details like numbers, characters, and signature and helps the individuals from fraud activities.

3.2 Bank Cheque Image Collection

The recommended automated bank cheque and signature verification framework gathers the bank cheque images from the datasets in Figure 2.

Dataset-1 ("Institution for Development and Research in Banking Technology (IDRBT) dataset"): The bank cheque samples are taken from the IDRBT dataset, and the link https://www.idrbt.ac.in/idrbt-cheque-image-dataset/: Access date: 2023-06-20.It has 112 cheque images. The cheque images are ink color and have diverse textures. The sample bank cheque images are indicated by SC_n^{cheque}.

4 Bank Cheque Number Extraction With Image Preprocessing and Description of Developed Optimization Algorithm

4.1 Image Preprocessing

The sample cheque images SC_n^{cheque} are inputted in the image preprocessing stage. Image preprocessing is utilized to enhance the image's quality and provide the strength to further process. Image preprocessing is done with the help of several methods. In this developed automated bank cheque and signature verification model used contrast enhancement by CLAHE and a median filtering process for image preprocessing.

Contrast Enhancement by CLAHE: CLAHE is the method used to increase contrast in images, especially when the dynamic range of pixel intensities is broad or spread unevenly. It is a development of the standard histogram equalization technique. The image is divided into smaller areas for the CLAHE method to function. To examine the distribution of pixel intensities inside each region, a histogram is computed.

Median Filtering: Median filtering aids in noise reduction and edge preservation and it is widely employed in image processing. It is a nonlinear filtering technique that swaps out each pixel's value in a picture for the nearby median value of the pixels. Median filtering is frequently used to enhance image quality, and the efficiency of subsequent image analysis algorithms in a variety of applications, such as computer vision approaches image denoising, and image restoration.

After these processes, the sample bank cheque images provide the preprocess image output. The preprocessed images are depicted by PI_u^{pre}.

4.2 OCR-Based Number Extraction

The preprocessed images $\mathrm{PI}_u^{\mathrm{pre}}$ are inputted in the extraction process. The OCR method helps to extract the numbers. OCR is a procedure that includes taking numerical data from images or scanned documents and then confirming the veracity of the numbers that were taken. OCR technology makes use of machine learning algorithms to recognize and extract characters from visual input, including numbers. By removing the need for human data entry and enhancing the speed and quality of data processing. Verifying the numbers using OCR provides considerable benefits in various sectors and applications. It has uses in accounting software, the processing of invoices, document management, and other fields where numerical data needs to be retrieved and verified. OCR number verification has many advantages, including better data accuracy, enhanced productivity, and less manual work. It is extensively used across many different sectors, including healthcare, finance, logistics, and retail. Then, the preprocessed images offer the verified numbers as the outcome. It is noted by $\mathrm{EN}_q^{\mathrm{ext}}$.

4.3 Developed URV-COA

The classical COA facilitates solving a wide range of tuning dilemmas and has various strategies to upgrade the exploration phase. Moreover, it has good convergence speed to resolve difficult optimization-based issues. Yet, the COA mechanism does not have any unique extension and also it faces much complexity to solve objective-based tuning issues. Hence, it is essential to rectify several limitations in the classical COA mechanism. So, several enhancements are performed in the classical COA mechanism and the newly developed technique is termed as URV-COA. The developed URV-COA assists in tuning the parameters for getting accurate outcomes in the developed automated bank cheque and signature verification framework. The developed URV-COA tunes the size of the layer in the developed ASAN model in different limits for increasing precision and accuracy. Moreover, the developed URV-COA mechanism is utilized to recognize the handwritten characteristics in the bank cheque. The proposed URV-COA mechanism effectively improves the accuracy rate of the system also it reduces the error rates in signature verification while validating the enormous information.

The adaptive concept is initiated in this work for upgrading the random number of COA by equation (4). The term r defines the random number of the developed URV-COA.

$$r = \left(\frac{\mathrm{BE}_f}{\mathrm{WO}_f}\right) * 0.45 \tag{4}$$

Here, the term BE_f indicates the best fit and WO_f the value of the worst fit.

ChOA: Chimps (Lin et al., 2021) are the ape's variety. The behaviors of the chimps are drive, barrier, chase, and attack. The subsequent sections provide the behaviors of the chimps.

Driving and Chasing the Prey: Chimps hunt their prey during the exploitation and exploration stages. The mathematical expression for driving is described in equation (5). The expression to determine the chasing prey is shown in equation (6).

$$c = |b.w_{\mathrm{pry}}(s) - l.w_{\mathrm{cmp}}(s)| \tag{5}$$

$$w_{\mathrm{cmp}}(s+1) = w_{\mathrm{pry}}(s) - z.c \tag{6}$$

In equations (5) and (6), the term s defines iteration numbers. The term z, l, and b denotes the vector coefficient, w_{pry} expresses the prey position's vector, and the term w_{cmp} describes the Chimp's vector position. The terms cmp and pry define the Chimp and prey, respectively. The expressions for z, l, and b are calculated using equations (7) and (8).

$$z = 2.e.r - e \tag{7}$$

$$b = 2r_1 \tag{8}$$

Here, the term e gets reduced from 2.5 to 0 via iteration. The terms r and r_1 define the random vector in $[0, 1]$ range. The random number r is updated by the new concept given in equation (4).

Attacking Method: Two tasks are modeled for Chimp's attacking method and they are, the Chimp can explore the location of prey and can encircle the prey. The process of hunting is done by attacking chimps. The expression for prey

Algorithm 1. Developed URV-COA

Population initialization of chimp
Initializes the parameters *z*, *l*, and *b*
Determine every chimp's location
Randomly separate the chimps
While (until satisfied the stopping condition)
Determine every chimp's fitness
Upgrade the random *r* numbers in equations (7) and (8) by new concept given in equation (4)
  While ($s <$ max iter)
    For every chimp:
      Extract the group of chimp
      Utilize chimp's grouping strategy for updating z, *l*, and *b*
      Utilizes the value of e and *l* for determining the value of *z* and *c*
    End for
      For every search chips
        If $\mu < 0.5$
          if($|a| < 1$)
            Upgrading the current location of chimp using equation (9)
          if($|a| > 1$)
            Random search is selected
          End if
        Else if $\mu \geq 0.5$
      Upgrading the current location using equation (12)
      End if
    End for
  $s = s + 1$
  End while
End

attacking is detailed in equations (9)–(11).

$$\begin{aligned} c_{\mathrm{Att}} &= |b_1 w_{\mathrm{Att}} - l_1 w|,\ c_{\mathrm{Barr}} = |b_2 w_{\mathrm{Barr}} - l_2 w|, \\ c_{\mathrm{Chas}} &= |b_3 w_{\mathrm{Chas}} - l_3 w|,\ c_{\mathrm{Driv}} = |b_4 w_{\mathrm{Driv}} - l_4 w| \end{aligned} \tag{9}$$

$$\begin{aligned} w_1 &= w_{\mathrm{Att}} - z_1(c_{\mathrm{Att}}),\ w_2 = w_{\mathrm{Barr}} - z_2(c_{\mathrm{Barr}}), \\ w_3 &= w_{\mathrm{Chas}} - z_3(c_{\mathrm{Chas}}),\ w_4 = w_{\mathrm{Driv}} - z_1(c_{\mathrm{Driv}}) \end{aligned} \tag{10}$$

$$w(s+1) = \frac{w_1 + w_2 + w_3 + w_4}{4} \tag{11}$$

Here, the terms Att, Chas, Driv, and Barr represent the attacker chimps, chaser chimps, diver chimps, and barrier chimps. The attackers, chasers, divers, and barriers identify the last position placed arbitrarily in the circle.

