# An Empirical Approach for Currency Identification*

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*Abstract* Currency identification is the application of systematic methods to determine authenticity of questioned currency. However, identification analysis is a difficult task requiring specially trained examiners, the most important challenge is automating the analysis process reducing human labor and time. In this study, an empirical approach for automated currency identification is formulated and a prototype is developed. A two parts feature vector is defined comprised of color features and texture features. Finally the banknote in question is classified by a Feedforward Neural Network (FNN) and a measurement of the similarity between existing samples and suspect banknote is output.

*Keywords*: currency identification, neural network, empirical approach

## I. INTRODUCTION

Throughout history, currency issuers have faced one common threat, the threat of counterfeiting. Despite the introduction of electronic currency, banknotes remain in abundance. The amount of counterfeit currency in circulation at any moment threatens the confidence and usability in currency. Confidence influences the inherent value and stability of the currency. Banknotes hold higher value than coins making them more susceptible to counterfeiting, and a higher economical risk. Since the epoch of civilization, we have relied heavily on the ability to trade with one another [1]. The value held in currency influences the strength that societies have to trade with one another and survive.

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Banknotes have a wide array of security features, the design, composition of raw materials, combined with difficult to replicate printing methods such as intaglio and offset lithographic methods add inherent security. Composition of raw materials is unique to a series of currency, maintaining uniformity within the currency series to keep each unit as indistinguishable from the next as possible. Printing methods used are extremely difficult to replicate, offset lithographic printing precisely aligns the main design on the obverse and reverse. Immense pressure from two printing plates or rollers creates a characteristic 3D effect resulting from minute bumps and grooves, and is extremely difficult to replicate.

In 2010, the US Government announced a heavily redesigned $100 bill that featured portrait watermark, security thread, color-shifting 100, raised printing, gold 100, micro-printing, portrait and vignette, symbols of freedom, color, F.W. indicator, federal reserve indicator, serial numbers, etc., On April 2013, the Federal Reserve announced the new $100 bill shown in Figure 1. This new launched banknote motivated us to investigate the security features of paper currency as shown in Figure 1.


1.Portrait Watermark 2. Security Thread 3. Color Shifting 100 4. Raised Printing 5. Gold 100 6. Microprinting 7.3D Security Ribbon 8. Tricker Watermark 9. More Ink

Fig.1 New U.S. one hundred-dollar bill

Currency identification is the application of systematic methods to determine authenticity of questioned currency. Questioned currency is one which is suspected to have been produced fraudulently. To determine the authenticity of questioned currency, banknotes are inspected for specific characteristic features. Final decision on questioned currency is made by performing a side-by-side comparison between a known good template and the suspect note. If questioned currency meets certain minimum requirements, then it is authentic.

The technological advancements available to both currency manufacturers and counterfeiters have fuelled an on-going arms race, traditionally counterfeiters required impeccable artistic skill to manually produce copies. Today, reprographic equipment available to the public has produced a new type of criminal, the casual counterfeiter. Desktop publishing, even commercial grade reprographic equipment has allowed for a wider array of criminals to illegally produce passable banknote replicas.

In this paper, we take digital banknote identification into consideration, our contribution is an empirical approach to automation of currency identification, the method for verifying the level of authenticity of banknotes is formulated. A two parts feature vector is obtained, the first part of feature vector is comprised of gray-level histogram shape descriptors: central moment, mean, skew, variance, standard deviation and kurtosis. Second part of the feature vector comprised of banknote image texture, i.e. the entropy level and GLCM (gray-level co-occurrence matrix) features: contrast, correlation, energy and homogeneity. The feature vector is classified by a Feedforward Neural Network (FNN) because FNN takes all the common features of real banknotes into consideration, finally a side-by-side comparison is made accompanied by a similarity measurement. In FNN, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the FNN, the computational complexity is low [17]. To the best of our knowledge, this is the first time the FNN classifier has been used with gray-level histogram and texture features to automate the process of banknote analysis.

