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Counterfeit Currency Recognition Using Deep Learning: A Review

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Abstract. This review article reviews some previous work in the literature about using deep learning techniques for recognizing fake notes from the real notes. A human-visual system can be utilized for identifying and confirming currency-notes. Yet, our eyesight cannot sense everything, and it is frequently hard for humans to recognize genuine currency without using technology assistance. Deep learning methods have been revealed to be more efficient for numerous applications. Consequently, deep learning has been used to enhance currency recognition accuracy. The methods that are used including Classic neural networks, CNN, and GANs for recognizing fake notes.
Keywords: Currency Recognition, Deep Learning, CNN.

1. Introduction

Today, many recognition techniques are implemented to recognize images, recognize faces, recognize car license plates, and recognize human behaviors. Currency is the primary average for circulation, and Various countries' currencies have different qualities. However, when the value of currency grows, there will be an increase in counterfeit currency. Counterfeit money might damage these nations' interests. As a result, one of the hottest subjects and a critical issue at the moment is how to use recognition technology to the genuine of money (Zhang, 2018).

Visual examination was used in the past to identify and genuine money, particularly currency notes. Our eyesight cannot sense everything; sometimes, it is not easy for humans to distinguish genuine currency from auth genuine entice currency without the aid of technology. Although UV-based-recognition With the developing sophistication of counterfeiting systems, a system is still in operation. Moreover, it's getting more impossible to tell the difference between fake and genuine currencies (Zhang, Yan and Kankanhalli, 2019).

From day to day, the progress of automated systems and techniques for currency recognition have improved (Jadhav, Sharma and Bhandari, 2019). Artificial intelligence (AI) has become ingrained in a variety of fields, including civil engineering, medical, and image processing. AI is built on neural networks used for currency recognition and for a variety of different currency related tasks, including detecting currency note-portrait, detecting fake-notes, recognizing currency note-serial-number, and extracting and identification of currency note features(Veeramsetty, Singal and Badal, 2020).

Deep learning techniques, such as multilayer neural-networks, have recognized to be effective in various applications (Zhang, Yan and Kankanhalli, 2019). This review article aims to explain the impact of deep-learning techniques in recognizing the fake currency notes from the real notes. This review presents some related works that support using deep learning techniques for recognizing counterfeit currency in machine learning and image processing. This review article is structured as follows: part two, a background on the topic is given—part three, overviewing the related literature and applied methods. The findings are demonstrated in part four. The last part concludes this review article.

2. Background

2.1 Deep Learning

"Deep Learning is a new area of Machine Learning research, which has been introduced with the objective of moving Machine Learning closer to one of its original goals: Artificial Intelligence" (p.6). Deep Learning explains learning numerous stages of illustration and concept that assist researchers in analyzing data, including images, sounds, and texts (Deng and Yu, 2013).

Deep learning is commonly correlated of a neural network with several layers that could learn from vast amounts of dataset, including a series of labeled images. Furthermore, this has mostly been applied to the area of vision and voice (natural-language-processing). The weights of any layer are learned by backpropagation in the deep learning process. Every layer have different effects on data analysis. Despite its complexity, the method has been effectively extended to a wide range of classification and identification problems (Zhang, Yan and Kankanhalli, 2019).

2.1.1 Deep Learning-Techniques:

1- Classic-Neural-Networks: Multilayer perceptron, where the neurons are associated to the continuous layer, and it is often used to identify Fully Connected Neural Networks. There are 3 functions involved in the presented system:

- Linear-function: Rightly-termed, this illustrates the only line that multiplies the inputs with the continuous multiplier.
- Non Linear-function: This is categorized into three sections.:

A- "Sigmoid Curve: It is a function interpreted as an S-shaped curve with its range from 0 to 1.
B- Hyperbolic tangent (tanh) refers to the S-shaped curve having a range of -1 to 1.
C- Rectified Linear Unit (ReLU): It is a single-point function that returns 0 if the input value is less than the set value and the linear multiple if the input value is greater." (Vadapalli, 2020).

