

# Smart Vision Based ATM Transaction using Deep Learning Neural Networks



Kalpana Devi S, Pranusha A, Priyanka S, Ram Abhishek RS

**Abstract:** *The necessity of credit cards and online payment techniques become extremely popular and simple to perform because of easy and safe money handling techniques. The usage of the ATM by visually challenged people is a problem. Though there are certain features for the visually challenged users like speech instructions, there is no conformity of the amount entered or of that transacted. As a result, these people have no security, ease or comfort during the ATM transactions. So, there is a need to provide a method for the visually challenged people to effortlessly perform ATM transactions with better security. Our proposed system designed a device that can act as an aid for the visually challenged to transact in the ATM. The devised system recognizes the amount to be transacted as entered on the screen using Optical Character Recognition (OCR) and conveys it to the user via speech. After transaction, the banknotes are recognized by the system using image recognition through vital banknote feature extraction and the verification is provided regarding the amount transacted and the intended amount.*

**Keywords:** ATM transaction, Optical Character Recognition (OCR), Image recognition, banknote recognition, feature extraction.

## I. INTRODUCTION

Nowadays, image recognition and machine learning are two of the most developing areas in the field of Interactive programming and software development. The areas to use image recognition are very vast. One such precise reimbursed usage of image recognition is to help challenged people. Around 2.9% of the people in the world are visually challenged with 14% of that population with eyes that have no reception of any light. These people find the process of performing ATM transactions really difficult due to lack of safety and ease of implementation. So, there are related papers to perform ATM transactions for visually challenged people. One such way the developing technologies and conceptual theories can be used to support visually challenged people is to facilitate them in the use of currency as the number of cases related to theft from blind people are widely increasing in the current age.

Manuscript received on March 12, 2020.

Revised Manuscript received on March 25, 2020.

Manuscript published on March 30, 2020.

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The primary idea of this model is to help them by providing a system that can help them to handle ATM transactions as well as day to day banknote detection for daily currency related work. Not just in ATM transactions, but in several other situations, the visually challenged people are liable and supposed to handle money. In many cases, these visually challenged people face several fraudulent and non-reliable people who tend to cheat or abuse them.

Thus, this model chiefly aims to act as an aid to the visually challenged people so as to help them handle currency. The system solves certain number of problems that the visually challenged people may face during ATM transaction as well as the use of currency.

## II. RELATED WORK

The contributions of various authors are surveyed and analysed to determine the merits and demerits of the existing systems in order to make the proposed system work better.

In paper [1], Ryutaro Kitagawa et.al have developed a model for the process of banknote portrait detection. The model uses convolutional Neural Network (CNN). The banknote sorting process in their proposed model involves four major tasks namely denomination recognition, counterfeit detection, damaged note detection and counting of the notes. As the model primarily focuses on portraits of the banknotes, the CNN which is taken to be AlexNet takes a set of the portraits as the inputs for the identification process. Thus, on providing a banknote, the proposed system successfully identifies the portraits on the banknotes and produces the output for the user by using moving rectangles on the screen indicating the possible portraits. As it uses AlexNet, though the same model has been proposed before, this system was able to achieve a 1.8% better accuracy and 34% higher time efficiency. In paper [2], Carlos M. Costa et.al have proposed that the identification of the old banknotes from the new banknotes can be effectively done if in addition to the analysis of the colour of the banknotes, the shape of the banknotes are also analysed. They have found that the proposed system works very effectively in the identification of the old banknotes from 80 test images even when the banknotes overlapped one other in the same image. They used OpenCV (Open source Computer Vision) library to implement the recognition of the banknotes. They implemented the Random Sample Consensus (RANSAC) methodology for the identification process. The inliers of the banknotes were considered to be the feature of the banknote that was used to classify the banknotes as old or new. They have found that their proposed system achieved 96.7% accuracy which was 15% higher than the existing system for that process.