The paper is organized as follows: section II describes observed literature related to currency identification. Our contribution of an empirical approach for currency identification is introduced in section III. Section IV describes the results and comparisons, where the performance of this technique is shown. Finally, section V concludes the paper.

## II. RELATED WORK

Supporting literature exists focusing on banknote recognition software intended for a variety of applications such as assisting the visually impaired [2], banknote sorting and Automatic Teller Machine (ATM) software [3], and banknote fatigue detection [4]. A trend observed is that an image is acquired, it is pre-processed then classified and finally the result is output. Various methods are employed at each stage, the correct combination to use is subjective to the currency in question. The same workflow is employed by our system to classify the note.

Image acquisition and image pre-processing techniques are employed, either the entire note or distinct Regions of Interest (ROI) are acquired and compared independently. Banknotes are authenticated on the basis of various security marks as shown in Fig 2 and these marks are explained in following paragraphs.

The serial number uniquely identifies an individual banknote, in some cases the location of manufacture can be pinpointed [1]. Therefore this adds a layer of security and can be computed [5]. If a note is found to have an incorrect or duplicate serial number, it is not authentic.

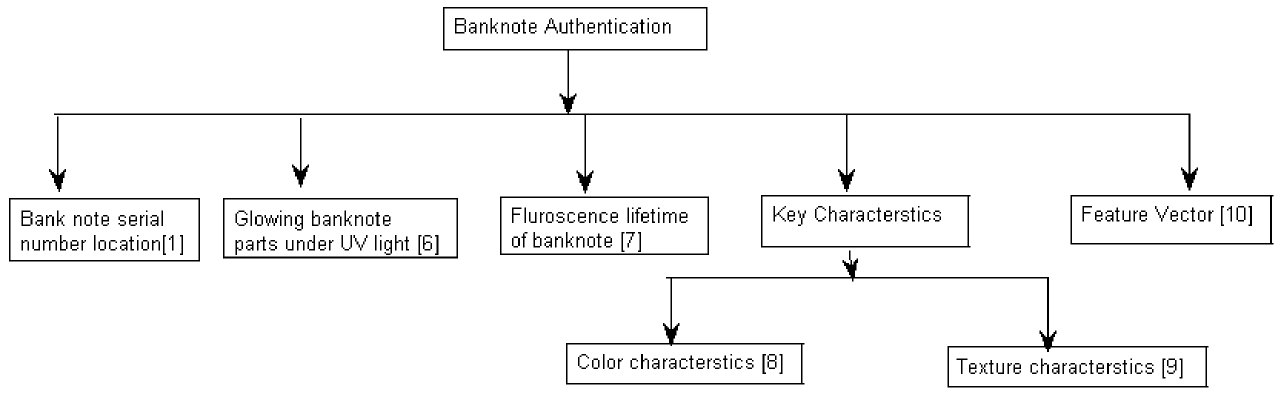


Fig. 2. Various marks for banknote authentication

Image acquisition techniques are explored, the aggregation of RGB color is with ultra-violet information [6]. Under ultraviolet light, a different visual appearance is observed, specific areas of the note glow displaying otherwise hidden information which is not seen by naked eyes, this places extra complexity on the casual counterfeiter.

The fluorescence lifetime is investigated [7], it is found using a two-photon laser excitation and time-correlated single photon counting (TCSPC) method, significant differences in the duration of fluorescence are observed when comparing genuine and counterfeit notes. This approach is an alternative to the image processing and classification model used by this study, yet due to the requirement for specialized equipment may not be a practical solution.

Image processing techniques are employed to extract key features, key characteristics are numerical measures computationally describing a banknote image. Two primary categories of key characteristics are used i.e. color and texture characteristics.  Key color characteristic includes color measurements described by the level of color by creating an intensity or gray-level histogram, shape descriptors. Texture describes the pattern of pixel color and their relationship with one another [8]. It is found that vector spaces composed of both texture and color features improve classification accuracy [9].