2- Convolutional-Neural-Networks: CNN is a more progressive version of the classic artificial neural-network-model with a lot of potentials. It is designed to handle higher levels of complexity, as well as pre-processing and data-compilation. It is based on the direction in which neurons in a human's visual cortex are arranged.
The CNN is built in four stages after the input data has been introduced in the convolutional system:
Convolution: is a procedure that generates feature maps from the input dataset and then applies a function to these maps.
Max Pooling: It assists C-NN in detecting an image based on the assumed modification.
Flattening: In this stage, the dataset produced is then compressed for a CNN to examine.
Full Connection: This is sometimes defined as a hidden layer that collects the loss function for the system(Veeramsetty, Singal and Badal, 2020).

3- Recurrent-Neural-Networks (RNNs): at the beginning, RNN was developed to aid in the prediction of sequences; for instance, the Long-Short-Term-Memory (LSTM) algorithm is widely recognized for its versatility. These networks are solely based on dataset sequences with variables input lengths (Vadapalli, 2020).

4- Generative-Adversarial-Networks: Using an efficient Generative system for generative counterfeit examples and recognizing original data objects from the generative ones, known as (GANs) (Goodfellow *et al.*, 2020; Ali *et al.*, 2019). In their research,(Ali *et al.*, 2019) used GANs and can tell the difference between fake and real banknotes with the highest level of precision. GAN.s are a type of neural network which works on two elements and is quite interesting. The generative-network is a first, and the discriminator network is the second. After applying GANs to the data-set and then using them for classifying the genuine and counterfeit notes, promising results were obtained. Figure.1 shows the proposed model, in which the Discriminator-Neural-Network (D) was learned using dataset from the training sets (original distribution) and generated-data (after perturbation i.e., added noises from the latent space). During a training procedure of every Discriminator-network and the Generator-Network (G), the loss functions were updated. Following training, the model could correctly categorize genuine and counterfeit currency note with 80% accuracy. Moreover, discriminator portion of GANs served as a classifier in image-recognition. The generator and discriminator, on the other hand, work together in the learning process.

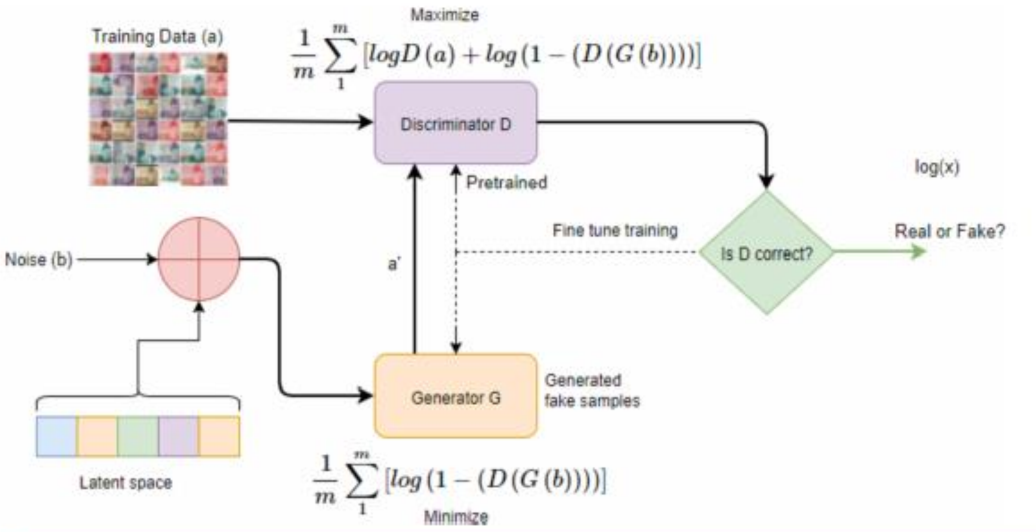

Figure 1 **DeepMoney: proposed counterfeit model.**

The basic idea behind currency note identification was that GANs highlighted two models. The generative model-creates counterfeit banknotes, while the discriminative-model D determines whether the dataset acknowledged from G came from the training dataset or from the generator itself. The priori was discribed in input noise variables Pb-(b) to comprehend the generator's distribution P-g over dataset (a), and after that characterizes a mapping to the banknotes dataset space as G-(b;θg), when G was a discriminable function epitomized by a multilayer perceptron with parameters θg. According to GANs networks, a second multilayer perceptron was also outlined D-(y;θd) that outcomes only scalar. Furthermore, banknotes that originated in the dataset, not the generator, were represented by D(a). The discriminator D was learned on genuine banknotes to improve its chances of suitably identifying the Dataset(a), and the example b was created using the generative-model G. This model G's loss-energy function can be expressed mathematically as:

