

Introduction

Currency is something that is released by the government to utilize services. Among all other alternative forms of currency, the most preferable form of the currency is the paper. As part of the technological progression introduced to the banking sectors, financial institutions and banking had started financial self-services. By using an ATM counter and a Coin dispenser automated banking system is achieved where machines are used to handle currencies. In such systems, the machine uses methods to recognize the correct currency.

Currency has two types of features internal and external features. External features include the physical aspects of the currency like width and size. But these physical features are not reliable because currencies may damage due to circulation. Due to this damaged currencies system may fail to recognize currencies. The internal feature includes the Color feature, which is also not reliable because currencies are passed through various hand and due to this, it becomes wrinkled. For currencies of each denomination, there is a specific color and size followed by RBI (Reserve Bank of India).

It is very simple for a human to identify the denomination of currency notes because our brain is extremely skillful in learning new things and discovering them later without much trouble. But this currency recognition task turns very challenging through machines (Computers), in cases when currencies become damaged, old, and faded due to wear and tear.

Security features are included in every Indian Currency which provides help in recognition and identification of the currency value. Various Security features are identification mark (shape), Center value, Ashoka, Latent image, See-through register, Security thread, Micro letter, Watermark, and RBI seal.

Basically, the images are read from different derivations. However, we delimit our system which can read the currency from the scanner. The device that the system needs is very common in our daily life, so we do not need to buy an extra device to realize the system.

There are a number of challenges while creating such a robust system, Including:

1. Most of the techniques are sensitive to illumination and many of them rely on taking images in fixed environment settings such as camera location and image background.
2. There is a requirement of the large dataset for training samples used to avoid overfitting and poor generalization.
3. Also, if the distribution of training samples is not uniform, then the result will not come as needed.
4. Removal of noise during image processing is very necessary. The recognition rate decreases due to them, which cannot be neglected.
5. During image processing, noise removal requires the processes of smoothing and local averaging which In turn blurs the edges of the images which is a necessary part of our recognition process.

6. The bigger is the dataset, the more complex is the neural network and hence we require powerful hardware and a stronger GPU system to reduce the time taken.
7. The images that are taken are in the form of pixels. Bigger dataset means millions of pixels are to be matched which we require an efficient and optimal algorithm to reduce the time is taken.

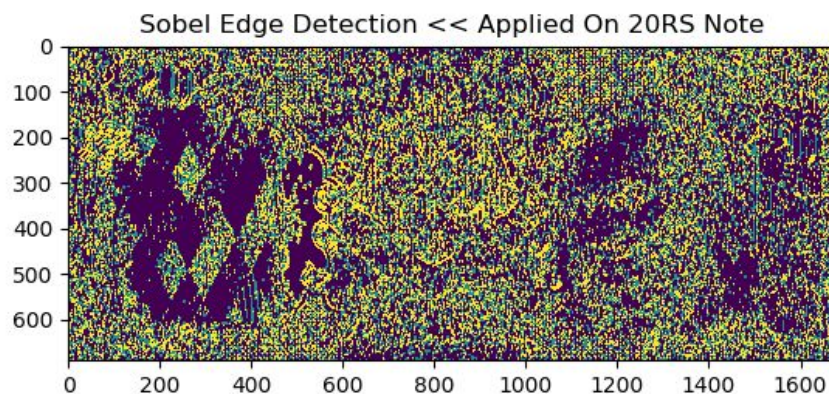
In our project, we have tried to solve most of these problems and get an optimum method to recognize currency.

Preliminary Information

1. **Edge Detection Techniques:** Edge detection is a type of image segmentation technique where edges are detected in the image. Edges are introduced as a set of connected points lie on the boundary between the two regions. The edges represent object boundaries and therefore can be used in image segmentation to subdivide an image into its basic regions or objects.

1. **Sobel Edge Detection:**

The Sobel operator measures a 2-Dimensional spatial gradient on an image and gives more attention to regions of high spatial gradient corresponding to edges. It is used for finding gradient magnitude at each point in a grayscale image. The Sobel operator is based on convolving the image with a small, separable, and integer-valued filter in the horizontal and vertical directions and is therefore relatively inexpensive in terms of computations.

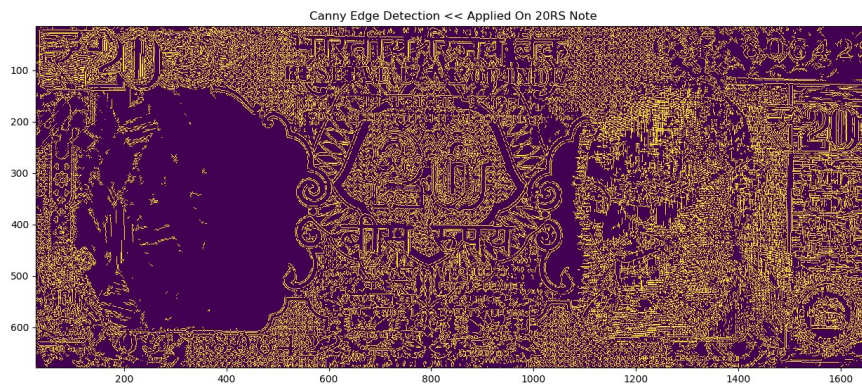


2. **Canny Edge Detection:**

The Canny edge detection algorithm was proposed to enhance the edge detection process. Three important criteria were taken into consideration for this purpose. The first and most important criterion was to detect all the important edges in the source image. This means the goal was to lower the error rate. The second

criterion was that the edge points to be detected as close as possible to the true edge also called localization. A third criterion was not to have more than one response to a single edge. The first two were not significant enough to remove the possibility of more than one response to an edge due to which the third one was implemented.