The feature vector acts as input into a classifier where it is essentially compared against known good values. In the literature, many classification techniques are employed on a wide array of currencies, the classification method chosen is subjective to the currency in question and characteristics extracted. Many variants of the classical Artificial Neural Network (ANN) are proposed, using the Back Propagation (BP) learning model with Genetic Algorithm (GA) improves in learning performance [10].

In order to determine banknote authenticity, a measurement is calculated upon comparisons of the suspect note and sample image. This measurement is used as the determining factor of similarity, the distance measurement is used specifically on ROIs [4] to determine the fatigue of banknotes. It is anticipated, synonymous to fatigue determination, discrepancies occurring during counterfeit production will provide dissimilarity measures which substantially deviate from known good templates.

Different from the existing work, in this paper our research scope is paper currency security, we present our work in currency feature selection and classifier selection. To the best of our knowledge, this is the first time the FNN classifier has been used to automate the process of comparing banknotes.

## III. OUR CONTRIBUTIONS

Our approach is to use image processing and classification techniques to identify banknote denomination. The proposed approach has three processes as shown in Figure 3, the first process is to extract features of color and texture; the second process is to classify banknote using a collected database. Last one is authentication, in which a similarity measurement is calculated for side-by-side comparisons.

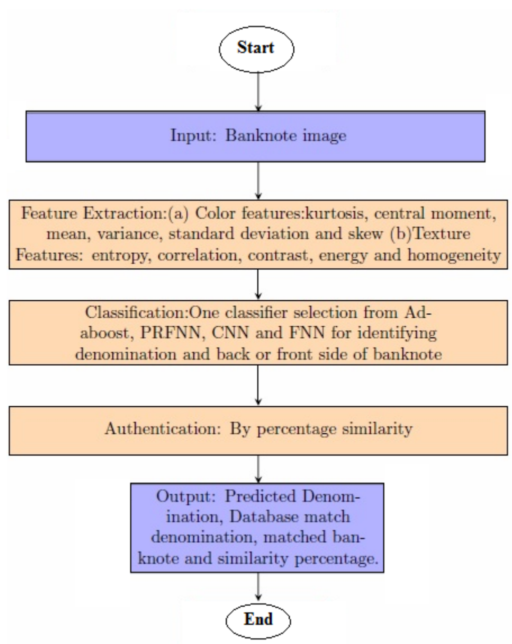

Fig. 3. Flow chart of proposed algorithm

All processes are explained in detail below:

*A. Feature Extraction*

Gray-levels are calculated to form an intensity image of 640×312 pixels, two sub-categories of features are extracted. A gray-level histogram is calculated with 256 bins describing the frequency of dark to light color. From the histogram, six shape descriptor metrics are obtained: kurtosis, central moment, mean, variance, standard deviation and skew.