$$\frac{1}{m}\sum_{1}^{m}[log(1-(D(G(b))))]$$

and the loss function of the Discriminator can be represented as:

$$\frac{1}{m}\sum_{1}^{m}[logD(a)+log(1-(D(G(b))))]$$

2.2 **Single-shot-multibox-detector:** is an extensive figure system in detecting items (Dai *et al.*, 2016). It creates bounding boxes using function maps from various layers. It would build various border boxes based on various classifications; after that, one can find out what the item was. This system can also be utilized in real time detecting, and it has the potential to be quicker than R_C-NN and

Res Net. Furthermore, SSD not only makes sure that detection is quick, but also ensures detection accuracy (Zhang, Yan and Kankanhalli, 2019).

2.3 **Multilayer perception:** this is one of the kinds of neural-network made up of input layer and node that work together to generate one or more hidden and outcomes layers. To calculate the output, a nonlinear function is needed, and the back-propagation-algorithm can be utilized to train MLP's classification and regression. Furthermore, MLPs were feedforward neural network that were made up of numerous layer of nodes connected by a one way link and trained using back-propagation (Zhang, Yan and Kankanhalli, 2019).
Furthermore, an input vector **X** of N dimensions was the basic component of MLP, and the output vector is M-dimensions (Zanaty, 2012). Traditional approaches may be replaced by multilayer perception. Set x is a binary vector; o to be the scalar output; and w to be the weight. The perceptron-algorithm is then demonstrated in Equation (1):

$$\alpha = \sum_j w_j x_j. \qquad \text{Eq.(1)}$$

3. Related Works

A lot of researchers have contributed to the development of currency-recognition techniques in various ways. The previous work in currency recognition techniques is reviewed in this section and showed the main points in Tabel.2.

(Zhang, Yan and Kankanhalli, 2019) used CNN, SSD, and MLP for currency recognition. They chose 5-NZD, 10-NZD, and 20 -NZD as the monetary denominations for their currency-recognition research. They started by videoing each side of these three denominations separately. They attained fifty image samples of individual denomination, for an overall 300 image samples in the data-set, with every particular image having a resolution of 1280x720 pixels. For deep learning, this amount of data is insufficient. As a result, they performed datasets augmentations on the original dataset and generated novel datasets for accomplishing well training. They had a five-step procedure for data augmentation that included zoomings to uniform sizes, random-clip or expand, randomly rotating, zooming to uniform sizes, and adjusting colors randomly. They compare and contrast the experimental approaches and outcomes of two further systems. Even though the recognition time of P-CA+ BPNN using the classifier FNN was 0.4249 seconds, the accuracy was higher. After comparision of F-NN, PRFNN, C-NN, and Ada-Boost, Technique two discovered that F-NN had the highest accuracy. Even if they only achieve 96.6 percent accuracy with CNN, the dataset training is intense, and the detection rate is fast, mentioned in table.1.

Table 1 Comparative results

Name	Model	Accuracy (%)
Method I	CNN	96.6
Method II	PCA + BPNN	99.6
Method III	FNN	92.4

The main goal in (Jadhav, Sharma and Bhandari, 2019) study was to use deep learning to distinguish between fake and real currency notes. The tests were carried out in order to identify fake currency notes from India and Saudi Arabia. The camera was used to capture the images, and then the proposed technique was used for extracting characteristics from the captured photos. Dissimilarity and discontinuity were used to differentiate between genuine and counterfeit currency image. Furthermore, extracted features were used to detect counterfeit money. The comparison degrees of the two notes were used to determine whether a note was fake or genuine. They used a MATLAB tool to automatically recognize counterfeit and real rupees and currency from other countries based on a deep-learning process. Their proposed method is more cost-effective and efficient than the existing one.