The Canny edge detector was thus implemented on these criteria. It first smooths the image to eliminate noise. Then the image gradients are calculated to point out those regions where the gradient difference is maximum, which have high spatial differences. Finally, it then tracks along these regions and discards any pixel that weakly defines an edge (non-maxima suppression) in order to make the edges thinner.



2. Convolutional Neural Network:

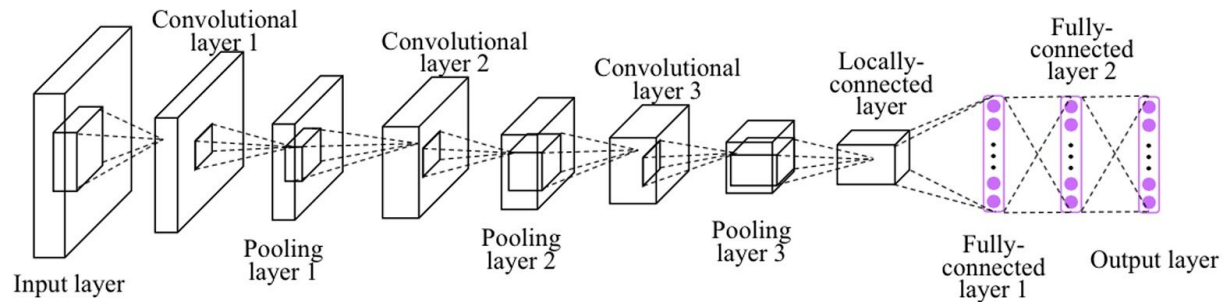
The convolutional neural network (CNN) is a class of neural networks of deep learning. CNN is a major innovation in image recognition. They are most often used to analyze visual images and often work behind the scenes on the classification of images. We find them at the heart of everything from tagging Facebook photos to autonomous cars.

A convolution retrieves blocks from the input resource map and applies filters to them to compute new resources, producing a map or converted resources (whose size and depth may be different from the input resource map).

The convolutions are defined by two parameters:

1. Size of the extracted blocks (usually 3x3 or 5x5 pixels).
2. The depth of the output resource map, which is the number of filters applied.

During the training, CNN "learns" the optimal values of the filter matrices to extract important resources (textures, borders, shapes) from the input resource map. As the number of filters (output resource mapping depth) applied to the input increases, the number of resources that can be retrieved by CNN also increases.



Problem Statement

To create an application for efficient and correct recognition of Bank Notes.

This project would be helpful in numerous fields to be its banking system or helping the blinds to detect which Bank Note is presented to him/her.

However, currency recognition systems that are based on image analysis entirely are not sufficient. Most of the present systems only recognize Banknotes which are not wrinkled. Due to this, they are not very effective to be used in real life.

Our system is based on image processing and makes the process automatic and robust.

Objectives

The objective of this Intelligent Currency Recognition System is to analyze and detect a banknote fed to it as input and generate favorable output in an efficient manner by the use of Image Processing and Machine learning techniques.

1. To process and identify banknotes as inputted by the user in less time.
2. To propose a cost-effective solution to the problem of Currency recognition.
3. To efficient recognize banknotes with wear and tear with utmost accuracy.
4. To replace the outdated method of currency recognition with a more efficient and effective system.

Literature Survey

A large number of researchers have made several contributions toward developing techniques for currency recognition. The different properties between coins and bills make researchers deal with the recognition task differently for each one of them.

It has been previously proposed an image processing technique to extract paper currency denomination. The extracted Region of Interest (ROI) is used with pattern recognition and neural network matching techniques. In this method, they captured the images by the simple flat scanner with a fixed size and then some filters are applied to extract the denomination value of the banknote.

1. *Authors: Iyad Abu and Doush Sahar*

Currency recognition using a smartphone: Comparison between color SIFT and grayscale SIFT algorithms: Journal of King Saud University – Computer and Information Sciences Volume 29, Issue 4, Pages 484-492, October 2017

Currency recognition in an uncontrolled environment (i.e., using a smartphone) is not an easy task because of the multiple variable conditions that could affect the quality of the image. The experimental results have shown the effectiveness of the SIFT algorithm in general for Jordanian banknote recognition, although our algorithm is tested in a more challenging dataset with the images taken in different conditions. The system depends on the appearance of the object at specific interest points. The results show that the recognition accuracy for coin currencies is less than recognition accuracy for paper currencies. This happened because of the illumination condition that affects the coin's image.

Critical Reviews:

The paper provided good results in the case of paper banknotes except for some cases such as:

- I. Too wrinkled: it was difficult to match the exact descriptors (some key-points did not appear or changed).
- II. Folded several times: it was difficult to match the exact descriptors (some key-points do not appear or changed).
- III. Take image from a close distance: crop large portion of the image which means it was difficult to match the exact descriptors (a large number of key-points do not appear).
- IV. Take image from too far distance: crop large portion of the background which means it was difficult to match the exact descriptors (large numbers of redundant key-points appear).