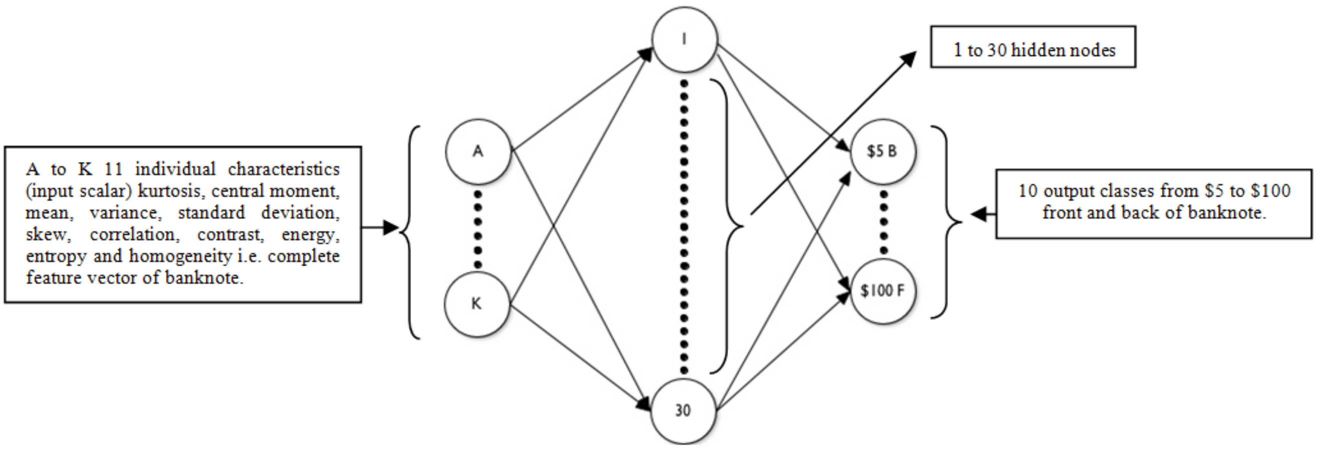


Fig. 4. The FNN structure for digital currency identification

Five texture features are extracted, the entropy level is calculated along with four features from the gray-level co-occurrence matrix (GLCM), namely correlation, contrast, energy and homogeneity. Together the color features and texture features are concatenated into a single feature vector which is input into a classifier.

The feature vector obtained in the feature extraction step is directly input as a scalar to a FNN classifier as shown in Figure 4. A to K represent the 11 individual characteristics (input scalar), 30 hidden nodes and 10 output classes from $5 to $100 front representing the possible classes.

*B. Classification*

The note is then classified into its respective denomination, back or front side. The FNN was trained using Bayesian regulation back propagation, Bayesian regulation back propagation can train any network where the weight, input, and transfer functions have derivative functions. Training stops when any of the following conditions occur: the maximum number of epochs is reached, the maximum time is reached, goal performance is reached or the performance gradient falls below a minimum gradient level [11]. Initial pilot tests were conducted, it was concluded AdaBoost [14], pattern recognition trained Feedforward Neural Network (PRFNN), Cascade forward Neural Network (CNN) and FNN were suitable candidates.

*C. Authentication*

Currency identification is the measurement of similarity or dissimilarity based on comparisons between suspect note and sample note. When a note in question does not meet the required threshold, it is not authentic. To analyze a note, the note must be compared against known good values. An initial database consisting of 167 sample banknote images was collected. This database is comprised of obverse and reverse sides of the banknote denominations. Once the denomination has been determined, the feature vector from the suspect note is then compared against a vector from the sample database using the inner product of the two vectors. Our algorithm of currency identification is shown in the algorithm (1).

**Algorithm 1**: Banknote classification & similarity measurement

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**Input**: Test image and currency database

**Output**: Identification of banknotes

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Procedure:

**Step1**: Normalization of the input image

Resize the input image to 640×312

Histogram equalization

**Step2**: Extract features from the normalized image;

Calculate histogram;

Calculate entropy;

Calculate the GLCM;

**Step3**: Classify the input image for identification;

**Step4**: Measure the similarities;

## IV. EXPERIMENTS

### A. *Experiments Settings*

The currency identification scheme shown in Figure 5 has been prototyped in the MATLAB environment running under the Apple Mac OSX Lion platform. A second experiment was performed, 11 FNN networks were trained each using the feature vector minus one characteristic. The intention was to determine the level of accuracy upon removing a particular characteristic, therefore, determining each characteristic's contributing effectiveness.