(Veeramsetty, Singal and Badal, 2020), in this research, the novel-lightweight-Convolutional-Neural Network (C-NN) system for recognizing Indian currency notes was established for web and cellphone applications efficiently. Moreover, to create the dataset, the total of 4657 images were taken. All acceptable currency notes, such as Old-new 10-rupees note, old- new 20-rupees note, old-new 50-rupees note, old and new 100-rupees note, new 200, 500, and 2000-rupees note, were used. Before providing the photos to the models as inputs, they are all resized to 1024x1024 pixels. The currency note images are augmented with data to increase the data-set size. Zoom, Rotattion-90, Rotattion-270, Tilting, Distortion, and Fliping are the various types of augmentations used. There were 11657 images in the data-set after data augmentation. The CNN in the following are used: one. Input-images, two. Convolution, three. Nonlinearity operations were utilizing ReLU, four. Pooling, five. Flattening, six. Layer's full connection. According to findings, the proposed model outperforms six commonly recognized existing architecture in the area of training and testing accuracies.

(Chowdhury, Jana and Parekh, 2020) proposed a system utilizing image-processing and deep-learning methods to develop an automatic model for recognizing banknotes in India that was independent of orienting the face sides of the banknotes. Moreover, images were gathered from scans of the originals copies that were accessible on the internet as well as by photographing genuine banknotes. For the training set, the system used eighty different images from eight categories, with ten sample for each catagory (this includes both front and opposite sides). Furthermore, The eight denominational classes are – ten rupees, twenty rupees, fifty rupees (old), fifty rupees (new), hundred rupees, two hundred rupees, five hundred rupees, and two thousand rupees. And 34 images for test set. The samples of the notes were being switched to their original horizontal direction after being pre-processed if they were rotated to the position. The denominations were identified in 2 ways: first, extracting color and textures data as a feature for every banknote and classified them by utilizing KNN. The second way was feeding pre-processed samples banknotes in India to the C-NN; simultaneously, all the samples were twisted with a particular kernel, sub-sampled to system feature map, after that classifying them by a dense-layer with softmax-classifier corresponding to mentioned feature maps. The total accuracy of KNN was 91%, while C-NN has a 100% accuracy rate.

(Ali *et al.*, 2019) the machine_ assisted system dubbed DeepMoney was developed to recognize counterfeit banknotes from real banknotes. State of-the-art systems of machine-learning named Generative-Adversarial-Networks were used. Unsupervised learning was utilized by GANs to train a system that could be used to make supervised predictions. Pakistani banknotes were applied to this technique. The total method of the valid input was designed using image-processing and feature-recognition methods. In their experiments, augmented examples of all image examples were utilized, demonstrating that a high accuracy machine could be established to identify real paper-money. Their presented GANs technique for detecting fake currency achieved an accuracy of 80%.

In (Laavanya, M. and Vijayaraghavan, 2019) The features of security-threads money note was extracted to identify counterfeit money. The most widely used Deep-Neural Network method, transfer training with Alex-net, was used to detect fake currency. Using augmentation, 100 images were created for each note. Moreover, for increasing the database counts, augmentation processes such as resizing, and rotating were used. The MATLAB 2018a were used. Transfer trained Alex networks with Adam-optimization were used in the proposed method. The developed network was put to the test with a data-base of 100 samples per money, 50 of which were captured images and 50 of which were augmented-images. The image samples of Indian money 50-rupees, 200-rupees, 500-rupees, and 2000-rupees and genuine banknotes were taken from a database. The average accuracy was equal to 81.5 percent and 75 percent for genuine and fake currencies, correspondingly. The model's overall processing time was three seconds. Thier proposed system outperformed the VGG network by about 26% in terms of accuracy.

(Pachón, Ballesteros and Renza, 2021) introduced a comparison between custom models and models based on transfer learning in the mission of banknote recognition and counterfeit detection. The most suitable freezing-points in C-NN architectures (sequential, residual, and Inception) were known for the transfer learning (TL) strategy. A unique system built on a sequential C-NN of the AlexNet type was proposed. A Colombian banknote dataset was used to train and compare both the TL and custom models.

7280 images, including rotations, partial views of the banknotes, and non-aligned banknotes, were captured and stored (560 images per class). Natural light may enter the system due to environmental conditions. Data augmentation by varying lighting conditions was used to solve this problem. 60% of the data-sets were used for learning, 20% for validating, and 20% for testing. After comparison between the system and the four TL_based models (AlexNet, SqueezeNet, ResNet18, InseptionV3), ResNet18 had the highest accuracy, with a score of 100 percent. The proposed custom network had the shortest inference times, with performance up to 6.48 times quicker in C-P-U and 16.29 times quicker in G-P-U than the inference time with transfer learning systems.