In paper [3], N.A.J. Sufri et.al have proposed a system for the identification of the banknotes as the visually challenged people have some issues in the identification of the banknotes. They used the AlexNet structure for the neural network implementation which has been proven to be the best neural network model to implement the classification and identification processes.

They analysed all the available algorithms that can be used to classify the banknotes and the results were compared. They took four major classification algorithms into consideration namely the Support Vector Machine (SVM), K-Means, Bayesian Classifier and the Decision Tree Classifier. The results were produced in the confusion matrix and it was identified that the Decision Tree classifier and K-Means algorithm achieved 99.7% accuracy while Bayesian Classifier and SVM achieved 100% accuracy when implemented together. Thus, their proposed system implements both the algorithms in a cascading style to achieve the best results. In paper [4], Faiz M. Hassanuzzaman et.al have proposed a system in which the component based classifier algorithm with Speeded Up Robust Features (SURF) methodology is used to obtain a feature rich detection of the banknotes. They also make use of a standard feature classification algorithm. They have found that the proposed model for the banknote identification process has achieved 100% accuracy even when confronted with challenging images and data. The model they proposed uses a sequential algorithm where the query images are produced to the SURF detectors. The SURF detectors then perform point level and region level tests to obtain the result of the classification process. The proposed system was able to achieve 98% accuracy but still the algorithm proved to be a very complex one resulting in lesser efficiency and higher execution time. In paper [5], Tamarafinide V. Dittimi et.al have proposed a system that uses a highly optimized custom algorithm to identify the banknotes. They use the Principal Component Analysis (PCA) on the Histogram of Gradient (HOG) by using the image of the banknote that is to be identified. The algorithm that they have projected for the system is Multi-Class Support Vector Machine (MCSVM) based gradient feature extraction processing to perform classification. They have identified that MCSVM has achieved an accuracy of 98% which has matched up with the accuracy of the random forest classification algorithm. But due to recognition rate and noise reduction processing, they have opted for MCSVM to implement their model. In paper [6], Vishnu R. et.al have proposed the various features that can be used for the identification and the classification of the Indian banknotes. The system that has been proposed by them makes use of the specific as well as the common characteristics of the Indian currency such as the central number, micro printing, numeral shape and the RBI seal. The results that were obtained were reduced with the help of Principal Component Analysis (PCA). The results that were obtained were fed into the WEKA tool that can be used to extract the features and produce a novel classification of the banknotes. Among all the specified features it was identified that the central number detection was the best feature with about 100% accuracy while the RBI seal detection was the worst feature to be exploited as it produced an accuracy of

just 60%. The other features had a decent average accuracy in the identification process. In paper [7], Byoung-Kyun Kim et.al have proposed a system for the banknote recognition under various different lighting conditions with the help of FFT (Fast Fourier Transform). The watermarks that are imprinted on the banknotes are categorized for the classification process in this system. The watermarks not only act as an excellent feature to identify the nationality of the banknote but also to respond to various different illuminations such as ultraviolet, infrared and white rays. They have proposed a discrimination model that implements SIFT and FFT for the identification. The result that is obtained is fed into the Multinational Banknote Recognition Engine (MBRE). The engine uses Approximately Nearest Neighbour algorithm widely called the ANN for the clustering process helping in valid identification. The feature results are plotted down as a histogram showing the capable recognitions possible for detection under different lightings. In paper [8], Snigdha Kamal et.al have proposed the various features that can be extracted for the identification of the Indian currency from the available training as well as the input data. They have successfully acknowledged and identified the various features of the Indian banknotes that can be used to uniquely identify the banknotes from the provided images. The exploitable features as recognized by them are the central number of the currency, RBI seal, colour band and the identification marks for the visually impaired. They identified that with a test set of 300 images of Indian currency, the features identification mark detection and colour matching techniques achieved 100% accuracy while the other features achieved a little lesser accuracy. The average accuracy was evaluated to be 97.02%. The proposed model made use of the SURF descriptor combined with PCA for dimensionality reduction and classification algorithms for identification. In paper [9], Zora Solymar et.al have discovered a model for the identification of the banknotes based on the classification algorithm specific to video processing. They have primarily focused on the identification of the banknotes in the captured videos by video processing. The system proposed by them makes use of a two level classification scheme implementing two different classifiers that are collectively used for the classification and identification of the banknotes as required. Both the classification algorithms are simultaneously used to perform their classification process and produce the results as obtained. The votes that are obtained from these systems are combined and an ensemble decider is used to obtain the final identified result. As all the other image processing models, this model also involves the binary conversion of the images and then pixel colour extraction technique to decide on the banknote. The model invokes supervised learning and after providing the training set, the accuracy obtained on the dataset is 98.95%. In paper [10], S. Lee et.al have proposed a system that can be used to significantly detect and identify the fitness of the banknotes that are produced. The system makes use of morphology to detect if the banknotes are fit or not.

