
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN2321-2152
www.ijmece .com
Vol 12, Issue.2 May 2024

VISION BASED SYSTEM FOR BANKNOTE RECOGNITION USING DEEP LEARNING

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Abstract

Visually impaired people faced a problem in identifying and recognizing the different types of banknote due to some reasons. This problem draws researchers' attention to introduce an automated banknote recognition system that can be divided into a vision-based system and sensor-based system. The main aim of this study is to have deeper analysis on the effect of region and orientation on the performance of Machine Learning and Deep Learning respectively using Malaysian Ringgit banknotes (RM 1, RM 5, RM 10, RM 20, RM 50 and RM 100). In this project, two experiments conducted on two types of banknote image: different region and orientation captured by using handphone camera in a controlled environment. Feature extraction of the RGB values called RB, RG, and GB from banknote image with different region were used to the machine learning classification algorithms such as k-Nearest Neighbors (kNN) and Decision Tree Classifier (DTC), Support Vector Machine (SVM) and Bayesian Classifier (BC) for recognizing each class of banknote. Banknote image with different orientation was directly feed to AlexNet, a pre-trained model of Convolutional Neural Network (CNN), the most popular image processing structure of Deep Learning Neural Network. Ten-fold cross-validation was used to select the optimized kNN, DTC, SVM, and BC which was based on the smallest cross-validation loss. After that, the performance of kNN, DTC, SVM, BC and AlexNet model was presented in a confusion matrix. Both kNN and DTC achieved 99.7% accuracy but both SVM and BC perform better by succeeded to achieve 100% accuracy. It also can be concluded that AlexNet can only perform great in testing new data if only the data had previously been trained with similar orientation. Orientation does give effect to the performance of AlexNet model.

INTRODUCTION

Modern day monetary transactions involve massive flow of paper-based currency, in spite of considerable technological advancements in the field of plastic money and e-commerce. This raises the eminence of methods for automation during cash-handling operations in financial institutions such as banks, vending machines, automated teller machines (ATMs), etc. Such automation essentially involves the primary task of currency recognition to be fulfilled. In addition to the need of automation, banknote recognition may provide assistance to visually impaired people in terms of better decisions of denominations inscribed on notes.

In context of denomination identification from the images of banknotes, several methods have been proposed earlier. Work presented a method for US paper bill classification using SIFT (Scale Invariant Feature Transform) and k-means clustering for fast and memory-efficient implementation on smartphones. Lee et. al. proposed a novel approach of distinctive point extraction and classification using neural networks for recognition of Euro banknotes. Authors proposed a method using extraction of digitized characteristics of banknote images and training a neural network and implemented the same on a digital signal processor (DSP). Debnath et. al. presented a method using ensemble neural network, where each neural network is trained via negative correlation learning such that it learns a specific part of the input patterns.a comparative study of speeded up robust features (SURF) and fast retina key point descriptor (FREAK) for suitability and robustness in identification of denomination from banknote images. A low cost system for Malaysian banknotes identification system has been proposed, which uses unique color of banknote for recognition. Work an approach of classifying principal components of Histogram of Gradient features using an efficient error-correcting output code method on a multi-class support vector machine (SVM). Extraction of distinctive features such as RBI (Reserve Bank of India) seal, color band, etc, from Indian currency note image and evaluated the developed method on different denominations currency with a mix of new and old notes in varying illumination conditions. Costa et. al. implemented a method using organized pipeline involving preprocessing, extraction of various descriptors including SIFT, SURF, etc., and subsequent matching for identification of denominations on Euro banknotes. Authors in proposed the portrait in banknotes as one of the distinctive elements for identification of denominations and hence used the convolutional neural network to detect them in banknotes for prediction of corresponding denominations.

A specialized domain from machine learning called Deep Learning (DL) has recently emerged out to yield efficient techniques for tasks of classification in recent years. Deep learning architectures have the capability to figure out on their own the most discriminative features relevant to the problem. The growth of DL only recently may be attributed to availability of massive corpus of digital data, faster and capable hardware, especially GPUs (Graphics

Processing Units) and, provision of better algorithms like Rectified Linear Units (ReLU) by researchers. Deep convolutional neural networks (CNNs) have brought about breakthrough in a wide range of applications such as image classification and natural language processing. Deep CNNs reduce the need of hand-crafted features for the problem in hand through automatic learning of hierarchical features from the large datasets. The deep network-crafted features may even surpass the discriminatory level provided by conventional feature sets for a specific problem.