The conclusion from the paper was that currency recognition in an uncontrolled environment is not an easy task because of the multiple variable conditions that could affect the quality of the image. The experimental results had shown the effectiveness of SIFT The algorithm in general for Jordanian banknote recognition, although the algorithm is tested in a more challenging dataset with the images taken in different conditions.

It was observed from the results that the number of detected features in the color SIFT is larger than that in the gray SIFT. The evaluation results show the high performance of color SIFT when compared with gray SIFT descriptors in terms of processing time and accuracy rate.

2. **Authors: B.Sai Prasanthi, D. Rajesh Setty**

Indian Paper Currency Authentication System using Image processing: International Journal of Scientific Research Engineering & Technology (IJSRET), ISSN 2278 – 0882 Volume 4, Issue 9, September 2015

The features are extracted using edge-based segmentation by Sobel operator and work well in the whole process with less computation time. The complete methodology works for Indian denomination 20,50,100, 500 and 1000. The method is very simple and easy to implement. If the hardware part of image acquisition is designed then it surely helps us to minimize the problem of counterfeiting currency. This technique is used to extract six characteristics of paper currency including identification mark, security thread, floral design, numeral watermark, watermark, micro-lettering in security thread. The system may extract the hidden features i.e. the latent image of the paper currency. The proposed work is an effort to suggest an approach for the characteristic extraction of Indian paper currency. The detailed approach is suggested from the beginning of image acquisition to converting it to grayscale image and up to characteristic features extraction.

Critical Reviews:

The proposed work was an effort to suggest an approach for the characteristic extraction of Indian paper currency. The detailed approach is suggested from the beginning of image acquisition to converting it to grayscale image and up to characteristic features extraction. The decision making is done within 0.5 seconds. The system designed is a low-cost system. The system is able to extract the features even the note has scribbles on it. The system can extract features even the test image sizes are different when compared to the reference image.

3. **Authors: S.K. Katiyar and P.V. Arun**

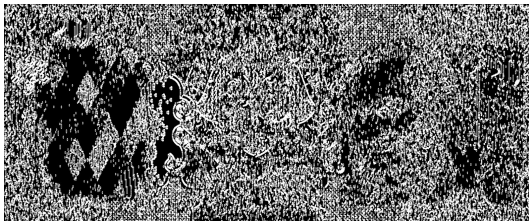
Comparative analysis of common edge detection techniques in the context of object extraction, Department Of Civil Engineering MA National Institute of Technology, India IEEE TGRS Vol.50 no.11b

The major disadvantage of the Sobel algorithm is that with the increase in noise the gradient magnitude of the edges also degrades which produces inaccurate results. Hence, was unable to detect the appropriate edges. The Canny edge detection, on the other hand, was accurate enough to produce the required results. The thresholding method provides good edge detection in Canny.

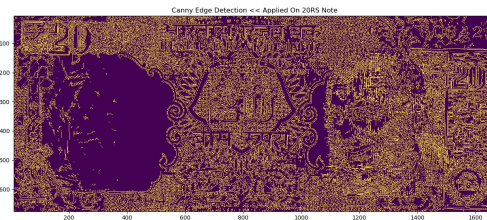
The difference between Canny and Sobel becomes clear through figure which shows the original image as well as the output image as produced by Canny and Sobel. The output of the Sobel operator is a blurred image with edges being overlapped. On the other hand, the Canny operator gives a clear difference in edges that come under the texture.



(Original Image)



(Sobel Edge Detection)



(Canny Edge Detection)

Critical reviews:

The investigations of present research work have led to the following conclusions:

- The canny method outperforms all the other methods even though its computational complexity is higher. Canny can be used for the extraction of even objects with feeble edges.
- The Sobel also detects the various features and is computationally more efficient as Canny but with more false edges. Sobel is optimum for objects with Strong edges as lakes, Stadium, etc.
- The other algorithms as Robert and Prewitt also detect the various features and stadiums but fail in case of smaller features and the range of usable thresholds is very low.
- For any method of edge detection, the computational complexity increases with the increase in spatial resolution.

The issues faced during the experiments were that the ground truth verification confirmed that the edge detection is affected by shadows, salt and pepper noise which deflated the expected results to a great extent.

4. **Authors: Wei Hu, Yangyu Huang, Li Wei, Fan Zhang, and Hengchao Li**
Deep Convolutional Neural Networks for Hyperspectral Image Classification
Journal of Sensors, Volume 2015, Article ID 258619, 12 pages

In this paper, they proposed a novel CNN-based method for HSI classification, inspired by the observation that HSI classification can be implemented via human vision. Compared with the SVM-based classifier and conventional DNN-based classifier, the proposed method could achieve higher accuracy using all the experimental data sets, even with a small number of training samples.

Their work is an exploration of using CNNs for HSI classification and has excellent performance. The architecture of their proposed CNN classifier only contains one convolutional layer and one fully connected layer, due to the small number of training samples.

Critical reviews:

The work done in this paper was an exploration of using CNNs for Hyperspectral image classification and had excellent performance. The architecture of the proposed CNN classifier only contains one convolutional layer and one fully connected layer, due to the small number of training samples.