The term morphology refers to the concept of analysis of the shape and the relative features of the banknotes that are provided. The system is widely implemented on both large as well as small scale. The large as well as small scale implementation of the model makes use of CDI (Closed Difference Images) and GDMDI (Generalized Dynamic

Morphological Difference Images) respectively. The GDMDI just includes a simple one on one comparison while the CDI includes pixel by pixel comparison and it is fit only if it surpasses a certain threshold. It had a significantly lesser error rate of 1.32% due to the combinational implementation of the model.

**Table 1: Comparison of various techniques used for currency recognition and classification**

S.No	Paper	Technique	Result	Issues
1	Banknote Portrait Detection Using Convolutional Neural Network	Convolutional Neural Network (CNN) and AlexNet.	A banknote recognition system with 1.4% better accuracy and 34% better time efficiency.	The system though has a better time efficiency, than the previous models, it is still pretty less than the proposed model.
2	Recognition of Banknotes in Multiple Perspectives Using Selective Feature Matching and Shape Analysis	OpenCV image recognition and RANSAC (RAN dom Sample Consensus) methodology.	An easy and simple system that achieved 96.7% accuracy which is 15% higher than the existing system.	The accuracy is less and IR and UV lights proved to be very difficult to act upon.
3	Vision Based System for Banknote Recognition Using Different Machine Learning and Deep Learning Approach	AlexNet model with K-means, Bayesian classifier, Support Vector Machine and Decision tree classifier.	A simple banknote recognition system that uses a combination of the algorithms to achieve 100% accuracy.	Though a single algorithm can sometimes produce better result, only combinations produces the best result.

4	Robust and Effective Component-based Banknote Recognition by SURF Features	The use of Speeded Up Robust Features (SURF) detectors for feature extraction.	The identification of the best features to exploit produces an accuracy of 98%.	As the best feature is to be identified, it has very high implementation time and very high complexity.
5	Multi-Class SVM Based Gradient Feature for Banknote Recognition	Histogram Of Gradient (HOG) for detection and Multi-Class Support Vector Machine (MCSVM) for classification.	It has achieved 98% accuracy which is equivalent to random forest classification.	The system is not always dependable and is sometimes prone to errors.
6	Principal Features for Indian Currency Recognition	RBI seal is used as the feature to identify banknotes and PCA is used for classification.	The use if RBI seals extraction helped to produce 100% accuracy.	Though the accuracy is reached in suitable circumstances, shape distortion affects the system's performance.
7	Feature Extraction using FFT for Banknotes Recognition in a Variety of Lighting Conditions	Use of SIFT and FFT for detection and Multinational Banknote Recognition Engine (MBRE) for classification that uses Approximately Nearest Neighbour algorithm.	The use of SIFT and FFT helps to identify banknotes even in poor lighting.	The system is very traditional, can easily become defective and can only work if the banknotes are in the exact shape as required.
8	Feature Extraction and Identification of Indian Currency Notes	SURF descriptor is used, with PCA for dimensionality reduction.	The central number is used to identify the banknote with colour and seal, helping to achieve 97.02% accuracy.	A false positive rate of 0.097 and a reticulate identification process.
9	Banknote Recognition for Visually Impaired	The use of ensemble decider for the classification of the banknotes to obtain a very ideal result as it simultaneously uses several algorithms to obtain the best result.	The best extraction technique and easy learning has helped the system to achieve a considerably high accuracy of 98.95%.	The classifiers need to be improved and the computational complexity needs to be optimized to obtain a pure mobile system that can be implemented.
10	Morphology-Based Banknote Fitness Determination	Morphology Based feature extraction on scale using combination of CDI and GDMDI to determine the fitness of the Banknote	The combined method GDMDI and CDI showed errors of about 1.32% for the banknotes	Combination of two techniques increase the time of computation