This paper presents a deep learning-based banknotes' denomination recognition framework which works on color banknote images of a minimal resolution. The framework utilizes the concept of transfer learning where a deep convolutional neural network already trained upon a huge dataset of natural images is re-utilized for the problem of classification of denomination from banknote images. The real images of banknotes taken under variable lighting conditions and different viewing perspectives are fed to a custom made neural network topped over the pre-trained convolutional base to learn the new classes associated with problem. The hence obtained classifier trained upon a modestly sized dataset, achieves considerably fair accuracy of 96.6 % on a held out testing subset. The method requires least preprocessing of images while feeding to the classifier and works well for recognition even in presence of background clutter.

LITERATURE SURVEY

focuses on the developing a system which can work sort of a bionic eyeglass that's mobile platform which integrates visual detection and recognition functions. Dataset images of banknotes were taken by mobile camera, relevant shapes are extracted from images using adaptive thresholding and morphological shape filters. In order to design a reliable and robust banknote recognition algorithm system had the goal to determine object or set of visual objects that are easy to detect and diverse enough to function as a basis of further recognition. The system is trained to use multiple features for classification of banknotes and subjects easily get to understand the way to use system confidently. Typical causes for errors were happened when executing the system like covering the region of interest with one or more fingers can cause problems in detection.

Along with the Identification of Banknotes it's necessary to detect the counterfeit banknotes as well , paper [2] proposes a system which will recognize not only counterfeit notes but also partially visible, folded, wrinkled or maybe worn by usage. This project uses Computer vision system for recognizing multiple banknotes with different view, scales and environment having variable light intensities. It used Computer Vision(OpenCV) for speeding up the process then by reducing noise and CLAHE for increasing contrast, Recognition process done by Scale Invariant Feature Transform(SIFT), sped up Robust Features (SURF), Features from Accelerated Segment Test(FAST), Oriented FAST and Rotated BRIEF (ORB), Binary Robust Invariant Scalable Key points (BRISK).This system achieved better contour estimation. Disadvantage of system is that for test images during which most of the banknotes regions were occluded, the local inliers ratio performed better. This happened due to local matching of patches avoids the removal of results of identification that have low inliers ratio.

The Paper [3] proposed a modular approach to review the model which will use feature detection and recognize Indian Currency notes. The main features of Indian currency are studied briefly in order that built systems are going to be advantageous for the visually impaired people to detect particular feature of particular note. For central numerals, a visible word vocabulary and training a classifier generated by binary Support Vector Machine (SVM) classifiers. The proposed system detects the emblem by training a cascade object detector in MATLAB and therefore the HOG descriptor used for recognizing the Ashoka Pillar emblem on currency where CIE LAB Color Space model has been worked for color analysis of the banknotes. The delta-E distance between training and testing of data to classify the currency and template matching for recognition of identification mark,both gives end in 100% accuracy. However, image histogram for color and Markov chain for texture analysis yielding a rather lower accuracy as various banknotes could have similar colors and textures, thus reducing the efficiency.

The lifetime of a banknote can't be predefined but it can have physical damages like dirtiness caused by sweaty touch of the many people, oil and mud carrying bacteria may accumulate on them. So as to prevent these damaged notes getting older and to stop them from circulating, the dataset for brand spanking new and old banknotes get studied in paper [4]. Image acquisition and pre-processing, feature selection and extraction, and classification model construction were the stages of project. Modified SMOTE Algorithm is employed to reinforce old banknotes. Banknote classification model is made using traditional Support Vector Machine (SVM) algorithm. By analyzing the study, the most advantages are that approach can improve the popularity accuracy ratio by about 20% and solve recycling problem up to some extent. But main problem is both absolutely the and therefore the relative quantities of samples of old banknote are far but those of latest banknote so dataset is usually imbalanced.

EXISTING SYSTEM

Several scholars have proposed numerous vision-based banknote recognition systems. The work implement a computer vision system capable of reliably recognize banknotes using a camera. The work captured the Hungarian notes by using a cell phone camera. The existing studies based on sensor-based system suffers from less accuracy because involvement of many electrical components and the limitation with the sensor. Therefore, vision-based system was chosen because it is one of the most practical and more accurate medium to take images.