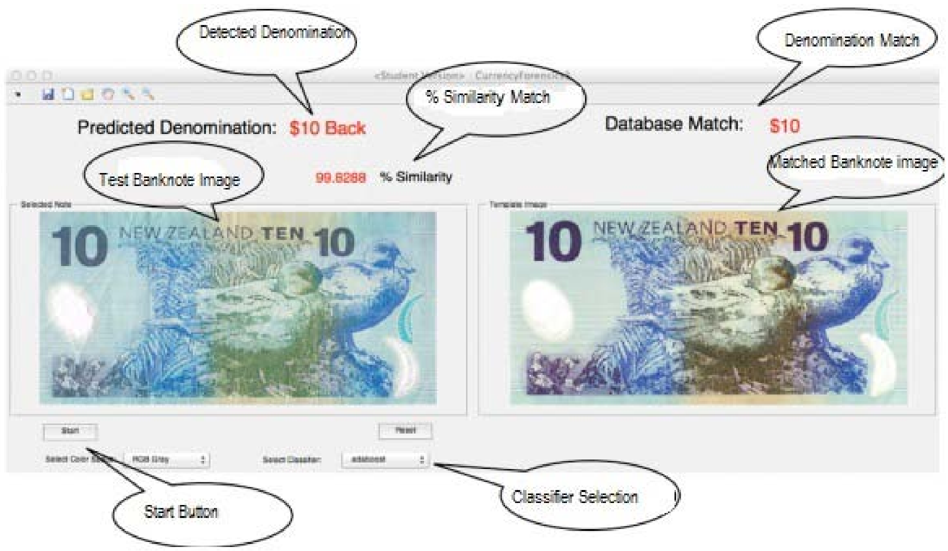


Fig. 5 Interface of the currency forensic prototype

During the initial training phase, a database was compiled consisting of 167 banknote images. Without loss of generality, we sacanned all banknotes at our hand and use them as our experimental samples. The database includes 19 $5 obverse, 19 $5 reverse, 18 $10 obverse, 17 $10 reverse, 19 $20 obverse, 18 $20 reverse, 16 $50 obverse, 16 $50 reverse, 14 $100 obverse and 14 $100 reverse. Notes of the lower denominations make up a higher proportion as these banknotes are both more abundant and frequently used, the variation in quality is higher in the lower denominations. Notes were obtained under varying conditions providing a mix of quality and lighting. An arbitrary database subset was compiled consisting of

10 notes from each subcategory, selected at random. The subcategories are used as the training set with a total of 100 sample notes for training, leaving the remaining 267 for testing.

### *B. Prototype*

As shown in Figure 5, a prototype of currency identification has been developed. The prototype allows the forensic investigator to perform side-by-side comparisons. Once the note has been classified the investigator is provided with a level of similarity. A CNN, PRFNN and FNN classifiers were trained using supervised learning by the Bayesian regulation back propagation training function and an AdaBoost classifier.

### *C. Results*

When classifying notes against the FNN classifier, we achieved a 98.6% accuracy rate on recall from outside of the training set shown in Table I. Compared to the Adaboost 53%, PRFN 95.7% and CNN 94.3%, it is concluded that when considering all variables of this study, the FNN classifier gives the highest accuracy. Notes within the training set match to the pre-selected template image vector within the range of 99.44% - 99.99% for the output similarity measure.

The candidate classification shortlisted from the literature were compared through direct comparison, the shortlisted candidates were selected through pilot tests and were the FNN, CNN, PRFNN, and Adaboost. It is found that FNN is the most suitable candidate for use in the digital currency forensic system when currency which uses color as a primary differentiating factor between denominations. It clearly shows that FNN is an ideal candidate classifier. Classifier analysis is shown in the Table II, III and IV with database training set, type of classifiers and results.

Table I. Feature analysis

| | | |
|---|---|---|
| Number of features | Color part has 6 histogram shape descriptors. | Texture part has 5 texture descriptors. |
| Features used | To describe the shape, the central moment, kurtosis, mean, standard deviation, skew and variance are used. | To describe the texture, entropy, contrast, correlation, energy and homogeneity from the GLCM are calculated. |
| Analysis | Variance is the least effective characteristic showing the lowest level of misclassifications when removed. Central moment, contrast, correlation, energy, entropy, homogeneity, kurtosis, mean, skew and standard deviation contribute substantially to the overall effectiveness as a high misclassification rate is observed when removed. | |