## III. PROPOSED SYSTEM

The proposed system primarily focuses on acting as a wholesome aid to the visually challenged people by providing a voice based completely bi – interactive system that stipulates the complete scenario. The proposed system though divided into three modules, has only two major working processes. The system induces the process of identification of the entered transaction amount as well as the banknote that has been transacted out from the ATM machine. The working system as proposed above contains two major reticulate processes. In the first process, the user is provided with the information regarding the amount that has been entered in the ATM machine. The process of how this works is explained in the below scenario explanations.

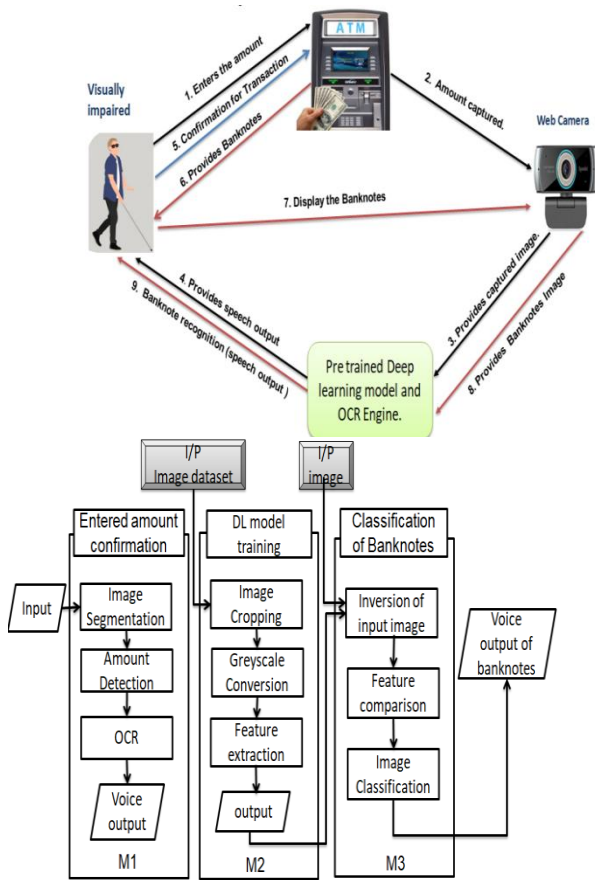


FIGURE 1. System Architecture

The process begins from the visually challenged person. The visually challenged person begins the system by entering the amount that is to be transacted from the ATM machine. Then, the OCR engine captures the amount that is entered and produces a voice output to ensure the user of the displayed amount so as to confirm them. Now, the user gets the transacted amount from the ATM machine. The banknotes that are transacted from the ATM machine are displayed by the user to the visual image recognition module. The final module is a DL model that is pre-trained with the banknotes data. With the supervised knowledge, the current banknotes that are displayed by the user are recognized by the model and the amount that is detected is

provided as the output so that the visually challenged user can guarantee that the amount that is transacted is accurate.