PROPOSED SYSTEM

The proposed work extracts distinct and unique features of Indian currency notes such as central numeral, RBI seal, colour band and identification mark for the visually impaired and employs algorithms optimized for the detection of each specific feature. The proposed technique has been evaluated over a large data set for recognition of Indian banknotes of various denominations and physical conditions including new notes, wrinkled notes and non-uniform illumination. Thorough analysis yields a high true positive rate (desired feature identified correctly) of 95.11% and a low false positive rate (undesired feature recognition minimized) of 0.09765% for emblem recognition, an accuracy of 97.02% for central numeral detection, and 100% accuracies for both recognition of identification mark and colour matching in CIE LAB colour space.

We propose an Indian currency recognition system which extracts the most prominent features of an Indian banknote viz. central numeral representing denomination, the national emblem, Identification mark for the visually impaired and the colour band. Specific algorithms, targeted and optimized to recognize these particular features are then employed for their detection and recognition.

This paper presents a deep learning-based method for identification of denominations of Indian Currency Rupee notes from their color images. A classification framework has been implemented using the concept of transfer learning where a large convolutional neural network pre-trained on millions of natural images is employed for classification of images from new classes. An image dataset of four banknote denominations is prepared by preprocessing and augmentation of real-bank note images acquired in different viewpoints and lighting conditions via smartphone camera. A new top layer upon the convolutional base of a pre-trained MobileNet model is trained for a few epochs upon a portion of the dataset to achieve an agreeable accuracy upon validation subset. With no hassle of feature engineering or extensive preprocessing tasks, the retrained lightweight model achieves an accuracy of 96.6

% on a held out testing subset. Experimental results prove it to be employable for development of dedicated portable systems for identification of banknote denominations.

IMPLEMENTATION

Deep convolutional neural networks (DCNN's)

DCNNs are the machine learning models that can learn high-level features from the low-level ones in a hierarchical fashion [13,14], which is translated by the stacking of operational neural network layers, essentially convolutional layers, one above other. The convolutional architecture of DCNNs is inspired from the visual cortex of animal brain, were neurons are arranged in a way that they produce response to the overlapping regions in their visual field. The CNN was originally applied to document recognition, however, it finds wide applications in several domains, where the data can be represented in two or more dimensional matrices and arrangement of data elements in such matrices carries significance. Hence, CNN's are as well applicable to areas of video recognition, natural language processing, etc.

CNN Architecture

Given a large set of images and their classification labels, a CNN can learn a hypothesis to classify new images into their respective classes. This is done through transforming the image data to the class predictions by passing it through a set of operations dictated by the constituent layers of the network. Figure 1 shows such operations on a single channel (grayscale) image till the class prediction scores, in a typical CNN. The idea is easily extensible to 3-channels (RGB, L*a*b, etc.) images, as is the case used in this work. The key elements of the network are:

Convolutional Layer:

It consists of a set of filters, which are convolved with the image to detect the presence of features dictated by them. Each filter is convolved with image to produce a feature map, which is an array containing convolved output at each pixel. So, in the shown example, each of the 3×3 filters contributes to a feature map of size 32×32, if the zero padding is applied prior to convolving. Each feature map will have positive response values at positions where the feature was found, while negative values or weak response at remaining positions.

Rectified Linear Unit (ReLU):

It aims at normalizing the feature maps by changing every negative valued element to zero and leaving the rest unchanged.Max-pooling Layer: This layer performs max-pooling operation on each feature map to reduce its size to half of both original width and height. Basically, max-pooling operation can be visualized as filtering operation using 2×2 max filter, which outputs the maximum of the 4 values under its field. This makes the features position-invariant to a certain extent as the position information of maximum value in each 2×2 region is simply discarded by keeping only its value in the output feature map.

Fully connected Layer:

Final feature maps are flattened into a single array of feature values. Then, a set of filters is applied on such large feature array. The filters (neurons) are connected fully to their input in the sense that, every feature value in the array contributes to the filter output. The contribution of the feature is dependent on its voting weight, i.e., how much certainty it provides to classify the image in to a particular class. Finally, at the output layer, neuron's output depicts prediction score that the image belongs to the class denoted by the neuron.