In (Pham *et al.*, 2020), this research aimed to recognize fake banknotes that made by re-production with general purpose imaging equipment for human with vision disabilities. They suggested a method that used CNN for detecting fake banknotes using banknote samples taken by cellphone cameras in noticeable light. Experiments on a self collected data-set of USD, Euro€, Korean-won₩, and Jordanian-dinarJOD banknotes revealed that their system outperforms state-of-the-art methods in the use of fake recognition.

In (Navya Krishna *et al.*, 2019) Automatic Fake Currency Recognition System (AFCRS) was created with CNN and the VGG 16 architecture to detect counterfeit paper currency and determine if it was genuine. They used Keras deep learning library in python to made their CNN. After fitted model, the screenshots were captured in their experimented method, AFCRS. The difference between a fake and an original currency note was clearly noticeable. As a result, it was advisable to use it as a smartphone application. application that was merely beneficial to society.

(Hoang and Vo, 2019) presented a method for recognition of paper currency based fundamental image processing using deep-learning for feature-extraction and recognition. Furthermore, image set such as 10000, 20000, 50000, 100000, 200000, 500000 Vietnamese dong and some other national currencies like dollars and euro were used and set of images taken from a counterfeit banknote that was made with a different material than the original banknote's paper. There was a total of 9,736 real banknote samples and 1,083 fake banknote samples, all of which were standardized to a similar resolution of 200x450 pixel. They used deep CNN for both feature extraction and recognition and SVM for classification. In place of face value recognition and counterfeit detection, the CNN model was used to extract features. Using the SVM technique, the color sample was divided into classes based on face value and national currency. This method was discovered to be useful in real-life applications, with a 99.97% accuracy rate.

(Sakazawa *et al.*, 2019) proposed applying a watermark to the learned D-NN model to secure their copyrights. In their paper presented a cumulative and visual watermark decoder and demonstrated that this performs in all cases. In the case of the MNIST water-mark input image samples, twenty image samples were chosen from a total of 60,000 to decode the watermark. At the twentieth sample in the term of MNIST, the decoded patterns were sufficiently obvious. Lum-[0][1], Lum-[2][0], Lum-[2][2] of#20 have identical pixels value in Cifar+WM, but if a meaningful pattern was embedded, it could be visually identifiable. Higher contrast was reached with lower accuracy. It means that embedding a strong watermark devalues the host DNN model's original mission. After comparing MNIST performed better (greater accuracy at the same contrast) than the other tests. It was because MNIST image samples for embedding had totally diverse characteristics from Cifar-10 dataset for initial learning. Cifar+WM images, on the other side, share a lot of similar features with Cifar10 data. As a result, watermark embedding input images could be of a different kind than the host-model training dataset.

In (Tajane *et al.*, 2018) paper, they presented the DeepLearning method to recognize and detect Indian-coins. Their proposed system was divided into two phases, the first of which was the software application of the work using MATLAB, then the second of which was the use of a Raspberry-Pi as a controlling board to control the system's operation. The project's hardware implementation began with capturing a photo of the implanted coin, which was after that processed by using the Raspberry Pi controller. The system was learned on over 1600 image samples and could differentiate between four types of items, including 1, 2, 5, and 10 rupee-coins. Thier trained system was put to the test on a variety of normal and own documented data-sets that include rotational, interpreted, and shifted image samples. They trained AlexNet to be able to recognize different coins in the first phase, and then they placed the 1-rupee coin in the face of the camera, and the learned network correctly recognized the coin as 1 rupee and 2 rupees.

AlexNet was trained and tested on a dataset of five- and ten-rupee coins. Recognition accuracy and response time were used to calibrate the output system. The obtained results presented method exceed traditional systems.