Prey Attacking: The chimps stop attacking the prey when the prey gets moved. The process of attacking is modeled by reducing e. The term z is considered as the random variable lies between $[-2e, 2e]$, where e the iteration period is from 2.5 to 0. The Chimp can locate its position among the prey's position and current location when a random value lies in the interval of $[-1, 1]$.

Search for Prey: The chimps are moving away to seek the prey and attacking prey. The moving stage is modeled; when the random number is $1 <$ or < -1 the chimps are allowed to get prey from the long distance. This helps to avoid the local minima in the last iteration and prevent the chimps from obstacles.

Social Incentive: The last stage's chaotic behaviors support chimps to reduce the issues of slow convergence and local optima. The chaotic map is utilized to enhance the ChOA's performance. This chaotic map is also the random behavior to determine the process. The expression for this process is described in equation (12).

$$w_{\mathrm{Cmp}}(s+1) = \begin{cases} w_{\mathrm{pry}}(s) - z.c & \text{if } \mu < 0.5 \\ \text{chaotic value} & \text{if } \mu \geq 0.5 \end{cases} \tag{12}$$

Here, the term μ indicates the random number in the interval $[0, 1]$. The pseudocode of the developed automated bank cheque and signature verification framework is depicted in Algorithm 1.

5 Handwritten Character Recognition and Signature Verification Process With Adaptive Shuffle Attention Network

5.1 Adaptive Shuffle Attention Network

The traditional shuffle attention models minimize the parameter count in the network and also it improves the system accuracy rate. Moreover, the attention mechanism achieved a better balance rate among the computational overhead and also boosted the system efficiency rate. Yet, the shuffle attention network has a complex structure which creates more limitations in the training phase. Furthermore, it requires rectifying the interpretability issues attained in the system. Hence, it is essential to tackle several limitations attained in the classical shuffle attention models, so several modifications are performed in the classical mechanism and the newly developed concept is termed ASAN. In the ASAN model, the layer sizes are optimized using the URV-COA mechanism in different ranges, which effectively enhances the precision and accuracy rate of the system while recognizing the handwritten characters and verifying the signature on the bank cheque. The developed ASAN mechanisms effectively improve the flexibility rate and also ease the training procedures. Moreover, the interpretability issues attained in the system are rectified and provide accurate signature verification and character recognition rates.

Shuffle attention networks (Zhang & Yang, 2021) have two types, and they are channel and spatial attention. These attentions are utilized to catch the dependence of the channel and pixel's relationship.

Features Grouping: The expression $W \in Q^{B\times V\times G}$ is provided as the input in features grouping; here, the term B indicates the channels and the terms G and V describes the height and width of the features maps. The features map W is divided into F groups $W = [W_1, W_2 \ldots W_F]$, and $W_h \in Q^{\left(\frac{B}{F}\right)\times V\times G}$. Then, every group is split into two subgroups beside the channel's direction $W_{h1}, W_{h2} \in Q^{\left(\frac{\left(\frac{B}{F}\right)}{2}\right)\times V\times G}$.

Channel Attention: Based on the average pooling function, the channel static is acquired. The global data is obtained by multiplying to the original value of the features after the activation of the sigmoid function. The feature contains the attention weight of the channel $W_{h1}{}'$ to improve the features, described in equation (13).

$$W'_{h1} = \sigma(e_b(q)).W_{h1} = \sigma(V_{1q1} + a_1).W_{h1} \tag{13}$$

In equation (13), a linear function is indicated as e_b, the term σ describes the sigmoid activation function and the term q_1 describes the average pooling features. The parameters of W_1 and a_1 get via the training network.

Spatial Attention: Spatial attention is based on channel attention. The spatial statistic is obtained based on the function of group norm normalization. The feature contains the attention weight of the channel $W_{h2}{}'$ to improve the features. The expression for this process is described in equation (14).

$$W'_{h1} = \sigma(V_2.G(W_{h2}) + a_2) - W_{h2} = \sigma(V_{2q2} + a_2) - W_{h2} \tag{14}$$

In equation (14), the term G indicates the function of group norm normalization and q_1 describes the normalized features. The parameters of W_2 and a_2 are via the training network.

Aggregation: Combing the features of W'_{h1} and W'_{h2}. The combined features are weighted with the help of spatial and channel attention, and return to the grouped dimensions $\mathrm{BF}^{-1} \times G \times V$, where c indicates the dimension of the channel, the term V, and G are the feature map's width and length. Then merge the group blocks and go back to the initial dimension $B \times V \times G$. After finishing features recalibration and attention learning, the subgroups are merged and combined $W_{h2}{}' = [W_{h1}{}', W_{h2}{}'] \in Q^{\left(\frac{B}{F}\right)\times V\times G}$. Next, every subfeature is combined. Finally, a channel grouping mechanism is performed.

5.2 Developed ASAN-Based Handwritten Character Recognition

The preprocessed images $\mathrm{PI}_u^{\mathrm{pre}}$ are inputted in the developed ASAN-based handwritten character recognition process. The developed ASAN model was used to extract and verify the characters in the preprocessed images. The size of the layer is tuned in the recommended ASAN model by the developed URV-COA algorithm to offer accurate results and increase the precision and accuracy of the developed automated bank cheque and signature verification model. The fitness task for the developed automated bank cheque and signature verification model is expressed in equation (15).

$$\mathrm{Fi}_f = \underset{\{\mathrm{sl}_z^{\mathrm{asan}}\}}{\arg\min} \left(\frac{1}{A_c Y + P_r E}\right) \tag{15}$$