Table II. Classifier analysis

| | |
|---|---|
| Classifiers trained | PRFNN, FNN, CNN and an Ada Boost classifier. |
| Training set. | 167 sample banknote images, 10 samples from each side of each denomination were used. |
| Analysis | FNN shows optimal performance at 98.6% accuracy when classifying outside of the training set whereas AdaBoost achieves 53%, PRFNN 95.7% and CNN 94.3% respectively. |

Table III. Classifier comparisons: percentages of correct classification

| | Notes Classifiers | $5F | $5B | $10F | $10B | $20F | $20B | $50F | $50B | $100F | $100B | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Percentages of correct classification | **AdaBoost** | 88% | 88% | 100% | 0% | 66% | 87% | 0% | 0% | 0% | 0% | 53% |
| | **PRFN** | 100% | 88% | 87% | 100% | 100% | 100% | 83% | 100% | 100% | 100% | 95% |
| | **CNN** | 100% | 77% | 100% | 100% | 100% | 66% | 100% | 100% | 100% | 100% | 94% |
| | **FNN** | 88% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 100% | 98% |
| Note: F means Front side of banknote and B means Back side of banknote for example $5F means $5 front side | | | | | | | | | | | | |

Table IV. Classifier comparisons: percentages of incorrect classification

| | Feature removed Notes | Central Moment | Contrast | Correlation | Energy | Entropy | Homogeneity | Kurtosis | Mean | Skew | Std-Dev | Variance |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Percentages of incorrect classification | **$5B** | 66.67% | 66.67% | 55.56% | 55.56% | 77.78% | 66.27% | 66.67% | 66.67% | 77.78% | 66.67% | 0.00% |
| | **$5F** | 77.78% | 88.89% | 66.67% | 88.89% | 66.67% | 77.78% | 66.67% | 66.67% | 77.78% | 55.56% | 0.00% |
| | **$10B** | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 37.50% | 62.50% | 75.00% | 62.50% | 0.00% |
| | **$10F** | 100% | 87.5% | 100.00% | 87.50% | 62.50% | 75.00% | 62.50% | 100.00% | 75.00% | 87.50% | 0.00% |
| | **$20B** | 87.5% | 75.00% | 87.50% | 75.00% | 87.50% | 87.50% | 87.50% | 100.00% | 87.50% | 87.50% | 0.00% |
| | **$20F** | 88.89% | 88.89% | 66.67% | 77.87% | 66.67% | 77.78% | 66.67% | 77.78% | 77.78% | 77.78% | 0.00% |
| | **$50B** | 100.0% | 100.00% | 80.00% | 60.00% | 80.00% | 60.00% | 80.00% | 100.00% | 40.00% | 80.00% | 40.00% |
| | **$50F** | 88.67% | 83.33% | 83.33% | 66.67% | 83.33% | 66.67% | 66.67% | 50.00% | 83.33% | 83.33% | 0.00% |
| | **$100B** | 75.00% | 75.00% | 50.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 50.00% | 25.00% |
| | **$100F** | 100.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 75.00% | 100.00% | 0.00% |
| | **Total** | 82.66% | 81.43% | 74.29% | 74.29% | 74.29% | 74.29% | 67.14% | 77.14% | 75.71% | 74.29% | 4.29% |
| Note: F means Front side of banknote and B means Back side of banknote for example $5F means $5 front side | | | | | | | | | | | | |

## V. CONCLUSION

In this study, we take paper currency into consideration, an empirical approach for automated digital currency identification is formulated and a prototype is developed. A two parts feature vector is formulated consisting of color features and texture features. The note in question is classified against a FNN classifier because FNN takes all the common features of real banknotes into consideration and reach the ideal accuracy, finally measurement of the similarity between template vector and suspect note vector is output. Future research will include refining the characteristics chosen, the Gabor texture and SIFT features will be compared against those of the GLCM used in this study [12, 13,14,15,16].

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