It proposed a novel CNN-based method for Hyperspectral image classification, inspired by the observation that HSI classification can be implemented via human vision. The conclusion of the proposed method was that it could achieve higher accuracy using all the experimental data sets, even with a small number of training samples.

The problems faced in the work done were:

- There was a problem of overfitting caused due to limited training samples
- There was a requirement of labeled samples significantly
- Computing performance could be improved

Proposed procedure

1. **Image Acquisition:** In image processing, it is defined as the action of retrieving an image from some source, usually a hardware-based source for processing. It is the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed.
2. **Image preprocessing:** Pre-processing is a common name for operations with images at the lowest level of abstraction - both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing.

2.1. Converting to GrayScale

Converting RGB image to Gray Scale image to reduce noise in the image and acquire better results.

2.2. Resizing the Image

2.3. Applying edge detection algorithms

Edge detection is a type of image segmentation technique where edges are detected in the image. Edges are introduced as a set of connected points lie on the boundary between the two regions. The edges represent object boundaries and therefore can be used in image segmentation to subdivide an image into its basic regions or objects.

3. Training and Testing

3.1. Convolution Neural Network

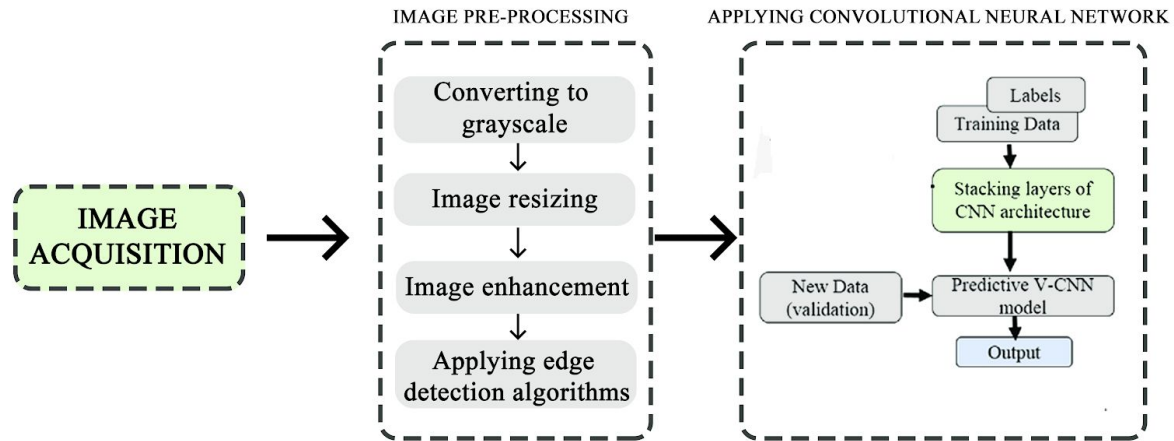
3.1.1. The Convolution layer: The image is entered into it. Imagine that the reading of the input matrix begins at the top left of the image. Next, the software selects a smaller matrix there, which is called a filter. Then the filter produces convolution, i.e. moves along the input image. The filter's task is to multiply its values by the original pixel values. All these multiplications are summed up. One number is obtained in the end. After passing the filter across all positions, a matrix is obtained, but smaller than an input matrix.

3.1.2. The Nonlinear layer: It is added after each convolution operation. It has an activation function, which brings nonlinear property. Without this property, a network would not be sufficiently intense and will not be able to model the response variable.

3.1.3. The Pooling layer: It works with the width and height of the image and performs a downsampling operation on them. As a result, the image volume is reduced. It is compressed to less detailed pictures.

3.1.4. Fully connected layer: After completion of a series of convolutional, nonlinear and pooling layers, it is necessary to attach this layer. This layer takes the output information from convolutional networks.

4. Interpreting the results



(Block diagram representing the working)

Experimental Analysis

1. Image Pre-processing

1.1. Results observed using Adaptive Threshold Vs Binary Threshold

1.1.1. Binary Threshold

It is a technique, which is the assignment of pixel values in relation to the threshold value provided. In thresholding, each pixel value is compared with the threshold value. If the pixel value is smaller than the threshold, it is set to 0, otherwise, it is set to a maximum value (generally 255). Thresholding is a very popular segmentation technique, used for separating an object considered as a foreground from its background. A threshold is a value that has two regions on its either side i.e. below the threshold or above the threshold.



1.1.2. Adaptive Threshold

In Simple Thresholding, the global value of threshold was used which remained constant throughout. So, a constant threshold value won't help in the case of variable lighting conditions in different areas. Adaptive thresholding is the method where the threshold value is calculated for smaller regions. This leads to different threshold values for different regions with respect to the change in lighting.



1.2. Contours Representing Regions of Interest

Contours can be explained simply as a curve joining all the continuous points (along the boundary), having the same color or intensity. The contours are a useful tool for shape analysis and object detection and recognition.