## IV. IMPLEMENTATION

### A. OPTICAL CHARACTER RECOGNITION PHASE

The first time the user enters the amount in the ATM machine, the proposed system captures the image of the ATM bank screen. This is done with the help of the webcam that is present in the system. Now, the image that has been captured by the webcam is provided as the input to the OCR engine. The term OCR stands for Optical Character Recognition. As the name suggests, the engine performs optical character recognition. The image that has been provided acts as the input. The engine takes the image and captures the amount that has been entered in the ATM machine. Now, the amount that has been captured by image segmentation and image cropping is given as the input to the OCR module. The optical character recognition is done with the help of PyTesseract which is actually an OCR engine. The pytesseract converts the digits from the image into string, which actually produces the amount that has been entered by the user. Now, the transaction amount that has been provided as the output is taken by the gTTS package in python. The Google Text To Speech converts the transaction amount to speech data and provides the data to the visually challenged people. The reason only the transaction amount is recognised and provided as the output is because, the amount entered is very sensitive and also because all the current ATM machines have fingerprint sensors as well as instructing module via speech to guide the users to transact. Now, after the desired amount that is to be transacted is provided as the output, the visually challenged user transacts the amount from the ATM machine with guarantee that the amount entered is accurate.

### ALGORITHM 1

**Step 1:** Start.

**Step 2:** Enter the amount that is to be transacted.

**Step 3:** Invoke the camera and capture a snapshot of the ATM screen.

**Step 4:** Now, invoke the OCR function to capture the amount entered and use the text to speech function to output the amount entered as speech.

**Step 5:** Stop.

### B. DL MODEL TRAINING PHASE

Now, after the amount is transacted from the ATM machine, the banknotes are classified and identified with the pre-trained DL model.

The deep learning model is a classifier model that is used to identify the banknotes produced with the help of feature extraction. The deep learning model is already provided with a large number of available datasets that are used widely recognized and provided as the input data to the model. Now, with these pre-processed data that are taken as the input, the model trains itself. The trained model now has the ability to classify the input data. The pre-processing of the data begins by producing four major images that are visually enhanced. The four different images are grayscale image which includes the different shades of grey to white based themes, the Gaussian blur image which blurs the background noise and unwanted information, the negative image that produces contrastive measures and the black and white image which contains only 0 or in the colour values, Now, with these pre-processed data, the relevant learning is done.

**ALGORITHM 2**

**Step 1:** Start.

**Step 2:** Prepare the dataset to be used for training.

**Step 3:** Design the Deep Learning model with the relevant training set data.

**Step 4:** Now, invoke the preprocess function to perform preprocessing of the images to be used for learning.

**Step 5:** Build the model using the build\_model() function.

**Step 6:** Now, train the deep learning model using the procured preprocessed dataset.

**Step 7:** After training the dataset, use some test data to check the result.

**Step 8:** Stop.

**C. BANKNOTE CLASSIFICATION PHASE**

With the pre learned deep learning model, the classification of the banknotes can be visually enabled and successfully executed. This is done with the process of the deep learning model making use of the features that are captured by the image capturing device. The image of the banknote that is to be classified by the model is displayed by the visually challenged user in front of the image capturing device which takes a snap and sends it to the classifier model. Now, the model uses the feature extraction module implementation process to obtain the exact amount that the banknote represents. The DL model is implemented with the help of Keras with Tensor flow. The two packages are accumulatively used to obtain the recliner classification implementation process. With this system, we get a complete aid to the visually challenged people as, the sensitive as well as the major implementation processes are guided by the system. Thus, the visually challenged user can use the proposed system to completely perform the entire transaction process without the help of any third person which ensures as well as enhances the safety and security in both the amount transaction as well as identification.