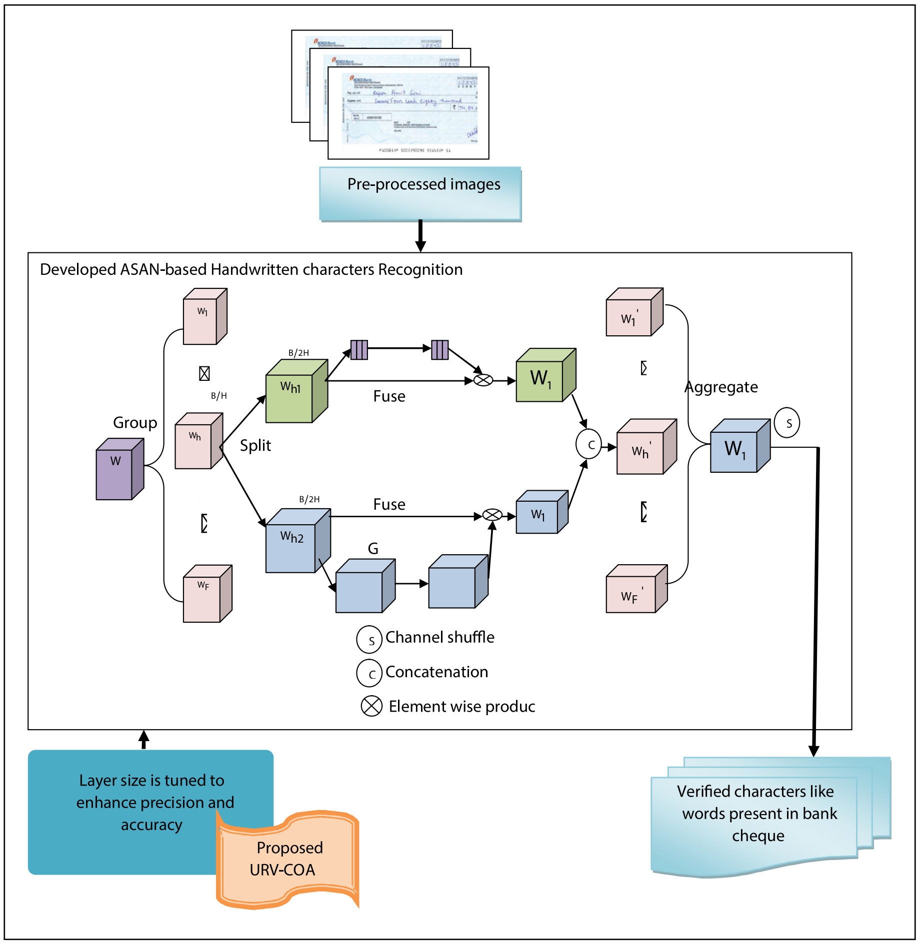


Figure 3. Pictorial depiction for the ASAN-based character recognition model. ASAN= Adaptive Shuffle Attention Net.

In equation (15), the term Fi_f defines the fitness function. The terms A_cY and P_rE express accuracy and precision. Moreover, $\mathrm{sl}_z^{\mathrm{asan}}$ represents the size of the layer in $[3, 6]$ the range. The function for accuracy and precision is evaluated using equations (16) and (17).

$$A_cY = \frac{(P_t + N_t)}{(P_t + N_t + P_f + N_f)} \tag{16}$$

$$P_rE = \frac{N_t}{N_t + P_t} \tag{17}$$

Here, the term P_t indicates the true positive, P_f the false positive, N_f the false negative, and N_t the true negative. Finally, it gives the output as verified characters, and it is noted by $\mathrm{Ef}_p^{\mathrm{ex}}$. Figure 3 shows the pictorial depiction of the ASAN-based character recognition model.

5.3 Signature Verification Steps With ASAN

The developed ASAN model does the signature verification process. The preprocessed images $\mathrm{PI}_u^{\mathrm{pre}}$ are inputted in the signature verification process. The developed ASAN model based on deep learning acts superior to enhance working performance. This process automatically extracts the deep features from the bank cheque by the proposed ASAN framework. At last, it provides the extracted features as the output. The extracted features are denoted by $\mathrm{SV}_p^{\mathrm{ext}}$.

Then, the extracted features are taken to verify the signature using a similarity check. The similarity check is used to define whether the signatures are genuine or forged. The extracted features are compared with the signatures available in the reference dataset. The similarity check is done by Euclidean distance measure. The Euclidian expression is described

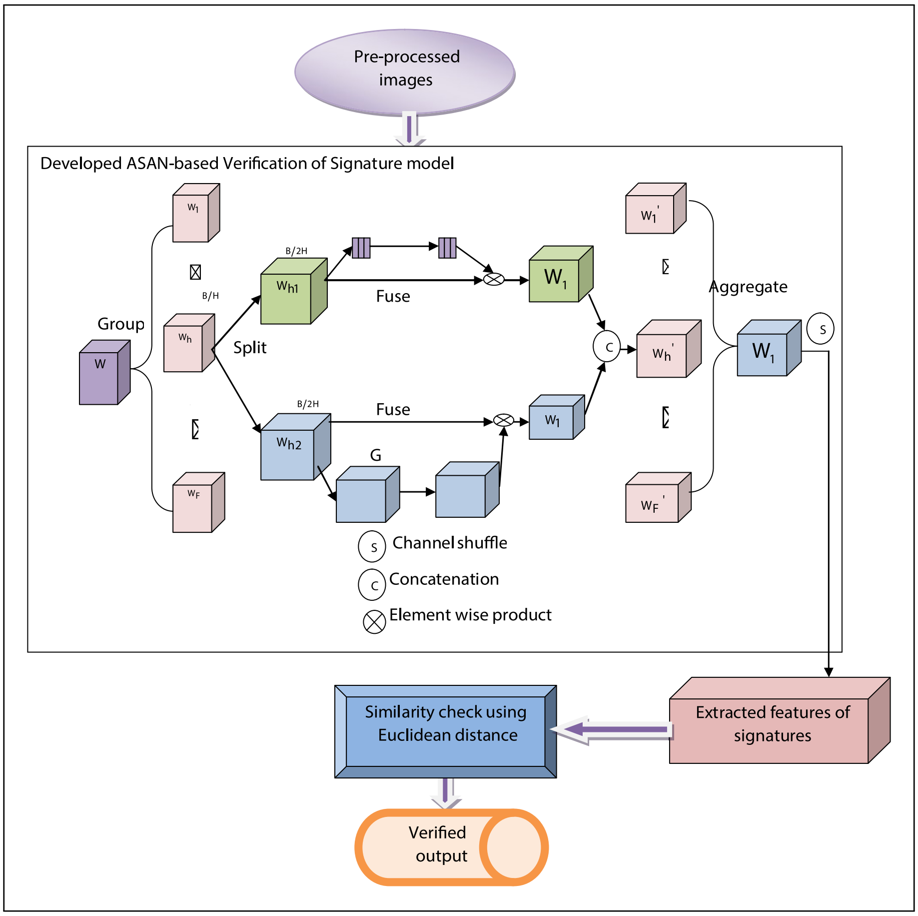


Figure 4. Developed ASAN-based signature verification model. ASAN= Adaptive Shuffle Attention Net.

in equation (18).

$$EUd(SC_n^{cheque}, SV_p^{ext}) = \sqrt{\sum_{a=1}^{D} (SC_n^{cheque} - SV_p^{ext})^2} \tag{18}$$

Here, the term SC_n^{cheque} defines the sample present in the reference dataset and SV_p^{ext} the extracted features. If the similarity more, the signature is considered genuine. The verification process is executed with accuracy, precision, sensitivity, and specificity. Finally, the extracted features provide the verified outcome by the similarity check. The developed ASAN-based signature verification model is shown in Figure 4.