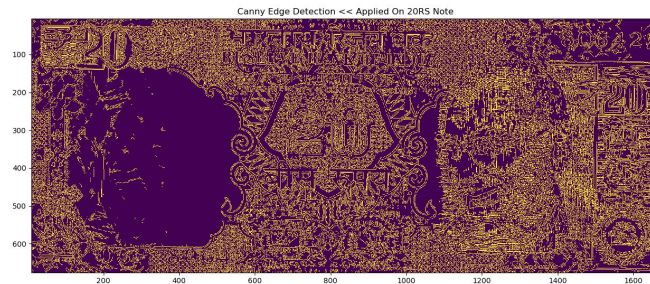
1.3. Canny Edge Detection

Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It has been widely applied in various computer vision systems. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations.

The Process of the Canny edge detection algorithm:

1. Apply Gaussian filter to smooth the image in order to remove the noise

2. Find the intensity gradients of the image
3. Apply non-maximum suppression to get rid of spurious response to edge detection
4. Apply double threshold to determine potential edges
5. Track edge by hysteresis: Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.



2. Training and Testing Neural Network Model

2.1. Supervised machine learning

is based on the idea that a user can select sample pixels in an image that are representative of specific classes and then direct the image processing software to use these training sites as references for the classification of all other pixels in the image. Training sites (also known as testing sets or input classes) are selected based on the knowledge of the user.

2.2. Convolutional Neural Network

Convolutional Neural Network has an input layer, an output layer, and hidden layers. The hidden layers usually consist of convolutional layers, ReLU layers, pooling layers, and fully connected layers.

- 2.2.1. Convolutional layers apply a convolution operation to the input. This passes the information on to the next layer.
- 2.2.2. Pooling combines the outputs of clusters of neurons into a single neuron in the next layer.
- 2.2.3. Fully connected layers connect every neuron in one layer to every neuron in the next layer.

CNN works by extracting features from images. This eliminates the need for manual feature extraction. The features are not trained! They're learned while the network trains on a set of images. This makes deep learning models extremely accurate for computer vision tasks. CNN's learn feature detection through tens or hundreds of hidden layers. Each layer increases the complexity of the learned features.

2.2.4. Activation Function

It is used to determine the output of neural network like yes or no. It maps the resulting values in between 0 to 1 or -1 to 1 etc. (depending upon the function).

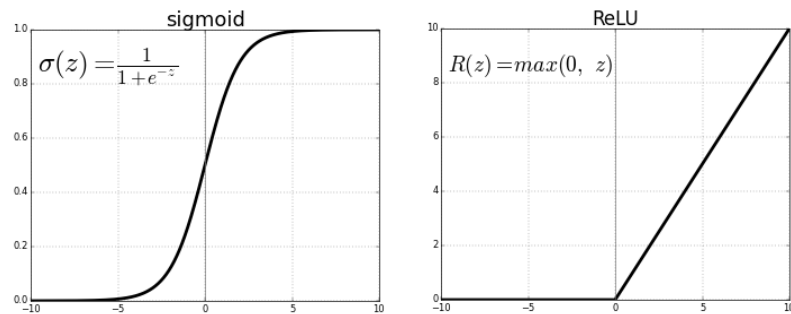
2.2.4.1. ReLU (Rectified Linear Unit) Activation Function

The ReLU is the most used activation function in the world right now. Since it is used in almost all the convolutional neural networks or deep learning.

As you can see, the ReLU is half rectified (from bottom). $f(z)$ is zero when z is less than zero and $f(z)$ is equal to z when z is above or equal to zero.

Range: [0 to infinity)

The function and its derivative both are monotonic.



2.2.5. Pooling

Pooling progressively reduces the size of the input representation. It makes it possible to detect objects in an image no matter where they're located. Pooling helps to reduce the number of required parameters and the amount of computation required. It also helps control overfitting.

2.2.6. Flattening

You flatten the pooled feature map into a sequential column of numbers (a long vector). This allows that information to become the input layer of an artificial neural network for further processing.

2.2.7. Dropout

A dropout is an approach to regularization in neural networks which helps to reduce interdependent learning amongst the neurons. It prevents overfitting of data.

2.2.8. Effect of batch size

Higher batch sizes lead to lower asymptotic test accuracy. Using too large a batch size can have a negative effect on the accuracy of your network during training since it reduces the stochasticity of the gradient descent.