**ALGORITHM 3**

**Step 1:** Start.

**Step 2:** Obtain the image of the banknote that is to be classified using the camera.

**Step 3:** Now, provide the input image to the pretrained model from the previous phase.

**Step 4:** Use the classify() function to invoke the model and obtain the predicted result.

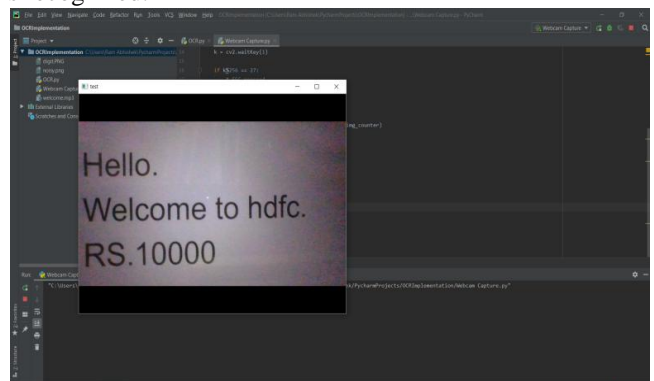
**Step 5:** Now, the obtained classification result is given to TTS() function to convert text to speech.

**Step 6:** Use this to provide the voice output to the visually challenged user.

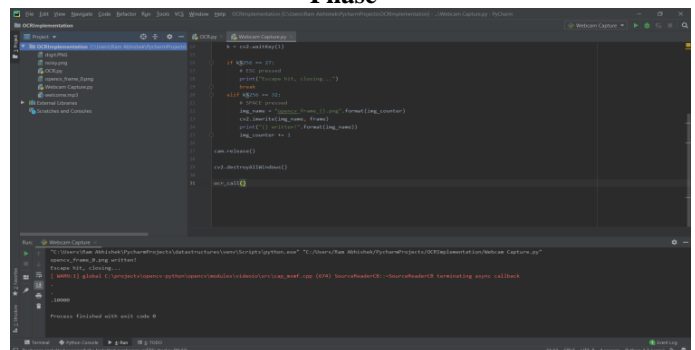
**Step 7:** Stop.

**V. RESULTS AND DISCUSSION**

The abovementioned phases are accumulatively implemented to ensure that the system acts as a complete support to the visually challenged people. In the first phase, the transaction amount that is to be transacted from the ATM machine is entered and the entered amount is verified with the user by providing the speech output of the data that is recognized.



**Figure 1: Input of the Optical Character Recognition Phase**



**Figure 2: Output of the Optical Character Recognition Phase**

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For the second implementation, the various available data that can be used for training the model is obtained. The dataset is used to train the model to classify between the available banknotes that can be possibly obtained.

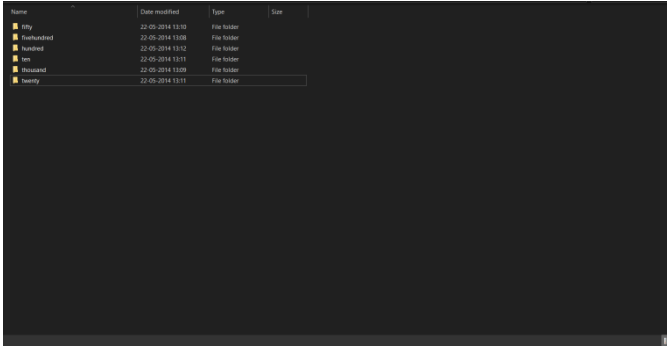


Figure 3: Input training dataset to the DL model

Now, use the trained model to classify the desired banknote. The webcam capture of the banknote is done and the image is fed into the network to classify the images as to be a particular banknote.