6 Result and Discussion

6.1 Experimental Setup

Python was used to develop the automated bank cheque and signature verification system. The recommended model had 10 numbers of populations, the length of the chromosome was 50, and the developed model took 50 numbers of iterations to execute the process. The recommended model was analyzed with some classifiers and algorithms to provide the best outcome. The classifiers were Long Short-Term Memory (LSTM) (Lin et al., 2021), Recurrent Neural Network (RNN) (Wang et al., 2020), ResNet (Li & He, 2018), ASAN (Chan & Kobayashi, 2000), and MSTUnet++ (BCVerifyNet: Optical Character Recognition-based Number Verification and Transformer Efficient Net-based Handwritten Character and Signature Verification in Bank Cheques (in communication)). The algorithms were Honey Badger Algorithm (HBA) (Elgamal et al., 2020), Harris Hawks Optimization (HHO) (Deng, 2022), Rivest-Shamir-Adleman (RSA) (Jain & Singh, 2020) and Chimp Optimization Algorithm (COA) (Lin et al., 2021).

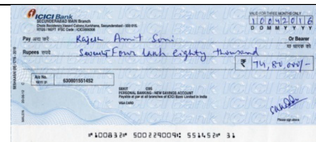
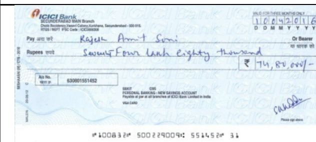
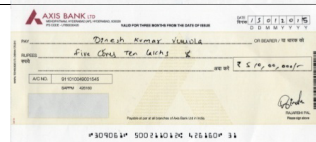
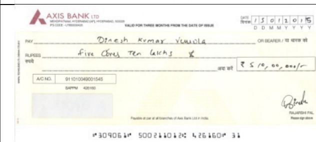
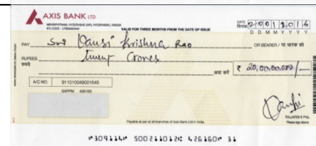
Image Description	Original Image	Pre-Processed Image
Image-1		
Image-2		
Image-3		

Figure 5. Preprocessed bank cheque image results.

Table 2. Detected Bank Cheque Results.

Cheque description	IFSC number	Account number	Amount	Cheque number
Bank Cheque-1	ICIC00063080	630801551452	Seventy-Four Lakh Eighty Thousand	100832
Bank Cheque-2	UTIB0000426	911010049001545	Five Crores Ten Lakhs	309061
Bank Cheque-3	UTIB0000426	911010049001545	Twenty Crores	309114

6.2 Experimental Setup

The developed automated bank cheque and signature verification model uses the following matrices to perform the process.

(a) The specificity can be calculated using equation (19).

$$S_pY = \frac{N_t}{N_t + P_f} \tag{19}$$

(b) Sensitivity S_eY is detected using equation (20).

$$S_eY = \frac{P_t}{P_t + N_f} \tag{20}$$

6.3 Preprocessed Bank Cheque Result

The result obtained from the preprocessing process is described in Figure 5.

6.4 Detected Results on OCR

The OCR detected the results from the bank cheque is described in Table 2.

6.5 Confusion Matrix Report on Developed Model

The confusion matrix analysis of the developed automated bank cheque and signature verification system is illustrated in Figure 6. The confusion matrix is compared with the predicted and actual levels. It provides an accuracy of 96.41%.

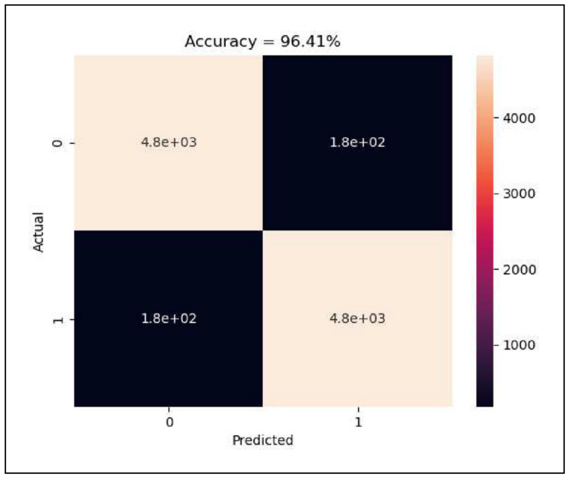


Figure 6. Confusion matrix analysis of the developed automated bank cheque and signature verification.

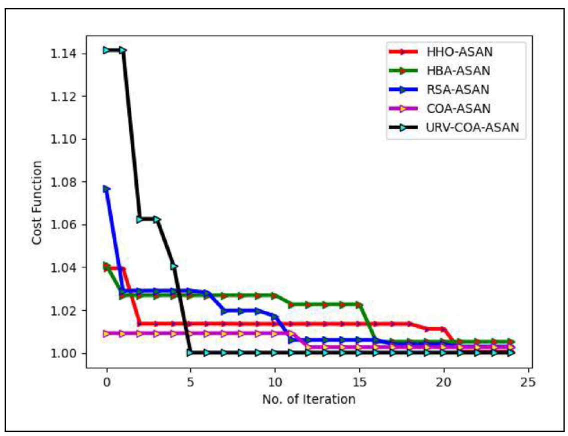


Figure 7. Cost function report of the developed automated bank cheque and signature verification system.

6.6 Cost Function Analysis on Developed Model

The cost function report of the developed automated bank cheque and signature verification system is described in Figure 7. The cost function of the recommended URV-COA-ASAN model is 1.47% enhanced than HHO-ASAN, 2.91% more than HBA-ASAN, 3.28% enhanced than RSA-ASAN, and 0.99% superior to COA-ASAN when at fifth iteration. It described that the developed model has a higher cost function rate than other models.

6.7 Classifier-Based Analysis on Developed Model

The classifier-based analysis is depicted in Figure 8. In Figure 8(c), the sensitivity of the developed URV-COA-ASAN framework is 11.76% increased than LSTM, 11.76% more than RNN, 10.46% enhanced than ResNet, 9.19% more than ASAN, and 7.95% improved than MSTUnett++ when observing the linear function. This proved the developed automated bank cheque and signature verification model attained supremacy over others.