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epoch 1/20
16/646 [.....] - ETA: 2:22 - loss: 1.3778 - accuracy: 0.332/646 [.....] - ETA: 1:34 - loss: 5.3607 - accuracy: 0.24
16/646 [.....] - ETA: 1:17 - loss: 4.6150 - accuracy: 0.264/646 [.....] - ETA: 1:07 - loss: 3.8302 - accuracy: 0.280/
16/646 [==>.....] - ETA: 1:00 - loss: 3.3655 - accuracy: 0.296/646 [==>.....] - ETA: 56s - loss: 3.0475 - accuracy: 0.27112/64
16/646 [=====] - 55s 85ms/step - loss: 1.6319 - accuracy: 0.2740 - val_loss: 1.3880 - val_accuracy: 0.2469
epoch 2/20
16/646 [=====] - 53s 82ms/step - loss: 1.3702 - accuracy: 0.3034 - val_loss: 1.3804 - val_accuracy: 0.2901
epoch 3/20
16/646 [=====] - 52s 81ms/step - loss: 1.3208 - accuracy: 0.3529 - val_loss: 1.3609 - val_accuracy: 0.3210
epoch 4/20
16/646 [=====] - 52s 81ms/step - loss: 1.2015 - accuracy: 0.4752 - val_loss: 1.2046 - val_accuracy: 0.4568
epoch 5/20
16/646 [=====] - 52s 81ms/step - loss: 1.0680 - accuracy: 0.5387 - val_loss: 1.2576 - val_accuracy: 0.4815
epoch 6/20
16/646 [=====] - 53s 82ms/step - loss: 0.9664 - accuracy: 0.6068 - val_loss: 1.1105 - val_accuracy: 0.5679
epoch 7/20
16/646 [=====] - 53s 83ms/step - loss: 0.8671 - accuracy: 0.6502 - val_loss: 1.1207 - val_accuracy: 0.5370
epoch 8/20
16/646 [=====] - 53s 83ms/step - loss: 0.7878 - accuracy: 0.6708 - val_loss: 1.1961 - val_accuracy: 0.4630
epoch 9/20
16/646 [=====] - 55s 85ms/step - loss: 0.6473 - accuracy: 0.7337 - val_loss: 1.1466 - val_accuracy: 0.5556
epoch 10/20
16/646 [=====] - 60s 93ms/step - loss: 0.6028 - accuracy: 0.7755 - val_loss: 1.2700 - val_accuracy: 0.5185
epoch 11/20
16/646 [=====] - 46s 71ms/step - loss: 0.5769 - accuracy: 0.7724 - val_loss: 1.2119 - val_accuracy: 0.5802
epoch 12/20
16/646 [=====] - 44s 68ms/step - loss: 0.4739 - accuracy: 0.8173 - val_loss: 1.4156 - val_accuracy: 0.5617
epoch 13/20
16/646 [=====] - 45s 70ms/step - loss: 0.4453 - accuracy: 0.8406 - val_loss: 1.4503 - val_accuracy: 0.5556
epoch 14/20
16/646 [=====] - 45s 70ms/step - loss: 0.3836 - accuracy: 0.8529 - val_loss: 1.6119 - val_accuracy: 0.5556
epoch 15/20
16/646 [=====] - 45s 70ms/step - loss: 0.3592 - accuracy: 0.8591 - val_loss: 1.6712 - val_accuracy: 0.5123
epoch 16/20
16/646 [=====] - 46s 72ms/step - loss: 0.3237 - accuracy: 0.8731 - val_loss: 1.6941 - val_accuracy: 0.5370
epoch 17/20
16/646 [=====] - 45s 69ms/step - loss: 0.3023 - accuracy: 0.8078 - val_loss: 2.0359 - val_accuracy: 0.5370
epoch 18/20
16/646 [=====] - 45s 69ms/step - loss: 0.2413 - accuracy: 0.8211 - val_loss: 1.8137 - val_accuracy: 0.8617
epoch 19/20

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(Batch size : 400 Validation accuracy: ~80%)