Back propagation:

During filtering of the image right up to the output scores, the network needs to decide the optimal values of filter weights as well as voting weights for the correct classification. This is done through the process of back propagation, where the prediction scores are compared with the actual classification answers to find the error. Weights are then adjusted depending upon this error by propagating back through the whole network. These adjustments are made using the technique of gradient descent. For each feature pixel and voting weight, its value is adjusted up and down and the change in error is observed. So, the optimization problem boils down to reach the valley where the error is least, through adjustment of weights. This can be accomplished in several iterations of the back propagation during training

CONCLUSION

A deep learning-based classifier using the concept of transfer learning has been proposed for identification of banknote denominations from their images. The images of banknotes of four different denominations have been acquired under variable conditions in terms of lighting, pose and quality of the notes. The paucity of images for retraining the CNN has been addressed using augmentation technique. The prepared dataset has been used to train a new softmax layer on top of the pre-trained convolution base of fully-sized and fully resolved Mobile Net. The hence trained model exhibits fairly good accuracy of denomination identification upon the testing set.

REFERENCES

[1] Paisios, Nektarios, Alex Rubinsteyn, Vrutti Vyas, and Lakshminarayanan Subramanian. "Recognizing currency bills using a mobile phone: an assistive aid for the visually impaired." 24th annual ACM symposium adjunct on User interface software and technology, ACM, Santa Barbara, California, USA, October 16 - 19, 2011, pp. 19- 20.

[2] Lee JK, Jeon SG, Kim IH. "Distinctive point extraction and recognition algorithm for various kinds of euro banknotes." International Journal of Control, Automation, and Systems, June, 2004, 2(2), pp. 201-206.

[3] Takeda, Fumiaki, Lalita Sakoobunthu, and Hironobu Satou. "Thai banknote recognition using neural network and continues learning by DSP unit." Knowledge-Based Intelligent Information and Engineering Systems, Springer Berlin/Heidelberg, 2003, vol 2773, pp. 1169-1177.

[4] Debnath, Kalyan Kumar, Sultan Uddin Ahmed, Md Shahjahan, and Kazuyuki Murase. "A paper currency recognition system using negatively correlated neural network ensemble." Journal of Multimedia 5, no. 6, January, 2010, pp. 560-567.

[5] Mulmule-Shirkhedkar, Dhanashri, and Ajay R. Dani. "Comparative study of SURF and FREAK descriptor on Indian Rupee Currency notes." 2015 International Conference on Information Processing (ICIP), IEEE, Pune, India, December 16-19, 2015, pp. 784-789.

[6] Olanrewaju, Rashidah Funke, and Fajingbesi Fawwaz Eniola. "Automated Bank Note Identification System for Visually Impaired Subjects in Malaysia." 2016 International Conference on Computer and Communication Engineering (ICCCE), IEEE, Kuala Lumpur, Malaysia, July 26-27, 2016, pp. 115-120.

[7] Dittimi, Tamarafinide V., Ali K. Hmood, and Ching Y. Suen. "Multiclass SVM based gradient feature for banknote recognition." 2017 International Conference on Industrial Technology (ICIT), IEEE, Toronto, ON, Canada, March 22-25, 2017, pp. 1030-1035

[8] Kamal, Snigdha, Simarpreet Singh Chawla, Nidhi Goel, and Balasubramanian Raman. "Feature extraction and identification of Indian currency notes." 2015 Fifth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), IEEE, Patna, India, December 16-19, 2015, pp. 1-4.

[9] Costa, Carlos M., Germano Veiga, and Armando Sousa. "Recognition of Banknotes in Multiple Perspectives Using Selective Feature Matching and Shape Analysis."2016 International Conference on Autonomous Robot Systems and Competitions (ICARSC), IEEE, Braganca, Portugal, May 4-6, 2016, pp. 235-240.

[10] Kitagawa, Ryutaro, Yoshihiko Mochizuki, Satoshi Iizuka, Edgar SimoSerra, Hiroshi Matsuki, Naotake Natori, and Hiroshi Ishikawa. "Banknote portrait detection using convolutional neural network." 2017 Fifteenth IAPR International Conference on Machine Vision Applications (MVA), IEEE, Nagoya, Japan, May 8-12, 2017, pp. 440- 443.

[11] Hahnloser, Richard HR, Rahul Sarpeshkar, Misha A. Mahowald, Rodney J. Douglas, and H.

Sebastian Seung. "Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit." Nature 405, no. 6789, June 22, 2000, pp. 947-951.

[12] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." Nature 521.7553, May 28, 2015, pp. 436-444.