6.8 Algorithms-Based Analysis on Developed Model

The analysis based on algorithms is given in Figure 9. In Figure 9(d), the specificity of the developed URV-COA-ASAN model is 1.3% improved than HHO-ASAN, 1.19% improved than HBA-ASAN, 1.11% increased than RSA-ASAN and 0.89% enhanced than COA-ASAN when observing the softmax function. This proved that the developed model provided the best result and was analyzed with different algorithms to give the best performance matrices.

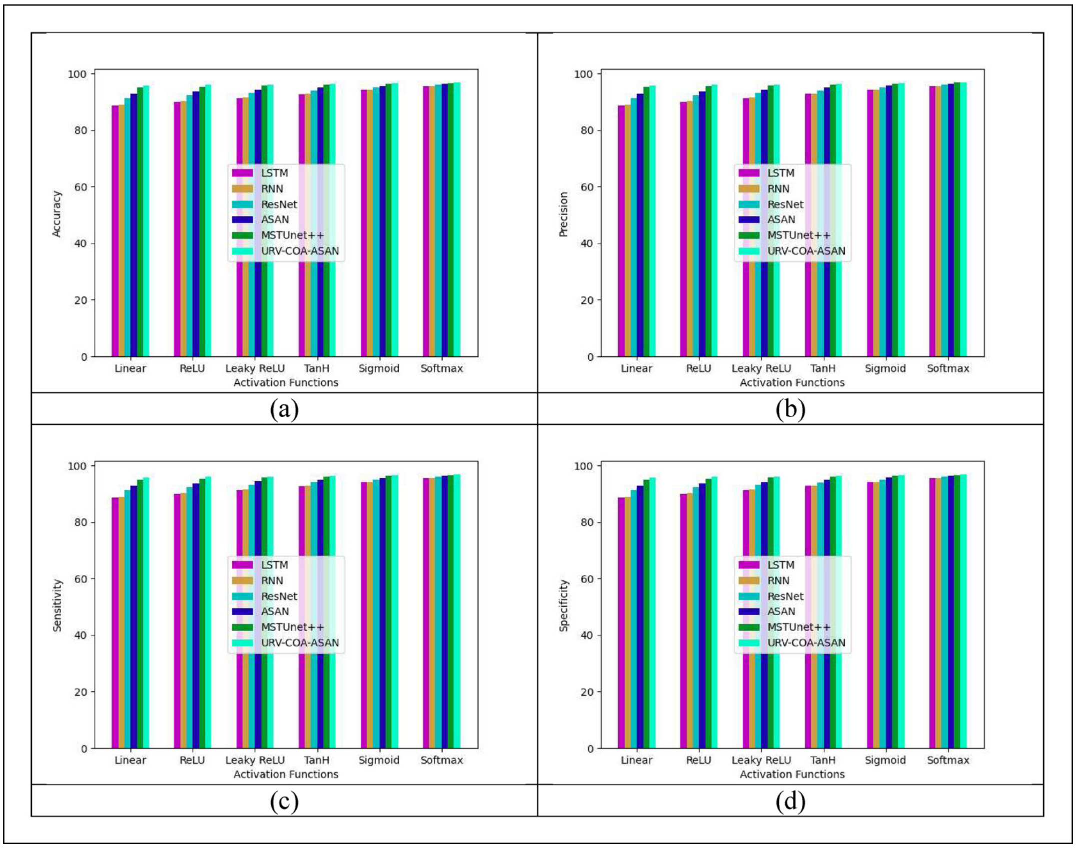


Figure 8. Classifier-based analysis of the designed automated bank cheque and signature verification model.

Table 3. Statistical Report of the Developed Automated Bank Cheque and Signature Verification System.

Algorithms	HHO-ASAN (Elgamal et al., 2020)	HBA-ASAN (Deng, 2022)	RSA-ASAN (Jain & Singh, 2020)	COA-ASAN (Khishea & Mosavi, 2020)	URV-COA-ASAN
Best	1.001	1.005	1.003	1.003	1.000
Worst	1.039	1.041	1.077	1.009	1.141
Mean	1.013	1.019	1.016	1.006	1.018
Median	1.013	1.023	1.006	1.003	1.000
Standard deviation	0.009	0.011	0.016	0.003	0.041

ASAN= Adaptive Shuffle Attention Net; HBA= Honey Badger Algorithm; HHO= Harris Hawks Optimization; RSA= Rivest-Shamir-Adleman; URV-COA=updated random vector-based chimp optimization algorithm.

6.9 ROC Report on Developed Model

The Receiver Operating Characteristic (ROC) of the developed automated bank cheque and signature verification system is provided in Figure 10. The ROC of the developed URV-COA-ASAN model is enhanced than LSTM, improved than RNN, superior to ResNet, more than ASAN, and increased than MSTUnet3++. Thus it proved the developed system has increasing ROC performance.

6.10 Statistical Report on Developed Model

The statistical report of the developed automated bank cheque and signature verification model is shown in Table 3. In Table 3, the best value of the developed URV-COA-ASAN model is 54% enhanced than HHO-ASAN, 62.73% improved than HBA-ASAN, 74.37% more than RSA-ASAN, and 36.67% improved than COA-ASAN. The result demonstrated that the developed automated bank cheque and signature verification have a higher performance rate than other techniques.