(Kamble *et al.*, 2019) created a Deep CNN model that identifies counterfeit notes without manually extracting image features. The model learns from the created dataset and can detect a counterfeit note by training it on it. They used 40,000 images as a dataset, 32,000 image samples for training, and 8,000 image samples for testing. Moreover, the median_blur filter was used to pre-process the images for training. The model's architecture consisted of five convolution-layers, a flatten-layer, and four fully connected-layers. Furthermore, training dataset is subdivided once more into 30 000 image samples for training and 2 000 image samples for cross validation. The system was learned, and the training and cross-validations accuracy was determined based on the built architecture. After that, of image in the testing data set was preprocessed (using the median-blur filter). The accuracy of the testing was around 85.6 percent. Thus, the training and validation accuracy was 98.57 percent and 96.55 percent.

Table.2. Summarizing the main points of the literature review.

Authors	**Aim**	**Method**	**Data-set**	**Result**	**Limitation**	**Year**
(Zhang, Yan and Kankanhalli, 2019)	They gave a thorough overview of currency recognition.	used Convolutional Neural Networks (CNN), Single shot multibox detector (SSD), and Multilayer perception (MLP) for currency recognition	5 NZD, 10 NZD, and 20 NZD. Total of 300 images.	They compare and contrast the experimental methods and outcomes of two other methods. Although the recognition time of PCA+ BPNN using the classifier F-NN was 0.4249 seconds, the accuracy was higher. After the comparisons of FNN, PRFNN, C-NN, and AdaBoost, Technique II discovered that FNN had the highest accuracy. Even if they only achieve 96.6 percent accuracy with CNN, The dataset is well-trained, the detecting speed was fast.	Their system just work for NZD denomination currency recognition.	2019
(Jadhav, Sharma and Bhandari, 2019)	used deep learning to distinguish between fake and real currency notes.	used bank notes from different countries by extracting and analyzing their features in	to identify fake currency notes from India and Saudi Arabia.	The proposed system was more profitable and effective in comparison to the current system.	Extracting security features of currency is not considered.	2019

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		detail using deep learning				
(Veeramsetty, Singal and Badal, 2020)	a novel lightweight Convolutional Neural Network (CNN) model for recognizing Indian currency notes was developed for efficient web and mobile applications.	A lightweight three layers CNN	Old-new 10-rupees note, old-new 20-rupees note, old-new 50-rupees note, old and new 100-rupees note, new 200, 500, and 2000-rupees note. There were 11657 photos in all. The model was trained with 9326 images and validated with 2331 images.	Their developed model, which was trained with an image size of 1024x1024, a batch-size of 16, the learning degree 0.0001, had a 100% accuracy; also the testing-accuracy is 87.5 percent.	The drawbacks of their research is their system cannot identify counterfeit currency notes.	2020
(Chowdhury, Jana and Parekh, 2020)	Utilizing methods including image-processing and deep-learning, build an integrated method for recognizing Indian banknotes.	CNN, KNN employed on the extracted techniques. Classifier. G-LCM is utilized for color, feature extraction.	The eight denominational classes are – ten rupees, 20 rupees, fifty rupees (old), fifity rupees (new), hundred rupees, two hundred rupees, five hundred rupees, and two thousand rupees.	The total accuracy of KNN was 91%, while C-NN had a 100% accuracy rate.	Each of the rotated photos were shot in the equal backdrop, and the rotating at 180 was ignored	2020
(Ali *et al.*, 2019)	They used a machine-assisted device called DeepMoney to solve the problems of classifying currency notes as	Generative Adversarial Networks (GANs)	Photos of rupees. 50 rupees. 500, and rupees. 1000 were used in the dataset.	GANs framework for counterfeit money detection achieved an accuracy of 80%.	Their system just work with Pakistani banknotes.	2019

	counterfeit or real.					
(Laavanya, M. and Vijayaraghavan, 2019)	The characteristics of security-threads currency note was extracted to identify fake currency.	Transferring learned Alex-networks with adam-optimization	100 images per currency, 50 of which were captured images and 50 of which were augmented images. The images of Indian money 50-rupees, 200-rupees, 500-rupees, and 2000-rupees genuine banknotes were used.	For genuine currency and faking, the average accuracy were 81.5 percent , 75 percent	Extracting security features of currency is not considered .	2019
(Pachón, Ballesteros and Renza, 2021)	comparison between custom models and models based on transfer learning in the mission of banknote recognition and counterfeit detection.	custom model based on a sequential CNN of the AlexNet type	7280 images of a Colombian banknotes.	The proposed custom network had the shortest inference times, with performance more than 6.48 times quicker in C-P-U, 16.29 times quicker in GPU than the inference time with transmission learning systems.	The biggest drawback of a custom model is the length of time it takes to train it, as well as the need for a sufficiently diverse dataset to allow for generalization during training.	2021
(Pham *et al.*, 2020)	recognize fake banknotes that made by reproducing with general purpose imaging devices for human with visual	CNN	self-collected data-set of USD, Euro€, Korean-won₩, and Jordanian-dinarJOD banknotes.	Their system overachieve state of the art techniques in the course of fake detection.	Their system for detecting and localizing banknotes using photographs taken by mobile cameras and combining false detection	2020