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Train on 697 samples, validate on 175 samples
epoch 1/20
2019-11-26 23:32:02.066120: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 75497472 exceeds 10% of system memory.
2019-11-26 23:32:02.227451: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 73932800 exceeds 10% of system memory.
2019-11-26 23:32:03.163102: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 73932800 exceeds 10% of system memory.
2019-11-26 23:32:03.352891: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 75497472 exceeds 10% of system memory.
16/697 [.....] - ETA: 2:45 - loss: 0.7263 - accuracy: 0.37502019-11-26 23:32:04.088415: W tensorflow/core/framework/cpu_allocator_impl.cc:81] Allocation of 75497472 exceeds 10% of system memory.
16/697 [=====] - 87s 125ms/step - loss: 0.7389 - accuracy: 0.4921 - val_loss: 0.6971 - val_accuracy: 0.4457
epoch 2/20
16/697 [=====] - 84s 121ms/step - loss: 0.6756 - accuracy: 0.5409 - val_loss: 0.5932 - val_accuracy: 0.7143
epoch 3/20
16/697 [=====] - 82s 118ms/step - loss: 0.5786 - accuracy: 0.7174 - val_loss: 0.5224 - val_accuracy: 0.7086
epoch 4/20
16/697 [=====] - 82s 118ms/step - loss: 0.4403 - accuracy: 0.8192 - val_loss: 0.4607 - val_accuracy: 0.7429
epoch 5/20
16/697 [=====] - 82s 117ms/step - loss: 0.3764 - accuracy: 0.8364 - val_loss: 0.2420 - val_accuracy: 0.8914
epoch 6/20
16/697 [=====] - 81s 117ms/step - loss: 0.3095 - accuracy: 0.8852 - val_loss: 0.2450 - val_accuracy: 0.8914
epoch 7/20
16/697 [=====] - 553s 794ms/step - loss: 0.3526 - accuracy: 0.8737 - val_loss: 0.2673 - val_accuracy: 0.8857
epoch 8/20
16/697 [=====] - 110s 2s/step - loss: 0.2635 - accuracy: 0.8810 - val_loss: 0.2357 - val_accuracy: 0.8971
epoch 9/20
16/697 [=====] - 85s 121ms/step - loss: 0.2339 - accuracy: 0.9024 - val_loss: 0.2161 - val_accuracy: 0.8971
epoch 10/20
16/697 [=====] - 85s 122ms/step - loss: 0.1848 - accuracy: 0.9283 - val_loss: 0.2078 - val_accuracy: 0.9429
epoch 11/20
16/697 [=====] - 84s 121ms/step - loss: 0.2004 - accuracy: 0.8694 - val_loss: 0.1868 - val_accuracy: 0.9200
epoch 12/20
16/697 [=====] - 85s 122ms/step - loss: 0.1708 - accuracy: 0.9283 - val_loss: 0.1782 - val_accuracy: 0.9486
epoch 13/20
16/697 [=====] - 84s 121ms/step - loss: 0.1207 - accuracy: 0.9541 - val_loss: 0.1767 - val_accuracy: 0.9657
epoch 14/20
16/697 [=====] - 84s 121ms/step - loss: 0.2082 - accuracy: 0.9197 - val_loss: 0.2599 - val_accuracy: 0.9029
epoch 15/20
16/697 [=====] - 85s 122ms/step - loss: 0.1462 - accuracy: 0.9455 - val_loss: 0.1647 - val_accuracy: 0.9486
epoch 16/20
16/697 [=====] - 81s 116ms/step - loss: 0.1299 - accuracy: 0.9512 - val_loss: 0.1954 - val_accuracy: 0.9371
epoch 17/20
16/697 [=====] - 81s 117ms/step - loss: 0.1242 - accuracy: 0.9555 - val_loss: 0.1401 - val_accuracy: 0.9771
epoch 18/20
16/697 [=====] - 81s 116ms/step - loss: 0.1078 - accuracy: 0.9856 - val_loss: 0.1539 - val_accuracy: 0.9714
epoch 19/20
16/697 [=====] - 168s 241ms/step - loss: 0.1388 - accuracy: 0.9555 - val_loss: 0.1345 - val_accuracy: 0.9429
epoch 20/20
16/697 [=====] - 91s 111ms/step - loss: 0.1054 - accuracy: 0.9856 - val_loss: 0.1111 - val_accuracy: 0.9541

```

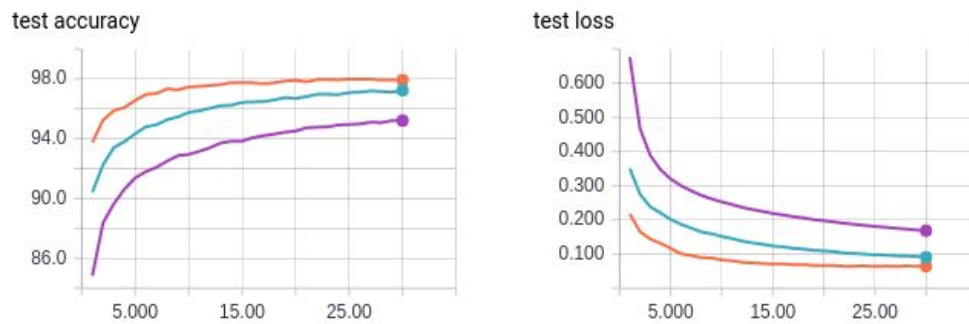
(Batch size : 100 Validation accuracy: ~95%)