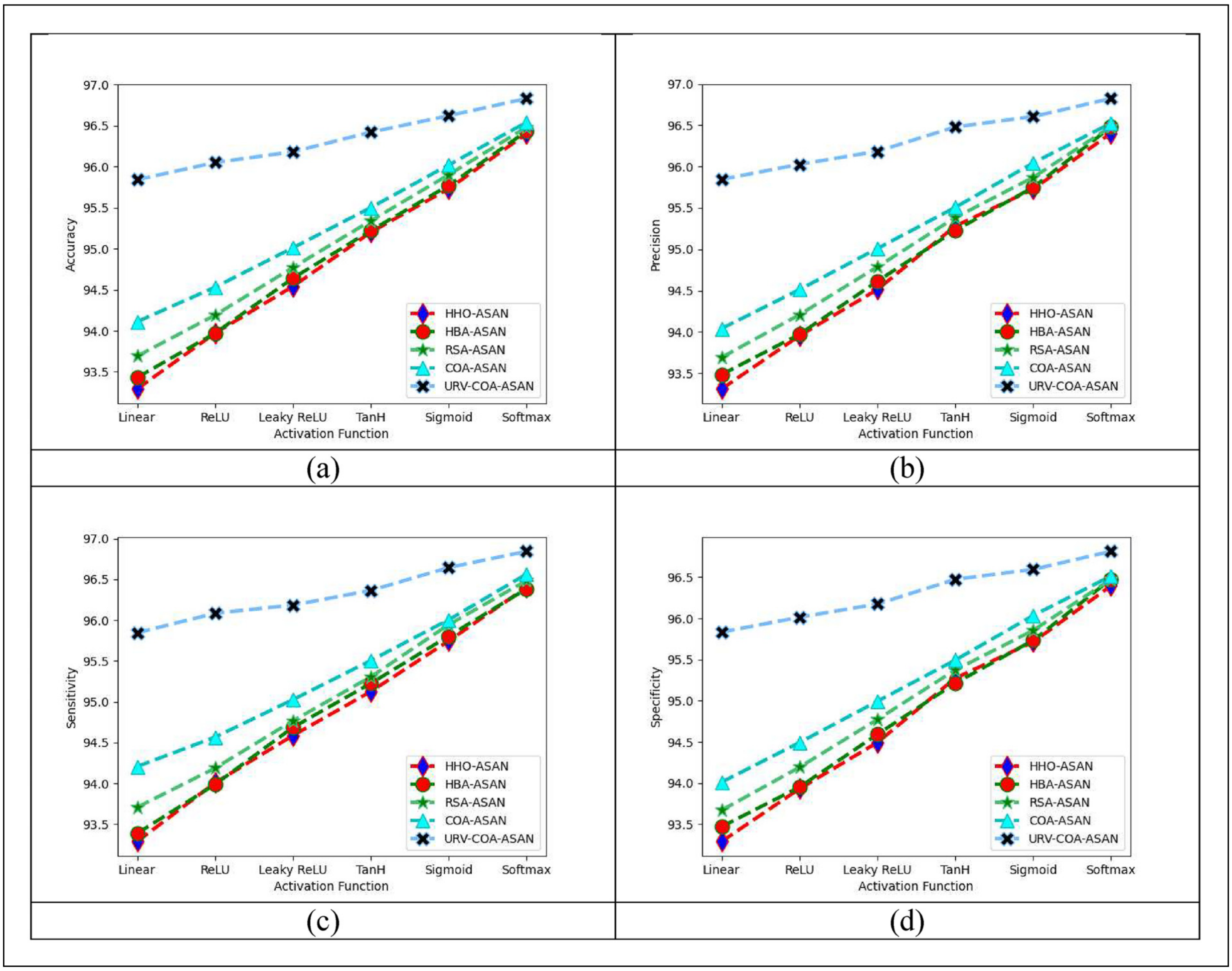


Figure 9. Algorithms-based analysis of the designed automated bank cheque and signature verification model.

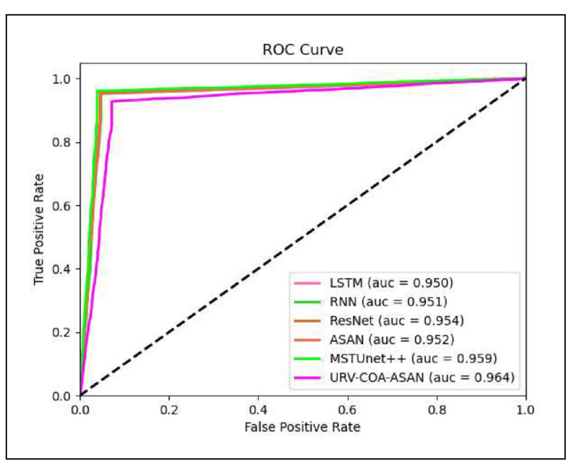


Figure 10. ROC-based analysis of the designed automated bank cheque and signature verification model.

6.11 Classifier-Based Report on Developed Model

The analysis based on classifiers is depicted in Table 4. In Table 4, the specificity of the developed URV-COA-ASAN model is 3.92% increased than LSTM, 3.79% more than RNN, 1.43% enhanced than ResNet, 0.93% improved than ASAN,

Table 4. Classifier-Based Analysis of the Developed Automated Bank Cheque and Signature Verification.

Terms	LSTM (Lin et al., 2021)	RNN (Wang et al., 2020)	RESNET (Li & He, 2018)	ASAN (Chan & Kobayashi, 2000)	MSTUnet++ (BCVerifyNet: Optical Character Recognition-based Number Verification and Transformer Efficient Net-based Handwritten Character and Signature Verification in Bank Cheques (in communication))	URV-COA-ASAN
Accuracy	92.780	92.930	94.120	95.050	96.110	96.420
Sensitivity	92.730	92.910	94.168	94.987	96.095	96.365
Specificity	92.830	92.950	94.072	95.113	96.125	96.475
Precision	92.841	92.966	94.093	95.120	96.190	96.481

ASAN= Adaptive Shuffle Attention Net; URV-COA=updated random vector-based chimp optimization algorithm.

Table 5. Algorithms-Based Analysis of the Recommended Automated Bank Cheque and Signature Verification System.

Terms	HHO-ASAN (Elgamal et al., 2020)	HBA-ASAN (Deng, 2022)	RSA-ASAN (Jain & Singh, 2020)	COA-ASAN (Khishea & Mosavi, 2020)	URV-COA-ASA
Accuracy	95.200	95.220	95.340	95.500	96.420
Sensitivity	95.127	95.227	95.307	95.506	96.365
Specificity	95.273	95.213	95.374	95.494	96.475
Precision	95.279	95.227	95.383	95.506	96.481

ASAN= Adaptive Shuffle Attention Net; HBA= Honey Badger Algorithm; HHO= Harris Hawks Optimization; RSA= Rivest-Shamir-Adleman; URV-COA=updated random vector-based chimp optimization algorithm.

and 0.36% improved than MSTUnett++. This showed the developed automated bank cheque and signature verification model performs more to attain the best result.

6.12 Algorithms-Based Report on Developed Model

The analysis based on algorithms is depicted in Table 5. In Table 5, the sensitivity of the developed URV-COA-ASAN model is 1.3% enhanced than HHO-ASAN, 1.19% improved than HBA-ASAN, 1.11% more than RSA-ASAN, and 0.89% improved than COA-ASAN. Finally, the developed model outperforms the other algorithms.

6.13 Snap Shots of the Result Execution

Snap shots related to the developed automatic bank cheque and signature verification models are displayed in Figure 11.