Figure 6: Input image to the trained model

```
Unfiled3 Last Checked: Last Wednesday at 1:50 AM (autohide)
File Edit View Insert Cell Kernel Widgets Help
Python 3.0

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten, Conv2D, MaxPooling2D
from tensorflow.keras.callbacks import TensorBoard

import pickle
import time

DIR = "banknote_recognition_data"
tensorboard=TensorBoard(log_dir='./logs')

pickle.load(open("x.pickle","rb"))
pickle.load(open("y.pickle","rb"))

x=x.reshape(-1,28,28)
y=y.reshape(-1,10)

model = Sequential()
model.add(Conv2D(32, (3, 3), input_shape=(1, 1, 28, 28)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), (2, 2)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dense(1000))
model.add(Activation('relu'))
model.add(Dense(10))
model.add(Activation('softmax'))
optimizer=adam
metrics=['accuracy']
model.compile(loss='sparse_categorical_crossentropy',
              optimizer=optimizer,
              metrics=['accuracy'])
model.fit(x,y, batch_size=100, epochs=10, validation_split=0.1)
model.save('500-DNN.model')
```

Figure 4: Code for the DL model Classification

```
In [2]: import cv2
import tensorflow as tf

CATEGORIES = ["fifty", "hundred", "ten", "thousand", "twenty"]

def prepare(filepath):
    IMG_SIZE = 40
    img_array=cv2.imread(filepath)
    new_array=cv2.resize(img_array, (IMG_SIZE, IMG_SIZE))
    return new_array.reshape(-1, IMG_SIZE, IMG_SIZE, 3)

model=tf.keras.models.load_model('500-DNN.model')

predict=model.predict([prepare('41.jpg')])

print(CATEGORIES[predict[0][0]])

fifty
```

Figure 7: Output from the trained model

## VI. CONCLUSION AND FUTURE WORK

As proposed above, the system has the ability to provide a complete aid and support the visually challenged people to perform the transaction process without the help of any third person or strangers. Thus, the security and accuracy of the transaction process is ensured. The further development can be done in terms of the algorithms used and the process implementation. With the increasing number of algorithms day to day, there is much scope in increasing the complexity and the quality of the system. Also, it is possible to increase the dataset content so as to ensure accuracy and also scalability by using the system to classify various widespread banknotes. The ways by which the operations are done can be further enhanced for future works.

```
Train on 2060 samples, validate on 109 samples
Epoch 1/10
2060/2060 [=====] - 67s 32ms/sample - loss: 1.5384 - acc: 0.2883 - val_loss: 1.3766 - val_acc: 0.3678
Epoch 2/10
2060/2060 [=====] - 93s 45ms/sample - loss: 1.2626 - acc: 0.4688 - val_loss: 1.2031 - val_acc: 0.4679
Epoch 3/10
2060/2060 [=====] - 88s 43ms/sample - loss: 1.0183 - acc: 0.5874 - val_loss: 1.2871 - val_acc: 0.4387
Epoch 4/10
2060/2060 [=====] - 78s 38ms/sample - loss: 0.8243 - acc: 0.6699 - val_loss: 0.9947 - val_acc: 0.5788
Epoch 5/10
2060/2060 [=====] - 70s 34ms/sample - loss: 0.6372 - acc: 0.7658 - val_loss: 1.1154 - val_acc: 0.5688
Epoch 6/10
2060/2060 [=====] - 103s 50ms/sample - loss: 0.4567 - acc: 0.8427 - val_loss: 1.2080 - val_acc: 0.568
Epoch 7/10
2060/2060 [=====] - 72s 35ms/sample - loss: 0.3705 - acc: 0.8825 - val_loss: 1.2205 - val_acc: 0.5688
Epoch 8/10
2060/2060 [=====] - 78s 34ms/sample - loss: 0.3011 - acc: 0.9005 - val_loss: 1.1522 - val_acc: 0.6147
Epoch 9/10
2060/2060 [=====] - 97s 47ms/sample - loss: 0.1646 - acc: 0.9515 - val_loss: 1.1760 - val_acc: 0.6239
Epoch 10/10
2060/2060 [=====] - 82s 40ms/sample - loss: 0.1135 - acc: 0.9699 - val_loss: 1.4560 - val_acc: 0.6239
```

Figure 5: Output of model after training with the training dataset

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