	impairment.				and denomination labeling does not perform well.	
(Navya Krishna *et al.*, 2019)	to detect counterfeit paper currency and determine if it was genuine.	CNN and the VGG 16 architecture	The images were gathered from a variety of Google sources as well as the Churan labeled Children's Bank of India. Initial notes and false notes are divided into two categories in this data collection.	The method of detection a fake note was fast and simple under the trained model.	The data collection was limited and did not represent the real-world situation of counterfeit currencies.	2019
(Hoang and Vo, 2019)	recognition of paper currency	deep CNN for both feature extraction and recognition and SVM for classification.	10k, 20k, 50k, 100k, 200k, 500k VND and some other national currencies like dollars and euro. There was a total of 9,736 real banknote samples and 1,083 fake banknote samples	This method was discovered to be useful in real-life applications, with a 99.97% accuracy rate.	High computational cost and More national currencies and face values were not taken into consideration when applying for the real-time banknote inspection scheme.	2018
(Sakazawa *et al.*, 2019)	To secure the copyright, watermarking is applied to trained DNN models.	1:integrating cumulative- and visual watermark decoding from D-NN systems,	In M-N-I-S-T watermark input data, the watermark was decoded using 20 images out of 60,000.	The initial task's precision was 0.752 with the MINST case and 0.725 with Cifar-WM, respectively.	Their method is unable to handle broader watermark patterns, such as company logos and T-Ms, due	2019

		2: Enabling third party identification by including a subclass of the massive decoding dataset			to a limitation of class size.	
(Tajane *et al.*, 2018)	recognizing and detecting Indian coins.	Deep learning approaches.	1600 images could differentiate between 4 item types, including 1, 2, 5, and 10 ₹ coins.	The obtained results confirmed that the presented method exceed traditional systems.	In real-time embedded systems, no algorithms were used.	2018
(Kamble *et al.*, 2019)	counterfeit notes recognition.	Deep CNN	500 rupees real and fake, 2000 rupees real and fake. 40,000 images as a data-set, 32,000 image-samples samples for learning and 8,000 image samples for testing, and 2000 for crossvalidation.	The accuracy of the testing was around 85.6 percent. The training outcome was 98.57 percent, and the validation accuracy was 96.55 percent.	Since their data set was small, the model was unable to learn and improve.	2019

4. Discussion

After studying all the reviewed articles, we came to understand the following points. First of all, most of the articles chose to use CNN to recognize currency notes after comparing with other previous works because it can get more accuracy. However, some of the articles used GANs for the same reason.

The use of CNN has several advantages, including, such as, CNN is well-known for its architecture, and the best part is that no feature extraction is needed. The main advantage of C-NN over its predecessor is that it can identify crucial feature without requiring people interaction.

Some drawbacks of CNN are, Images in different positions are classified; because of operations like max pool, a Convolutional neural network is substantially slower, If the CNN has many layers, the training phase can take a long time, if the machine does not have a powerful GPU and a CNN needs a big Data-set to process and train the neural network.

5. Conclusion

After reviewing the above articles, we understood that deep learning techniques are crucial to currency note recognition. Based on deep learning literature review, most of the researchers using Convolutional Neural Networks for recognizing fake notes from the real notes. This technique can get more accuracy after comparing this technique with other previous works.

Future researchers should build a system that can be used for currency recognition for all countries around the world because some of the models identify few different currencies. On the other hand, some of the current models cannot identify fake money. Furthermore, the researchers should create an application model for cellphones and web-application to recognize fake and real money, especially for people with visual disabilities. Finally, the researchers should crucially work on extracting security thread features.

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