6.14 Discussion

In 2023, Bird et al. (2023) have developed an CNN model with data augmentation procedures and tuned its parameters to secure a better signature verification than the classical mechanism. Moreover, a conditional generative adversarial network is implemented to provide the signatures according to the binary classes. In the experimental validation, the suggested model secured a better accuracy rate of 87.12% than the classical techniques in the convolutional layers. In 2023, Ren et al. (2023) have suggested a new mechanism Two-Channel and Two-Stream Transformer approach (2C2S) to resolve the issues attained in the signature verification phase. Here, the original streams are utilized to attain the original signature pairs and they are operated over the standard swin transformer block. Here, the developed 2C2S model achieved a better signature verification rate of 90.68% over accuracy metrics. In 2021, Parcham et al. (2021) have proposed a novel capsule neural network model to acquire the spatial characteristics from the signature to minimize the network complexity

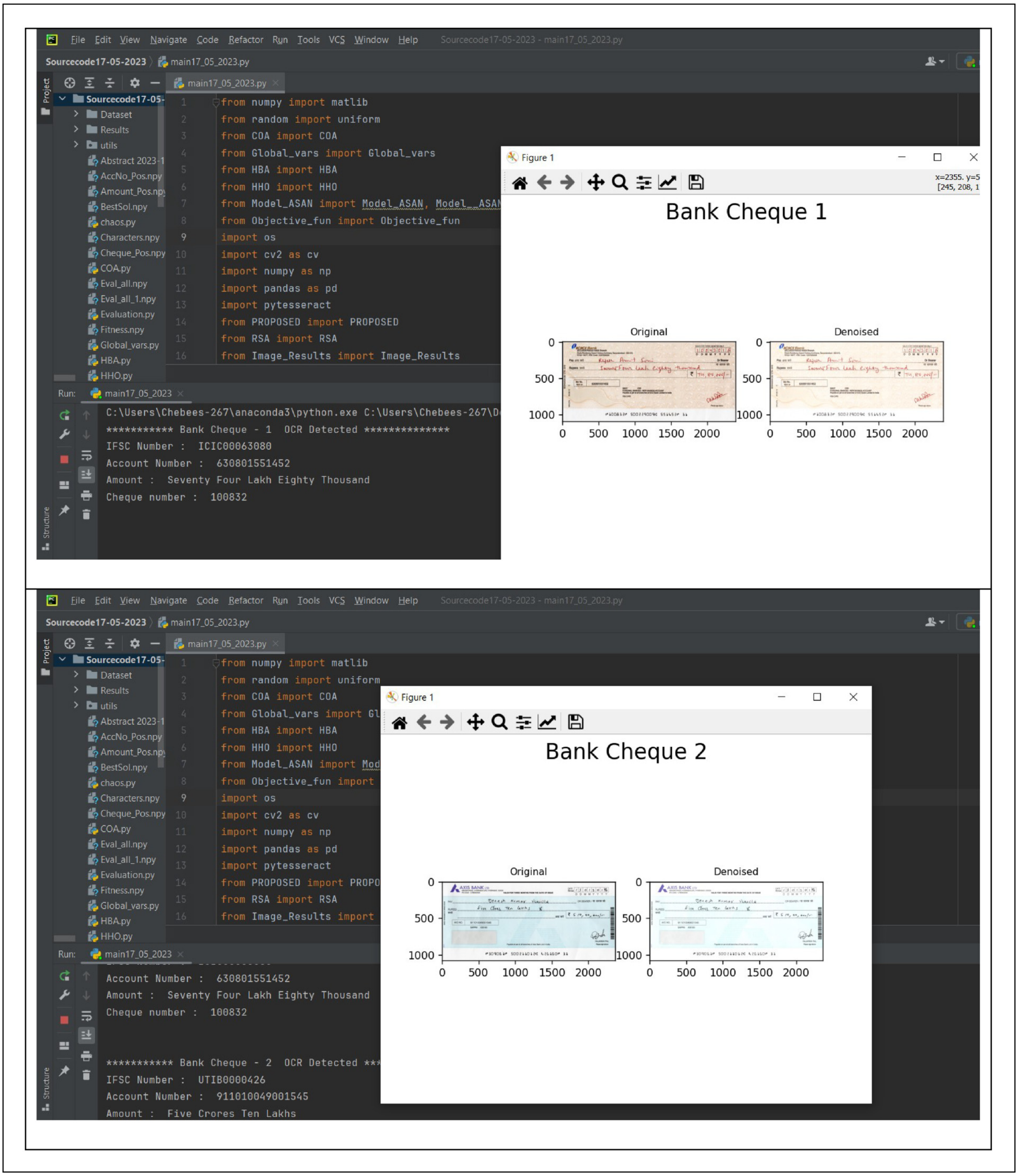


Figure 11. Continued.

rate. In this developed signature verification model accuracy of signature verification is improved by 88%. The classical signature verification mechanism with accuracy faces variability issues when it has a poor accuracy rate and also it creates more complicity while verifying the signatures. In some cases, they are subjected to more errors in the observation. Thus, a novel URV-COA-ASAN-based signature verification model is implemented in this research work to provide better accuracy as 96.42% while recognizing the signatures in the bank cheques. Hence, the developed model effectively helps the organizations and banking industry to identify the forged signatures accurately.