```

Train on 697 samples, validate on 175 samples
Epoch 1/20
697/697 [=====] - 119s 170ms/step - loss: 0.7110 - accuracy: 0.5308 - val_loss: 0.6897 - val_accuracy: 0.4743
Epoch 2/20
697/697 [=====] - 114s 164ms/step - loss: 0.6457 - accuracy: 0.6399 - val_loss: 0.5480 - val_accuracy: 0.7657
Epoch 3/20
697/697 [=====] - 115s 165ms/step - loss: 0.5228 - accuracy: 0.7331 - val_loss: 0.3842 - val_accuracy: 0.8171
Epoch 4/20
697/697 [=====] - 116s 167ms/step - loss: 0.4337 - accuracy: 0.8192 - val_loss: 0.4359 - val_accuracy: 0.8229
Epoch 5/20
697/697 [=====] - 115s 165ms/step - loss: 0.3738 - accuracy: 0.8494 - val_loss: 0.3105 - val_accuracy: 0.8629
Epoch 6/20
697/697 [=====] - 103s 148ms/step - loss: 0.2869 - accuracy: 0.8867 - val_loss: 0.2049 - val_accuracy: 0.9029
Epoch 7/20
697/697 [=====] - 85s 122ms/step - loss: 0.2847 - accuracy: 0.8752 - val_loss: 0.3042 - val_accuracy: 0.8571
Epoch 8/20
697/697 [=====] - 85s 122ms/step - loss: 0.2518 - accuracy: 0.9024 - val_loss: 0.1630 - val_accuracy: 0.9429
Epoch 9/20
697/697 [=====] - 88s 126ms/step - loss: 0.2326 - accuracy: 0.9182 - val_loss: 0.1547 - val_accuracy: 0.9429
Epoch 10/20
697/697 [=====] - 86s 124ms/step - loss: 0.1831 - accuracy: 0.9340 - val_loss: 0.1117 - val_accuracy: 0.9600
Epoch 11/20
697/697 [=====] - 84s 121ms/step - loss: 0.1448 - accuracy: 0.9512 - val_loss: 0.0798 - val_accuracy: 0.9829
Epoch 12/20
697/697 [=====] - 84s 121ms/step - loss: 0.1187 - accuracy: 0.9512 - val_loss: 0.1252 - val_accuracy: 0.9829
Epoch 13/20
697/697 [=====] - 85s 122ms/step - loss: 0.2062 - accuracy: 0.9254 - val_loss: 0.1012 - val_accuracy: 0.9543
Epoch 14/20
697/697 [=====] - 84s 121ms/step - loss: 0.1344 - accuracy: 0.9512 - val_loss: 0.2081 - val_accuracy: 0.9029
Epoch 15/20
697/697 [=====] - 84s 120ms/step - loss: 0.1230 - accuracy: 0.9584 - val_loss: 0.0907 - val_accuracy: 0.9829
Epoch 16/20
697/697 [=====] - 84s 120ms/step - loss: 0.1262 - accuracy: 0.9498 - val_loss: 0.0936 - val_accuracy: 0.9543
Epoch 17/20
697/697 [=====] - 81s 116ms/step - loss: 0.1274 - accuracy: 0.9613 - val_loss: 0.0511 - val_accuracy: 0.9886
Epoch 18/20
697/697 [=====] - 81s 116ms/step - loss: 0.0690 - accuracy: 0.9799 - val_loss: 0.0692 - val_accuracy: 0.9829
Epoch 19/20
697/697 [=====] - 84s 120ms/step - loss: 0.0379 - accuracy: 0.9900 - val_loss: 0.0363 - val_accuracy: 0.9886
Epoch 20/20
697/697 [=====] - 84s 121ms/step - loss: 0.0495 - accuracy: 0.9813 - val_loss: 0.0630 - val_accuracy: 0.9829

```

(Batch size : 16 Validation accuracy: ~98%)



Orange curves: batch size 16
Blue curves: batch size 100
Purple curves: batch size 400

Layer (type)	Output Shape	Param #
batch_normalization_1 (Batch Normalization)	(None, 192, 192, 3)	12
conv2d_1 (Conv2D)	(None, 192, 192, 32)	896
conv2d_2 (Conv2D)	(None, 190, 190, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 63, 63, 32)	0
dropout_1 (Dropout)	(None, 63, 63, 32)	0
conv2d_3 (Conv2D)	(None, 63, 63, 64)	18496
conv2d_4 (Conv2D)	(None, 61, 61, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 20, 20, 64)	0
dropout_2 (Dropout)	(None, 20, 20, 64)	0
conv2d_5 (Conv2D)	(None, 20, 20, 128)	73856
conv2d_6 (Conv2D)	(None, 18, 18, 128)	147584
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 128)	0
dropout_3 (Dropout)	(None, 6, 6, 128)	0
flatten_1 (Flatten)	(None, 4608)	0
dropout_4 (Dropout)	(None, 4608)	0
dense_1 (Dense)	(None, 2)	9218
Total params: 296,238		
Trainable params: 296,232		
Non-trainable params: 6		

(Visualizing the Model)

Results

```
Using TensorFlow backend.  
<<<<<<< Enter the File You Want to Open >>>>>>>  
  
<<<<< You have chosen file path as :  
C:/Users/HP/Desktop/Minor Project/data/ten/7.jpg  
Loading file structure...  
  
Loading training images...  
  
The total number of images in data/ten/ = 413  
The total number of images in data/twenty/ = 413  
The total number of images in data = 826  
(826, 2)
```

(Importing Test Image and Training Data)

```
Our Models accuracy is :  
accuracy: 97.59%  
  
<<<<<<< Here is the Output Class for your Input Image >>>>>>>  
  
Your predicted class is :    [0]  
Detected denomination: Rs.  Ten  
  
<<<<< Thank You for using our Currency Recognition System >>>>>  
<<<<< Created By : Mridul Goyal , Sankalp Chelani , Jayant Rana >>>>>
```

(Final Result validated on ten rupee note)

Tools and Environment

1. Python IDE
2. Sublime Text Editors

Python Libraries used

1. Keras
2. TensorFlow
3. Numpy
4. Cv2
5. Matplotlib

Conclusion

Paper Currency Recognition is an important application of Pattern Recognition. Many studies were made to recognize paper currencies using Image Processing schemes. The method is quite reasonable in terms of accuracy. However, there is room to improve the processing time. The proposed algorithm is fully automatic and requires no human intervention. This work is in progress as a subsequent work together with the issue of considering currencies with noise in it.

The dataset that we picked up is a standard Kaggle dataset that had around 2123 images. The dataset was initially skewed and we had to filter it. finally, a uniform dataset of 1732 images was finally used for training. The dataset that is used has various types of images which include blurred notes, folded notes, worn and torn notes, etc. We have tried to solve the problem of illumination in our project. The dataset also had images with irregular orientations.

The dataset is then classified into four classes with each class labeled as Ten, Twenty, Fifty and Hundred rupees banknote. In our project, we have used a **Convolutional Neural Network** which is a trainable and highly efficient neural network. It is majorly used for image classification.

CNN image classifications take an image as input, then preprocessing is applied to it and classifies it under defined categories.

Despite all the issues we encountered the final accuracy that we achieved was around 89%. Adding to this, the project is also optimized for low-end PCs as most of the existing systems required a high-end GPU which makes this project cost-friendly as well as efficient.

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