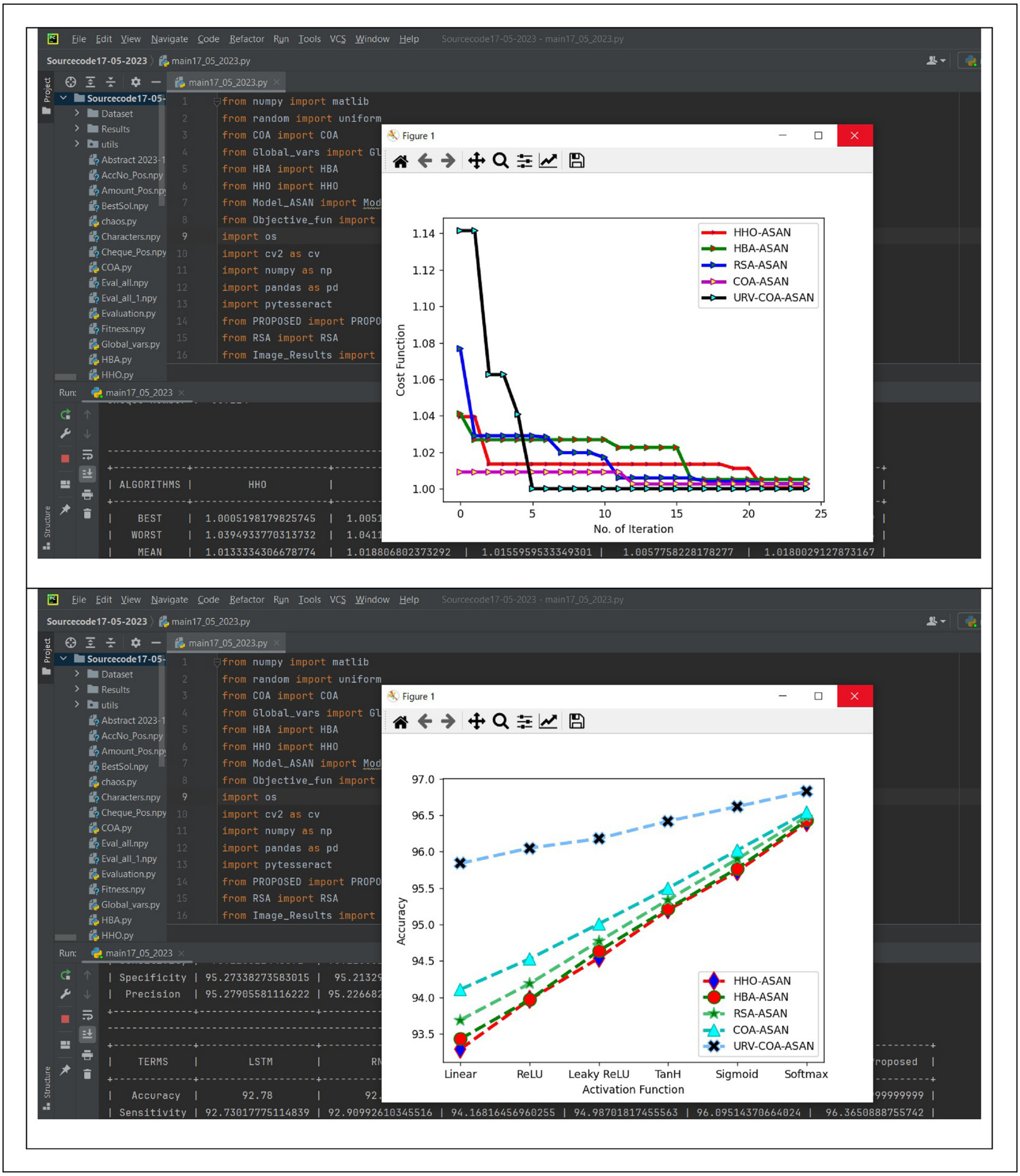


Figure 11. Continued.

7 Conclusion

Presently, signatures were considered the essential biometric authentication model for the banking and financial industry. But, identifying the original signature over the fraud signature is a difficult task. So, a novel deep learning mechanism was implemented in the automatic bank check and signature verification framework to reduce fraudulent activities in the banking industry. Here, the CLAHE mechanism was used to perform the contrast enhancement rate in the developed system with median filtering procedures. Next, the preprocessed images were provided for the numbers extraction phase

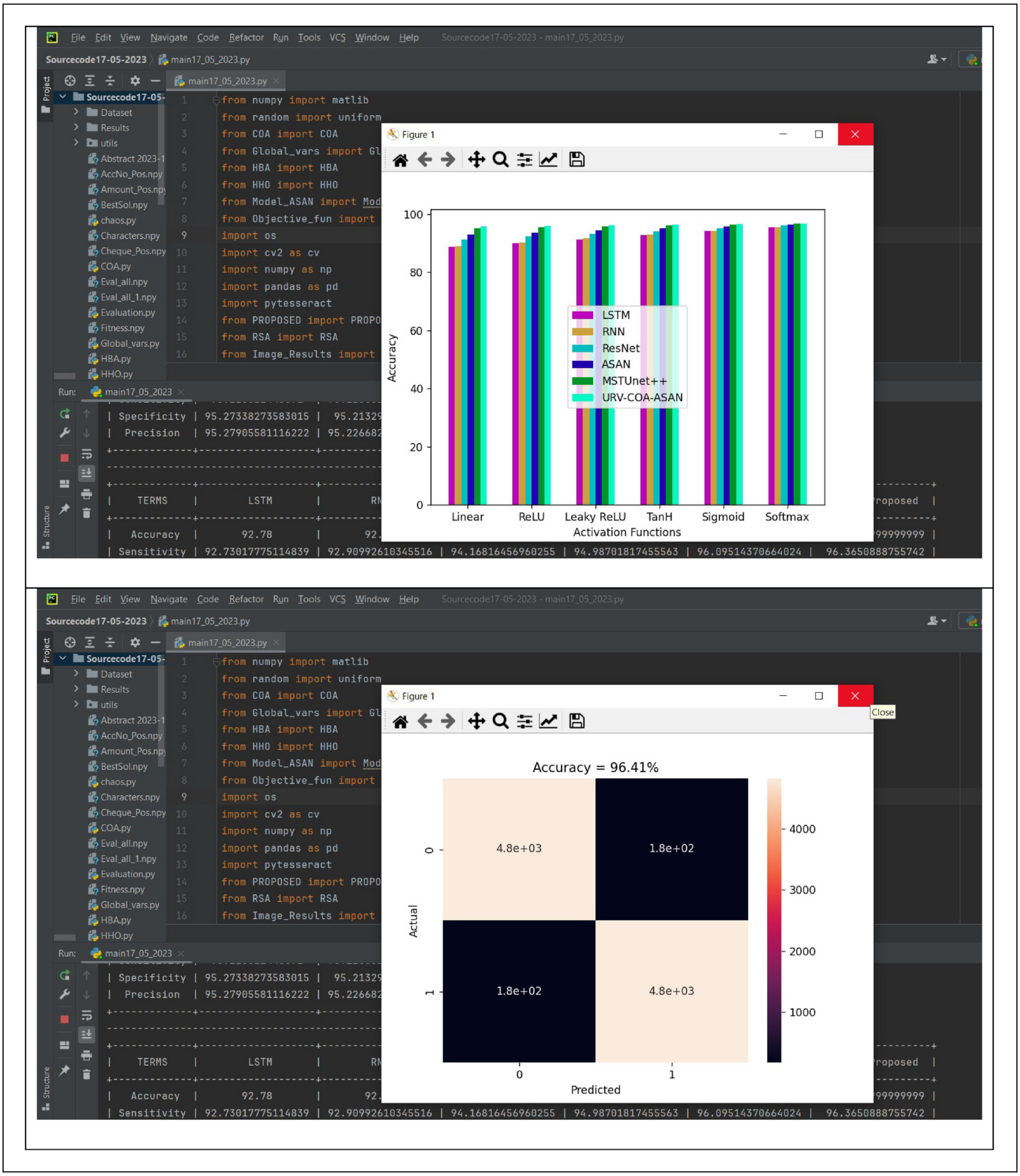


Figure 11. Representation of snap shots of developed automated bank cheque and signature verification framework.

using the OCR technique. Furthermore, the characters of the cheque were extracted using the ASAN technique from the preprocessed image, and also its parameters like layer size were optimized using the suggested URV-COA technique for improving the precision with higher accuracy. Moreover, the signatures on the cheque were verified using the developed ASAN technique. Later, the verified characters from the check were used to perform the similarity check to determine whether the signature was forged or real. The accuracy of the recommended URV-COA-ASAN model was 1.28% enhanced than HHO-ASAN, 1.26% improved than HBA-ASAN, 1.13% more than RSA-ASAN, and 0.96% improved than COA-ASAN. The performance of the designed automated bank cheque and signature verification system was explored and compared with several techniques regarding bank cheque signature verification. Hence, the developed bank cheque verification models were widely used in mobile and web-based banking applications to protect the system from fraudulent activities. Yet, the recommended bank cheque signature verification framework needs to protect the sensitive information of the individual from attackers. So, a security-based bank cheque and signature verification model is more essential.

Statements and Declarations

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Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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